Long-Term Determinants of Agricultural Output in Smallholder Farmers in Rwanda

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Abstract

This paper analyses the household level drivers of agricultural output in Nyabihu District, a densely populated area of rural Rwanda, over the past 26 years. We use a unique two-wave panel dataset spanning a 26-year period, linking the split-off households in 2012 to the original households in 1986. The findings identify the relative importance of labor, land, and capital for output growth in the study area. Over the studied period, the agricultural output has been characterized by decreasing elasticities of land and capital; whereas the elasticity of labor has grown three-fold. The findings also suggest a substantial impact of mobile phone technology adoption by farm households. Using propensity score matching, we find that agricultural output for mobile phone users is at least 38 percent higher than non-users.

Key words: long-term determinants, Cobb-Douglas function, agricultural output, ICT adoption, smallholder farmers, Rwanda, Africa

1. INTRODUCTION

Agricultural growth has long been recognized as an engine for economic growth and poverty reduction in developing countries (Byerlee, Diao, & Jackson, 2005; Headey, Rao, & Alauddin, 2005). Agriculture is also the backbone of the economy in Rwanda, being the second biggest contributor to the Gross Domestic Product (31 percent in 2010/2011), after the service sector. Moreover, the agriculture remains the main employer, especially of the poorer, smallholding farmers, and less educated segments of the population. More than 87 percent of the population in Rwanda derive their livelihoods from crop production in, usually, fragmented small plots on erosion-prone hills (MINAGRI, 2009). The real agriculture growth averaged at 4.9 percent between 2006 and 2010. It attained a record 7.7 percent in 2009, but slowed to 4.6 percent in 2010 (Hansl, Niyibizi, Ronchi, & Mwumvaneza, 2011).

The vision of Rwanda is to transform itself from a subsistence agricultural to knowledge-based economy by 2020 (MINECOFIN, 2000). The achievement of this vision will require an intensification and market-orientation of agriculture, on the one hand, and a diversification of the economy through a proliferation of non-agricultural sectors on the other hand (Hansl et al., 2011).This requires substantial increases in agricultural factor productivity (MINAGRI, 2005).

Therefore, there is a need for an empirical approach to understand the sources and determinants of agricultural growth over time in Rwanda, especially for smallholder farmers who constitute a large segment of the population, and for whom agriculture is the main source of income. Existing literature on agricultural research in Rwanda by Diao, Fan, Kanyarukiga, and Yu (2010) Donovan, Mypisi, and Loveridge (2002), McKay and Loveridge (2005), Clay et al. (1996) and von Braun, de Haen, and Blanken (1991) do not capture the farm productivity in the long run because they had used single-year data in their analyses. Thus, the research question on the drivers of agricultural growth in Rwanda remains so far unanswered.

Therefore, this study contributes to the existing literature by assessing the drivers of agricultural growth over time among smallholder farmers in rural Rwanda. First, the Cobb-Douglass production function is estimated, using a unique dataset that spans a 26 year-period, originating from two detailed household surveys conducted in 1986 and 2012, respectively. Second, the impact of information and communication technology (ICT) on agricultural growth and household welfare is assessed using the propensity score matching technique.

The rest of the paper is organized in two parts. The first is about the determinants of agricultural growth over the past 26 years in Rwanda, and the second presents the impacts of mobile phone adoption on agricultural growth in the country.

2. THE DETERMINANTS OF AGRICULTURAL GROWTH

2.1. Theoretical basis and literature review

Since the seminal work of Cobb and Douglas (1928), the concept of "production function" has undergone a long debate among economists. The first attempt of a common definition is attributed to the school of early marginalists and neoclassical economists who found the production function to be a purely technical relationship that is void of economic content (Chambers, 1988). As the fundamental concern of economists is to study economic phenomena, the technical aspects of production are also interesting because they impact upon the economic agents' behavior. Originally, it is assumed that there is a relationship between inputs and output that can be represented in a mathematical equation, $y = f(x)$, separating output and inputs (Chambers, 1988). This means that, a single output level is obtained by a unique combination of inputs x, where the economic agent is supposed to choose among different output levels, and select the highest level. Therefore, a production function represents the maximum output that can be achieved using an arbitrary input vector $x = (x_1, \dots, x_n)$, and it is used by economists to carry out different sensitivity analyses, and to compute measures of technical efficiency (Hackman, 2008). It is also defined as the amount of output that can be produced with a given amount of inputs, through the use of a given production technology (Rasmussen, 2011).

The theory of agricultural growth, considered as an engine for overall growth for developing countries (Tiffin & Irz, 2006), has dominated growth literature over the past half century. Schultz (1944) has pointed out the conditions necessary for economic progress in agriculture. He argued that the policy should minimize the excess of labor in agriculture by labor saving technology that is introduced into farming, and increase the rate of expansion of labor force in non-agricultural industries. Traditionally, the use of capital and other intermediate inputs in agriculture is thought to be very limited and the volume of agricultural output is mostly determined by land and labor (Cornia, 1985). Over time, agriculture has become more input intensive but the evolution of input shares depends on the degree of technical substitution between land, labor and capital. Labor and capital are substitutable in long run, but mechanization is very limited in rural areas (Cornia, 1985). This has been the cause of high output elasticities of land obtained from production function estimation in Asian countries in the 70s (Lau & Yotopoulos, 1971; ÍOkawa, 1972) with the former's tendency to decrease over time in favor of labor and capital elasticities.

Recent literature has associated the long-term agricultural growth with the growth in productivity which is induced itself by investment in research, extension, human capital, and infrastructure, and emphasized on the magnitude and contribution of total factor productivity of growth (TFP) to total output growth (Rosegrant & Evenson, 1995). Deininger and Okidi (1999) estimated a production function for Uganda and found that farm size, the use of seeds and fertilizers are important factors of agricultural output growth in Uganda. Besides, households' characteristics such as head age, head sex, education level, and farmer's experience were found to be relevant to agricultural productivity. Tripathi and Prasad (2009) used the Cobb-Douglas Production function and time series data from India found that land is the most important source of agricultural growth and that Indian agriculture is characterized by increasing returns to scale. Similar model relating output to inputs (land, labor, fertilizers) and other conditioners such as land quality and household characteristics was used by Clay (1996) when studying the determinants of farm productivity in Rwanda using cross sectional data. He found that land size and labor have positive and significant effects, while farmer age has significant negative effect on the agricultural output value. von Braun et al. (1991) identified the substantial role of farm size for crop production in a land scarce environment. Using cross sectional data from rural Rwanda, they found that the production elasticity of land was higher than the production elasticities of labor and capital.

Factors of agricultural growth include the effects of population growth (Boserup, 1965, 1981) and other factors affecting agricultural intensification, including changes in market prices, technology (whether or not induced by population growth). While numerous studies have shown a positive relationship between population growth and environmental degradation (Cropper & Griffiths, 1994; Hohm, 2002; Pat-Mbano, 2012), there are also many examples showing that high population growth and densities may be consistent with sustainable agricultural practices (Pender, 1998). They may result from technical change or technical progress through the invention of new techniques of cultivation (Boserup, 1981).

2.2. Conceptual Model

In their production and consumption activities, farm households respond to price incentives, changes in technology, and factor prices. According to Sadoulet and De Janvry (1995), two elements determine the producer's response: the technological relation between any combination of factor inputs and the level of output, and the producer behavior on the choice of alternative inputs, given the level of market prices and input availability. Therefore, the farmer is expected to define the production functions which will allow him to gain the maximum profit at minimum costs, given the economic environment in which she operates. The farm producer is expected to choose the combination of variable inputs and output that will maximize profit subject the technology constraints (Sadoulet & De Janvry, 1995). Assume the production function of a farm is given by:

$$h(q,x,z) = 0 \tag{1}$$

where q is the vector of output quantities, x is a vector of variable inputs such as labor, fertilizers, pesticides, seeds and others, and z is vector of fixed inputs such as land, and equipment. The objective of farm producer is stated as:

$$Max\ p'q - w'x, \text{ Subject to } h(q,x,z) = 0 \tag{2}$$

The solution to this maximization problem is a set of input demand and output supply function that can be written as:

$x = x(p, w, z)$ and $q = q(p, w, z)$ (3)

Hence,

$$\pi = p'q(p, w, z) - w'x(p, w, z) = \pi(p, w, z) \quad (4)$$

This indicates that, there is a one-to-one correspondence between the production function and the profit function. The farm producer determine the level of production having in mind the profit maximization problem, which also guide the choice of the nature, and the quantities of factors to be used in the production process.

Alternatively, the household is assumed to maximize utility derived from the consumption of an agricultural commodity and leisure subject to production, family labor and cash constraints. Following Baibagysh (2010); Kuiper (2005); Singh, Squire, and Strauss (1986); Taylor and Adelman (2003), the basic mathematical model for agricultural household model can be postulated as follows:

$$\max_{C_a, C_l, L_f, L_h} u(C_a, C_l) \quad (5)$$

Subject to,

$$Q_a = f(L_f, L_h, \bar{q}) \quad (6)$$

$$L_f + L_0 + C_l = \bar{T} \quad (7)$$

$$pQ_a + wL_0 = pC_a + wL_h \quad (8)$$

Where u is utility is function; C_a represents a food crop produced by the household; C_l stands for leisure; L_f is family labor; L_h is hired labor; the household may also work off farm (L_0) but the total labor use cannot exceed the family time endowment ($\bar{T}$). $\bar{q}$ is fixed input p is the price of food crop; and w is wage rate. The third constraint on utility maximization is the cash constraint because it is assumed that goods can only be bought if money is earned from production sales and off-farm work. If the production and time constraints are substituted into the cash constraint, the full income constraint is obtained, and household model is rewritten as:

$\max_{C_a, C_l, L_f, L_h} u(C_a, C_l)$

Subject to,

$$p(f(L_f, L_h, \bar{q})) - C_a = wL_h - (\bar{T} - L_f - C_l) \quad (9)$$

Then, the maximization of utility function subject to the full income constraint provides output level, input demand (seeds, fertilizers, labor and capital), and the household consumption level(Deininger & Okidi, 1999). These results may vary according to the market conditions.

2.3. Empirical Strategy

On practical point of view, there is no standard mathematical form to express a production function; different forms are used in various applications to describe production (Rasmussen, 2011). The most famous functional form of production function used in many applications is the Cobb-Douglas function that satisfies a large number of properties; and is also used in this study. The basic relationships will be evaluated using the cross section OLS regressions for the periods 1986 and 2012.

$$\ln Output = \ln A_i + \beta_1 \ln Land_i + \beta_2 \ln Labor_i + \beta_3 \ln Capital_i + \varepsilon_i \quad (10)$$

However, deriving conclusions from the above standard specification is problematic. von Braun et al. (1991) pointed out that some unobserved variables may affect both inputs and output levels. These may be household or location specific and need to be kept in mind while interpreting estimates from equation 10. Even if we have controlled for education level of the head (as proxy of farmer’s ability), and the land quality; a number of latent variables might not have been measured and their effect is not possible to capture with a cross section estimation.

To tackle this issue, the new panel model is specified in the second step and the will be estimated by fixed effects:

$$\ln Y_{it} = \ln A_{it} + \beta_1 \ln L_{it} + \beta_2 \ln M_{it} + \beta_3 \ln K_{it} + \alpha_i + \varepsilon_{it} \ ; \ \ i = 1,2, \dots n \ \ ; t = 1, .. T \quad (11)$$

Where A_{it} is an index that measures the household’s total factor productivity, Y_{it} is the household agricultural output value, L_{it} is the household’s farm endowment, M_{it} is the total household labor, K_{it} is agricultural capital endowment, α_i is the household specific fixed effect, and ε_{it} is an idiosyncratic error term. The β_i's are technology parameters to be estimated (elasticities of production) and are assumed to be constant across households. It is assumed that the total factor productivity index A_i of farm household is affected by education, farmer's experience, wealth, and other household and community characteristics (Deininger & Okidi, 1999) which need to be controlled for.

2.4. Methodology and data

The study was conducted in five selected sectors which belong to the former *commune* of Giciye[1] which was selected during the study on commercialization of agriculture under population pressure (von Braun et al., 1991) because of its high altitude, high population, level of agricultural commercialization, and proximity to Gishwati forest which constituted in that time a major source of agricultural commercialization. The five sectors under study are Jomba, Muringa, Rambura, Rurembo, and Shyira. They are currently collated in Nyabihu district. Today, the sample area is inhabited by 39 percent of the district population. Agriculture is still a major source of livelihoods, and almost half of agricultural land (49.32 percent) is located in these five sectors. The localization map is indicated in figure 1.

The dataset used in this study come from a two wave panel that spans a 26-year period. The first household survey has been conducted by the International Food Policy Research Institute (IFPRI) during the above-mentioned study. It targeted 190 households randomly selected across five sectors. A structured questionnaire was used to collect relevant information on household demographics, household expenditures, health and nutrition, agricultural production, crop use information, and others. The second wave of data come from a revisit to the same area in 2011-2012 and was supervised by the author. The activities consisted of retracing and re-surveying the same households as surveyed in 1986, and their split-off households. With a group of trained research assistants, and key informants from the area, 164 out of 190 original households (that is 86 percent) have been retraced and re-surveyed, together with their 200 split-off households

[1] After 1994, the local administrative units in Rwanda have been modified and given new names for Districts (former communes) and Sectors (District sub-units). In this study current names are being used and the old are recalled where necessary.

(offspring) who still reside in the district and its neighborhood. Only 14 percent of original households could not be retraced.

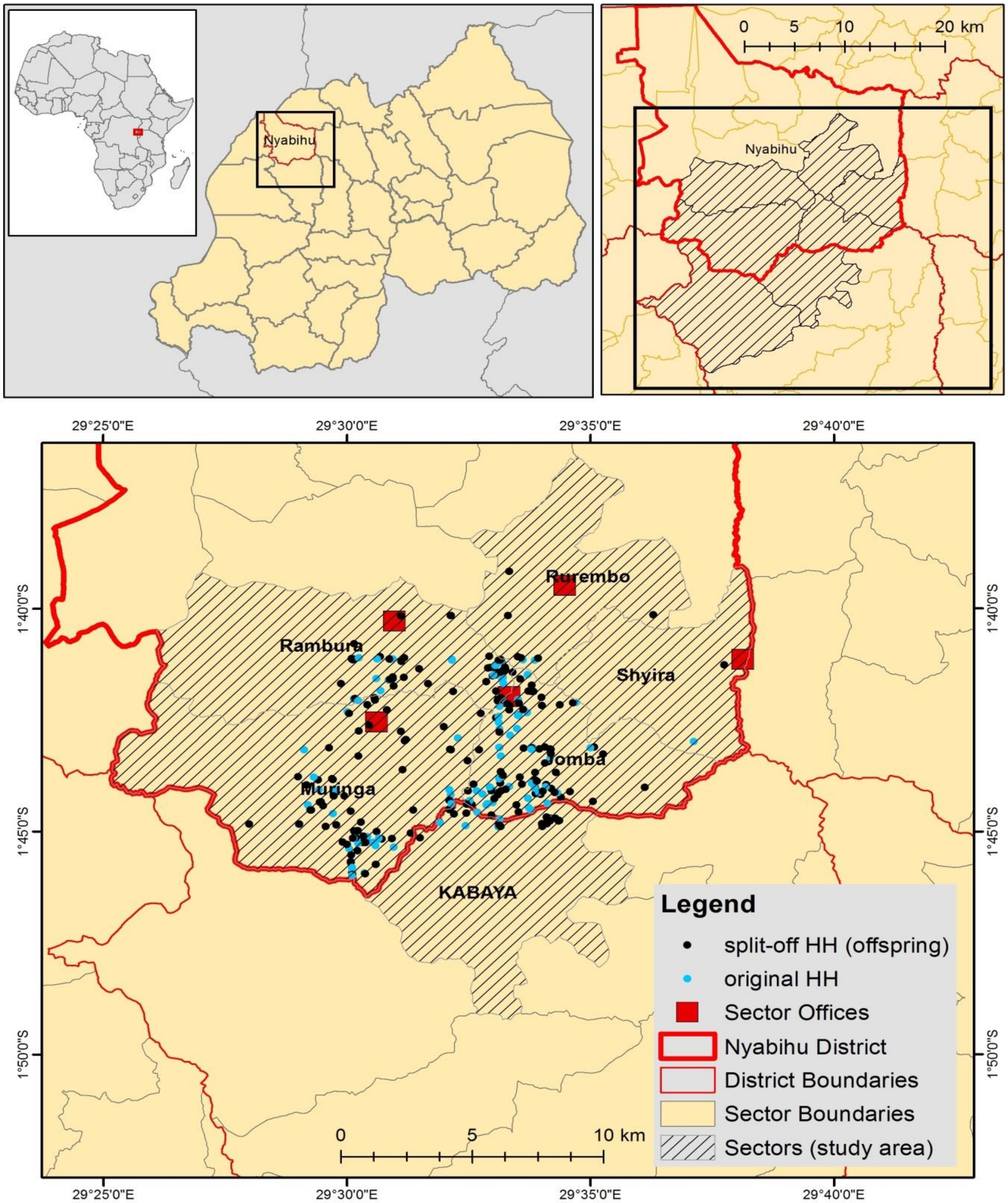

Figure 1. Map of the study area identifying the surveyed households

Source: Author's conception

The annual attrition rate of 0.6[2] percent is far below the attrition rates reviewed by Alderman, Behrman, Kohler, Maluccio, and Watkins (2001) among developing countries household survey and approved not to be a problem to obtaining consistent estimates. To check the possible impact of panel attrition on our results, we conducted the Becketti-Gould-Lillard-Welch (BGLW) by Becketti, Gould, Lillard, and Welch (1988). The test has been used by researchers to assess panel attrition impact on the different household surveys in USA and other developing countries (Alderman et al., 2001; Duncan & Hill, 1989; Fitzgerald, Gottschalk, & Moffitt, 1998). The rationale of the BGLW test is to compare the total sample and the "stayers" sample in order to assess how different parameter estimates would be from those in total sample if only "stayers" sample is used in analysis (Fitzgerald, Gottschalk et al. 1998). We found non-significant difference among the output regression coefficients from original sample and non-attriting sample (results available in Appendix 1). This is a good indicator that, if only the non attriting sample is used for the panel data analysis, there is no evidence that unbiased and inconsistent estimates will be obtained (Alderman et al., 2001; Becketti et al., 1988; Duncan & Hill, 1989; Fitzgerald et al., 1998), especially when the interest is to estimate the production function.

The unique feature of this study dataset is that it followed both the original and split-off households during the second wave. This allows us to construct an extended family data set and use for the current wave and use extend family as unit of analysis in panel regressions.

Table 1. Number of original and split-off households

	1986	2012
Household interviewed	190	364
Original household interviewd	190	164
Split-off household interviewed	-	200

Source: Household surveys, 1986&2012

The motivation of this procedure comes from a current debate on how much the economic decisions are made at the levels of families or extended dynasties. Cox and Fafchamps (2007) argued that, due to several reasons including the lack of safety nets in developing countries,

[2] Annual attrition rate=1-(1-q)$^{1/T}$ where q is the overall attrition rate, and T is the number of years covered by the panel (Alderman et.al., 2001)

households may rely on parents, friends, and other relatives for their livelihoods and their survivals. This social arrangement may also originate from the absence of financial and insurance markets in rural areas. Therefore, extended families play a key role in risk sharing by pooling their income and other resources to support their relatives, especially in agriculture-dependent societies where production and income variations are very frequent. If this is the case, it would be inappropriate to drop split-off households and base the analyses only on original households' panel. Witoelar (2013) suggested that researchers should consider extended families as unit of analysis while analyzing consumption growth and decisions. Even though the extended family does not fully act as unitary household, some important allocations are made at extended family level. Consequently, while analyzing changes in households' production, income, and consumption over time, using a panel of extended families is preferable to using a panel of original households only. In this view, our study links the split-off households (offspring) to their original parent households and takes advantage of this featured dataset to assess the determinants of long-term growth in agricultural production in the rural Rwanda.

2.5. Results and Discussion

2.5.1. Agricultural system in the study area

Agriculture is the backbone of subsistence in the area under study. The land is the major factor of agricultural production, and the major source of access to land is through inheritances (64 percent), followed by purchasing land (33 percent). The remaining three percent of land are obtained through gifts, free land, or rented out lands. The land ownership has registered a slight increase over time, from 0.76 hectares of land per household in 1986 to 0.95 hectares in 2012 on average per extended family. However, the number of households multiplied three-fold between two periods, and the sample population increased by 88 percent. The land scarcity is also attributed to the loss of land in Gishwati forest which was previously used for crop production, but inaccessible today due to conservation measures. Besides, the area has been exposed to severe soil erosion making land unsuitable for agricultural production. Table 2 summarizes, for each survey and by farm size quartiles, the land ownership among the sample households. Agriculture is mainly subsistence-oriented and, the application of modern inputs, chemical fertilizers by households has recently increased. It was previously used only in big agricultural development projects and tea plantations.

Table 2. Household size and land holdings and age of the household 1986/2012

Farm size group	Average Total Land		Average Person per Family		Average Age of Household Head	
	1986	2012	1986	2012	1986	2012
Bottom Quartile	0.19	0.17	6.2	7.4	41.99	47.29
Second Quartile	0.48	0.46	7.5	10.3	42.94	47.09
Third Quartile	0.85	0.84	9	12.8	46.10	45.75
Top Quartile	1.98	2.08	13	16	46.65	45.60
Average	0.76	0.95	5.7	11.7	42.37	46.40

Source: Author calculation based on survey data, 2013

Table 3 represents the transition matrix of land ownership between 1986 and 2012; the figures are the percentage of households. Among 100 households who were in the second quartile of land in 1986 for example, 33.3 percent lost a large part of their land over the past 25 years and found themselves in the first quartile of the landless or the families with less than 0.1 hectare of land. Of 100 households in the third quartile of land holding before, about 30 percent lost portions of their land to end up in the first (20 percent) and second (10 percent) quartiles. More than 60 percent of the top landowners in the first 1986 survey are also found among the smallholders, and only 37 percent are still in the top quartile of land in 2012. The transition matrix indicates a very high immobility of land holding across generations, and the share of land loss is higher than the share of land acquisition by households and extended families between the two periods of study.

The existing farming system in the study area is still based on small holder agriculture with a family labor as a major source of total labor input. Through the intercrop system is highly practiced. The major crops grown in the area include maize, sorghum, sweet potatoes, Irish potatoes, climbing and bush beans, wheat, peas, and a variety of vegetables. Many households also grow perennials such as banana trees (and/or plantains), while coffee and tea are nowadays not frequently grown on the household plots.

Table 3 Transition matrix of land holdings (percentage of households)

Quartiles of land/ Year		Percent, 2012				Total 1986
		Bottom	Second	Third	Top	
Percent, 1986	Bottom	44.4	30.6	13.9	11.1	100
	Second	33.3	23.5	21.6	21.6	100
	Third	20.0	10.0	22.0	48.0	100
	Top	14.8	14.8	33.3	37.0	100

Source: Author's calculation

Alongside with the mineral fertilizers introduced by the government through the extension services, land fertilization is facilitated by the presence of livestock within household farms. Most households rear livestock such as cows, goats, sheep and pigs. Between the two surveys, there has been a big decrease in the average number of goats and sheep per household. The average number of goats was 1.8 in 1986 (kept by 62 percent of households), but it has fallen to 1.7 goats per extended family in 2012 (kept by only by 45 percent of the sample extended families). The number of sheep averaged at 1 in the first survey (animals kept by 45 percent of the households), and rose to 1.5 sheep by household, kept by 42 percent of families. However, the decline in goats and sheep keeping observed in the area has been compensated by a considerable increase in the number of cattle which rose from 0.7 cows per household (cows only kept by 19 percent of the sample households) to the average of 3 cows per extended family, kept by 76 percent of the extended families in 2012. This was enhanced by the recent "*Girinka* Program", a Rwandan President's initiative to give one cow per poor family in order to eradicate food insecurity and poverty in rural areas of Rwanda (Kim, Tiessen, Beeche, Mukankurunziza, & Kamatari, 2012). The program targets more than 700 thousand poor households by 2035.

6.2 Regression results

The inclusion of profit maximization objective and the long term expectations related to crop and labor markets in the production decision make the production relationship in the rural agricultural system very complex. According to von Braun et al. (1991), it is not very easy to capture the interactions between agricultural system, especially the complementarity between capital, labor and land as the major factors of production and how they relate to aggregate output, using crop-specific analysis. An attempt is made to compare the cross sectional results from a Cobb-Douglass production function and, thereafter a remedy to the above mentioned constraint is attempted through panel data analysis.

Table 4 shows the mean statistics per year. The 1986 values are the average per original nuclear household, while the 2012 values represent the average per extended families. The statistics show that the levels agricultural output and the two factor inputs (farm size and capital) are significantly lower in 1986 compared to the current year. As showed in the previous sections, the family demand for labor decreased significantly over the past two and a half decades.

The dependent variable (gross output value) is calculated as total market value of all crops produced within a household, evaluated at constant prices (1986). The same evaluation also applies to the capital stock. It is the market value of all agricultural tools and equipment. Farm size (land) is evaluated in hectares while labor is captured by the number of person-days used in agriculture within a year. The land quality variable comes from a subjective judgment of farmers on their own land quality. Land quality takes values of one, two, and three for good, medium, and poor land quality, respectively. The positive relationship is expected between the three factors and agricultural output. The poor quality of land is believed to lower production.

Table 4 Summary Statistics of regression variables by year

Variable name	Variable definition	Mean 1986	Mean 2012	Mean difference 2012-1986
Output	The gross output value for all crops in Rwandan francs	19,199	40,490	21,291***
Land	Total farm size per household in hectare	0.76	0.95	0.19***
Labor	Total labor units (person-days) used per household per year	493	162	-331***
Capital	Total value in Rwandan francs of agricultural tools and equipment	1,264	7,993	6,729***
Land Quality	Subjective judgment on land quality: 1=very good, 2=good (medium), 3=poor (here: percent of households with at least good land quality)	96%	51%	-45***

Note: *** denotes a significance level at 1%. Values are expressed in constant prices.

Table 5 reports OLS regression results for independent cross sectional data of 1986 and 2012. There is a tremendous increase in the elasticity of labor from 0.20 in 1986 to 0.68 in 2012 and a decrease in elasticities of land and capital respectively from 0.53 and 0.19 in 1986 to 0.17 and 0.11 in 2012, respectively. Compared to 1986, agriculture in the study area is more labor intensive in 2012 due to the land scarcity and population pressure problems. The quality of land also matters for crop output growth in the study area.

Table 5 OLS results on determinants of agricultural output 1986 & 2012

Independent variables	(1) OLS 1986	(2) OLS 2012
Constant	7.524***	6.090***
	(0.743)	(0.546)
Land (log)	0.527***	0.181***
	(0.062)	(0.063)
Labor (log)	0.196*	0.679***
	(0.112)	(0.068)
Capital (log)	0.191***	0.107*
	(0.049)	(0.064)
Land quality		
2. Average	-0.149	0.084
	(0.110)	(0.149)
3. Bad	-0.375**	-0.078
	(0.167)	(0.151)
Observations	162	161
R_squared	0.534	0.653
F-statistic	51.801	77.895
Prob>F	0.000	0.000

*, **, and *** indicate the statistical significance at 10, 5, and 1 percent, respectively. Robust Standard Errors are reported in brackets. The dependent variable is the logarithm of agricultural output value. All continuous explanatory variables are expressed in logarithmic terms.

Nevertheless, as noted earlier the interpretation of the above cross section model should be done with caution due to unobserved household heterogeneity. To control for the hidden bias that may arise, panel data models that allow interpreting the changes in agricultural output over time are estimated and presented in table 6. Model (1) reports pooled OLS or Difference in Difference, while model (2) reports fixed effects results as per equation 4.18. The results confirm the predominant role of labor, capital, and land quality to output growth over time.

The Difference in Difference coefficients obtained on labor, land, and capital are almost similar to the independent cross sectional elasticities for 1986 period as presented in Model (1) of table 6. Elasticities in 2012 from pooled OLS are obtained by the sum of each variable coefficient and its interaction term with year dummy 2012. The results confirm that elasticities of land and capital have decreased by 0.35 and 0.08 respectively; while the elasticity of labor has increased by 0.48 over the past two and half decades. In both periods, the agricultural production is characterized by decreasing returns to scale, as indicated by the sum of output elasticities of land, labor and capital which is still slightly less than one.

Similarly, the fixed effects results in model (2) confirm that output elasticity of labor is higher than the combined elasticities of land and capital. Other things being equal, 10 percent increase in land ownership result in 1.3 percent increase in agricultural output over time. The decrease in land productivity may be attributed to the reduction of fallow periods accompanied by losses in soil fertility over the past decades. The continuing demographic growth has resulted in a very high pressure on land, and high agricultural intensity for subsistence purposes. Ten percent increase in person-days available for farming has a ceteris paribus increase of 5 percent in agricultural output over time.

The productivity of capital is 0.168 indicating that ten percent increase in agricultural capital increases agricultural output by almost 2 percent. The results also show that the poor quality of land decreases significantly agricultural output. Compared to cross section results, the fixed effects model shows that the sum of production elasticities is far below one, exhibiting more decreasing returns to scale economies in the sample area over time. The total factor productivity (indicated by the constant term in production function) is statistically significant at one percent. It suggests the role of technological progress and other farm specific variables to increase agricultural output.

Table 6 Panel model results for production function: Pooled OLS and Fixed effects

Independent variables	(1) POOLED OLS	(2) FIXED EFFECTS
Constant	7.508***	5.731***
	(0.735)	(0.531)
Land (log)	0.527***	0.125**
	(0.061)	(0.059)
Labor (log)	0.197*	0.488***
	(0.111)	(0.076)
Capital (log)	0.191***	0.168***
	(0.048)	(0.064)
Land quality		
2.Average	-0.136	-0.228
	(0.094)	(0.162)
3.Bad	-0.327***	-0.418**
	(0.124)	(0.175)
Year dummy 2012	-1.182	1.056***
	(0.890)	(0.174)
Land*year 2012	-0.352***	
	(0.087)	
Labor*year 2012	0.483***	
	(0.129)	
Capital*year 2012	-0.088	
	(0.080)	
Observations	323	323
R_squared	0.642	0.562
F-statistic	73.78	32.12
Prob>F	0.000	0.000

*, **, and *** indicate the statistical significance at 10, 5, and 1 percent, respectively. Robust Standard Errors are reported in brackets. The dependent variable is the logarithm of agricultural output value.

The significant coefficient obtained on year dummy suggests that agricultural output is higher in 2012. The growth observed in 2012 may be attributed to increased productivity of major crops, government green revolution, conductive climatic change, and intensity of fertilizer use(Bizimana, Usengumukiza, Kalisa, & Rwirahira, 2012).

The above results are consistent with those obtained in productivity analysis in Rwanda (D. A. Ali & Deininger, 2014; Clay et al., 1996) with respect to the predominant role of labor in agricultural production, and decreasing output elasticities of land over time. Table 4.8 summarizes the major findings on output elasticities in microeconometric studies in Rwanda over the past two and a half decades. Most studies show decreasing returns to scale, and suggest application and substitution of farm inputs with caution. Though these results rely on different approaches, study purposes, datasets, study areas, and different units of analyses, they show a similar trend of increasing productivity of labor.

Table 7 Output elasticities for selected microeconometric studies in Rwanda

Author and year	Land	Labor	Capital	Other Conditioners	Economies of scale
von Braun et. al. (1991)	0.526	0.22	0.192	-	Decreasing returns to scale
Clay et. al (1996)	0.38	0.54			Decreasing returns to scale
Ali & Deininger (2014)	0.308	0.410	-	0.313	Constant returns to scale
Our findings	**0.125**	**0.488**	**0.168**	**-**	**Decreasing returns to scale**

Source: von Braun et. al. (1991), Clay et. al (1996), and Ali & Deininger (2014)

Due to the nature of dataset used in this study, the decreasing returns to scale economics are confirmed for rural smallholding agriculture. Our findings also show a very small relative contribution of farm size to agricultural growth in the study area, and stress the relative importance of labor force. Both investment in land and agricultural capital are important to boost agricultural growth in the study area. However, the increasing productivity of labor over time does not mean that agricultural output will continue to grow, considering the law of marginal productivity of labor in the long run. Within decreasing returns to scale economies, pathways to new and less labor intensive agricultural innovations and off-farm employment are required in the area.

3. IMPACT OF INFORMATION AND COMMUNICATION TECHNOLOGY (ICT) ON AGRICULTURAL OUTPUT

3.1. Introduction

The rationale of this section is to investigate the impact of ICTs on agricultural output and income levels. Nowadays, ICTs are meant to include equipment that facilitate capturing, processing, display, and transmission of information such as computers (and their accessories), telecommunication equipment (and related services), and audio visual equipment and services. In the context of this study, we consider telephony (the use of cellular phones by farm households) as proxy of ICTs adoptions due to its outstanding role to facilitate improved access to information and communication on one hand, and to play as prerequisite to advanced technologies use such as internet on the other (Torero & von Braun, 2006).

Studies have stressed on leading role of ICTs in economic growth and development at both micro and macro levels. ICT has become a foundation of every sector of every economy, everywhere (Kramer, Jenkins, & Katz, 2007) because of its multifaceted role in expanding economic opportunities such as reduction of transaction costs and productivity increase, enhancing a flow of information, increasing choice in market place and widening the geographical scope and others. Goyal (2013) proved that ICTs can make difference by closing information gaps, and by empowering smallholders and improve market opportunities of farmers. According to von Braun (2010), ICTs may impact the poor's livelihoods by increasing their access to markets, improving the quality of public goods and services provision, improving human resources quality, and facilitating effective utilization of social networks. More specifically, cellular telephone technologies are believed to boost economic growth through job creation, increased agricultural and industrial productivity, and diffusion of innovation among farmers. However, much more skeptical views in respect to benefits of ICTs to the poor have emerged. They postulate that access to (or adoption of) ICTs is itself driven by a number of factors such as education, income, and wealth; and consequently, the shortage or lack of the above resources may prevent the poor from ICTs adoptions, widening information gap and increasing income disparities within and between countries(Torero & von Braun, 2006; von Braun, 2010).

Recent statistics show that more than 45 percent of Rwandan households use mobile phone technology in their daily activities (NISR, 2012). The Government of Rwanda believes that ICTs can open doors to more economic opportunities for rural poor; efforts have been put in ICT investments over the past decade. The e-Rwanda Project funded by World Bank and implemented by the Rwanda Information Technology Authority intends to empower rural farmers and enable a full access to information about market prices and successful farming. With a network coverage of about 80 percent of the whole territory, even farmers from very remote areas can use their mobile phone devices to check on agricultural commodity prices and can take better price decisions concerning their produce.

In the study area, more than 42 percent District households own a mobile phone and 32.7 percent work less than 20 minutes to reach the nearest public phone. However, though much is said about the role that mobile phones can play in agricultural development in Rwanda, no attempt was done to measure the extent at which this technology has impacted the level of output, fertilizer use and household income among smallholders. This study will refer on current survey data to measure these impacts. In the following subsections we consecutively present the ICT strategy in Rwanda, the relevant literature, empirical strategy, data description, results and subsequent interpretations.

3.2. Rwandan ICT strategies

The institutions and mechanisms to create an enabling environment for ICT development in Rwanda were established in 2000. Today, the most prevalent technologies in Rwanda are internet services, mobile applications, outsourcing, information security, clouds computing, and green ICT that aims at creating awareness on increasing environmental regulation. The National ICT strategies are adopted and implemented in four five-year phases under "National Information Communication Infrastructure (NICI)" designation and coincide with the main policy document "Vision 2020". The NICI I (or NICI-2005 Plan) was adopted in 2001 and its main focus was to create an enabling environment to the growth of ICT sector in Rwanda through establishment of sound institutional and legal framework. The second phase of ICT strategy (NICI II or NICI-2010) was adopted in 2006 and aimed at providing outstanding infrastructures that will support the future of ICT requirements(Rwanda, 2011).

The current phase of the strategy (NICI III or NICI-2015 plan) was adopted in 2011 and is being implemented with a special emphasis to improve ICT service delivery to the citizens. More specifically, as a pre-final phase of the ICT strategy that will drive the country towards its vision 2020, NICI III targets high skill and knowledge based-ICT, ICT enabled private sector development, E-Government, and cyber security.

In order to accomplish these missions, the government of Rwanda has set a number attainable objectives that include capacity building in ICT and enabling improved access to education and training, fostering innovation through research and development, developing a private-led competitive ICT sector, create ICT awareness in communities, and increased citizen participation and access to services through ICT-enhanced systems. In addition, through the NICI-2015 plan, the government intends to increase transparency and accountability through ICT, establish a legal environment enabling easy adaptation to emerging technologies, and ensure total protection of Rwanda's ICT infrastructures and systems against cyber-attacks. From these missions and objectives, a number of implementable projects have been designed and some being in their execution phases (Rwanda, 2011).

NICI-2015 is being implemented under a strong multi-stakeholder framework where Rwanda Development Board (RDB) is designated as coordinating and implementing agency of all ICT related initiatives. The strategic directions are provided by the National Steering Committee chaired by the Ministry in charge of ICT (MINICT). Through this partnership, Rwanda believes to obtain important and quantifiable measures of ICT contributions to the DGP.

3.3. Relevant Literature

A number of studies have emerged over the last decade on the relevance of mobile phones use on economic welfare in developing countries. Aker (2010) found that the expansion on network coverage accompanied by intensive use of mobile phone use by local traders in Niger have significantly reduced market disparities and improved market performance. It is believed that mobile phone adoption in Sub-Saharan countries have positive impact on agriculture and labor market efficiency even though empirical evidences on this matter are still thin (Aker, 2008; Aker & Mbiti, 2010).

Mittal, Gandhi, and Tripathi (2010) found that farmers use mobile phones as means of communication to check on the availability of inputs and market prices, resulting in higher crop yields because of better adjustment of supply to market demand. Similar effects have been observed on fishermen who registered a decrease in losses due to full market information. Mwakaje (2010) analyses the impact of access to ICT, including radios, telephone, internet and newspapers by rural farmers from Rungwe village in Tanzania and found that farmers who used mobile phones in their activities have sold more quantities and at better prices than others. However, the same study pointed out that access to ICT facilities is constrained by the lack of money income and electricity. Evidences from Uganda confirmed that the mobile network expansion enhanced market participation for producers of perishable products such as banana (Muto & Yamano, 2009). Regarding the determinants of mobile phone adoption, Muto and Yamano (2009) found that the household head age, the level of education of both males and females adults and the farm asset values are the most important determinants of mobile phone acquisition in Uganda. Younger household heads are likely to adopt the mobile phone technology, and this this also increases by the level of education and household assets. Evidences from Rwanda showed that mobile phone ownership is associated with wealth, education and gender (Blumenstock & Eagle, 2010).

Okello, Kirui, Njiraini, and Gitonga (2011) analyzed the drivers of ICT use by smallholder farmers in Kenya, and found that mobile phone adoption is driven by farm and farmer characteristics, capital endowment and regional characteristics. Other things being equal, the use of mobile phone is positively correlated to the male headship, household fare, education, income and assets and negatively correlated with the family size and age of the household head. Kirui, Okello, and Nyikal (2012a) found that the use of mobile phone-based money transfer services in Kenya has impacted agricultural production among smallholder farmers because farmers use the remitted funds to purchase inputs, equipment and to pay hired labor.

Houghton (2009) analyzed the impact of mobile phone use on agricultural productivity in selected developing nations using a two stages regression model. The micro-data results showed that mobile phone ownership significantly increase agricultural productivity at household level in Swaziland, Cambodia and Honduras. In their study on mobile phone and economic development in rural Peru, Beuermann, McKelvey , and Vakis (2012) found that the use of mobile phone has significantly contributed to household income consumption, and reduced extreme poverty by five percent in the area during the study period. The use of mobile phone by smallholder farmers in Oyo State in Nigeria (Bolarinwa & Oyeyinka, 2011) have enhanced a full time access to extension services and increased agricultural output more than non-mobile phone users. Chong, Galdo, and Torero (2009) also confirmed that the level of income per capita was higher for households with access to telephone services.

3.4. Empirical Strategy

Measuring the impacts of ICTs on rural households' welfare can be done through different methodologies. The frequently used techniques are compensating variations, willingness to pay, consumption functions, and matching (von Braun, 2010). To analyze the impact of mobile phone on outcomes such as agricultural output, fertilizer use and household income, we start from a linear function:

$$Y_i=\beta_0+\beta_1 X_i'+\beta_2 M_i+\varepsilon_i \tag{12}$$

Where Y_i is agricultural output, X_i is vector of inputs, M_i is a binary variable representing one if the household owned a mobile phone during the past 12 months, and zero otherwise; βi are unknown parameters to be estimated. Even though mobile ownership from the equation (12) is treated as exogenous, it may also happen that households with higher agricultural output and income are likely to own mobile phone. Then mobile phone ownership is not random and estimation of this equation by simple OLS will yield biased estimates. As pointed out by Owusu, Abdulai, and Abdul-Rahman (2011) the Heckman two-steps procedure has been used in many applications to correct the selectivity bias but it relies on restrictive normality assumptions. The instrumental variable (IV) technique as a second alternative is more demanding when it comes to find a good instrument and reveal itself difficult to apply.

To solve the selectivity bias associated with mobile phone ownership, we employ the propensity score matching (PSM) developed by Rosenbaum and Rubin (1983). Compared to the techniques described above, the PSM requires no assumptions about the functional form in specifying the relationship between outcome and outcome predictors (A. Ali & Abdulai, 2010; Owusu et al., 2011). As a non-experimental method, the PSM is judged suitable to a non-randomness of mobile phone adoption in our sample (Abebaw & Haile, 2013; Spreeuwenberg et al., 2010) and we will employ statistical matches to address the self-selection problem. The idea behind the PSM is to identify non-adopters of mobile phones who are similar to adopters in their observed characteristics; and the first step is to estimate by Logit model, the propensity score or the predicted probability that a farm household own a mobile phone such that:

$$P(Z_i) = Prob(M_i = 1 \mid Z_i), \tag{13}$$

Where M_i=1 if the household own a mobile phone, and M_i=0 otherwise; Z_i is a vector of observed personal, household and farm characteristics susceptible to influence mobile phone adoption. The next step of the PSM consists of selecting the best matching estimator which does not eliminate too many of the original observations in the final matching and try to provide equal covariate means for households in the treatment and control groups(Austin, 2009; Caliendo & Kopeinig, 2008).

Our principal concern is to answer the following question: "what would be the level of agricultural output, and household income in case the households had adopted mobile phone technology?" to answer this question, we will use the predicted propensity score from equation (4.29) to estimate the treatment effects. Following A. Ali and Abdulai (2010), Abebaw and Haile (2013); Owusu et al. (2011), the average treatment of the treated (ATT), which is in our case the average impact of mobile phone adoption on agricultural output, fertilizer use and income, is given by:

$$ATT = E\left(Y_{1i}^{k} - Y_{0i}^{k} \mid M_i = 1 \right) = E\left[E\left\{ Y_{1i}^{k} - Y_{0i}^{k} \mid M_i = 1, P(Z_i) \right\}\right]$$

$$= E[E\left\{ Y_{1i}^{k} \mid M_i = 1, P(Z_i) \right\} - E\left\{ Y_{0i}^{k} \mid M_i = 0, P(Z_i) \right\}] \tag{14}$$

Where Y_1 and Y_0 are the values of treatment variables of mobile phone adopters and non-adopters respectively; *i* stands for household; *k* refers to outcome variables being analyzed such as output, and household income.

The PSM is hereby employed as a probability that a farmer adopt mobile phone technology given pre-adoption socio-economic characteristics. In the absence of experimental data, the PSM technique uses the conditional independence assumption (Burke, Jayne, Freeman, & Kristjanson) to create the conditions of randomized experiment (A. Ali & Abdulai, 2010). This means that, mobile phone technology adoption is random and uncorrelated with the outcome variables if Zi are controlled for (Imbens & J.M., 2009). The literature suggests a number of algorithms the adopters and non-adopters of mobile phone technology with similar propensity score. The most widely used include the nearest neighbor matching which tries to match close adopters with the most close non adopter with similar characteristics, caliper matching which uses the nearest neighbor within each maximum propensity score and the kernel matching method which try to use more non adopters for each adopter in order to reduce variance (Kirui, Okello, & Nyikal, 2012b; Owusu et al., 2011).

However, a hidden bias may arise when the matching estimator is not robust (Rosenbaum, 2002) This problem is solved by controlling a large number of covariates to minimize the omitted variable bias; the sensitivity analysis is carried out in order to check how robust our estimates to hidden bias are.

3.5. Data Description

The data used in this section come from household survey carried out on 364 households from Nyabihu district in 2012. We use only 2012 wave of data because the mobile phone technology use is recent in Rwanda, no farm household used mobile phone in 1986. About 49 percent were using mobile phones at least 12 months before our visit in 2012 and they were principally households with relatively younger heads. Table 8 compares means of key characteristics of mobile phone adopters and no adopters. Mobile phone adopters work more outside the farm than non-adopters on average, and are relatively richer.

The levels of household asset, income, and output of mobile phone users are significantly higher than those of non-users. Besides, the summary statistics show that mobile phone users are more educated (5.5 years of schooling) than non-users (4.2 years). This may due to the fact that the manipulation of mobile phone device requires basic knowledge of at least one foreign language

(English or French); this limits the less educated people from adopting such technologies in rural area. The latter prefer use public phone services where dealers operate the devices on their behalf. Besides, statistics show that male headed households are more likely to use mobile phone technology in agriculture than female-headed households.

Table 8 Descriptive statistics of sample households by mobile phone adoption

Variable	Non adopters (51 percent)	Adopters (49 percent)	t-value for mean difference
Age of the head	46.72	41.73	3.07***
Gender (% male)	75	82	-1.57
Off-farm job (1=yes)	43.5	56.2	-2.42**
Institutional membership (1=yes)	68.8	71.3	-0.52
Farm size in hectares	0.40	0.46	-0.95
Assets in Rwandan francs (current)	193,836	289,610	-2.95***
Education	4.2	5.5	-4.46***
Output value (current Rwf)	125,578	207,916	-2.69***
Household income (expenditure)	289,207	409,808	-4.01***

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

3.6. Empirical results and discussion

As mentioned earlier, the point of departure to implement the propensity score technique is to calculate the propensity scores through a Probit or a Logit estimation of the treatment variable on control variables. The table 9 below presents Logistic results on the determinants of mobile phone adoption on household level. The age of household head, household assets, and the head level of education are important factors to enhance mobile phone use in the study area. Other things being equal, old household heads will reduce the log odds of adoption of mobile phone use by 0.017. However, there is a positive correlation between asset value and mobile phone use on one hand, and a significant positive relationship between education level of the head and the probability of mobile phone adoption on the other hand.

Table 9 Logit results of household level determinants of mobile phone adoption

Variable	Coefficients	Robust Standard Errors
Age of the head	-0.017**	0.008**
Gender (% male)	-0.139	0.313
Off-farm job (1=yes)	0.096	0.244
Institutional membership (1=yes)	0.034	0.251
Farm size in hectares (log)	0.048	0.116
Assets in Rwandan francs(log)	0.215**	0.101**
Education	0.105**	0.042**
Constant	-2.199*	1.294*
Number of observations	332	
Wald chi2	24.80	Prob>chi2: 0.0008
Pseudo R-squared	0.0613	LR=-215.97

*, **, and *** indicate the statistical significance at 10, 5, and 1 percent, respectively. The dependent variable is binary and equals 1 if a household has a mobile phone and equals zero otherwise.

Results from matching presented in table 10 indicate that mobile phone services have positive and significant impact on agricultural output value and household income (here household expenditure stands as income proxy). Both Kernel based and radius or caliper matching algorithms indicate that the level of agricultural output value is 38-43 percent higher for mobile phone users than their counterparts, while the level of household income is 26-27 percent higher for mobile phone users. These results are those expected since farmers who use mobile phone are likely to have access to information and stay informed on the availability of inputs and markets prices or both inputs and output. They can also get easy access to extension services more than non-users, which enable smoothness in production activities. With full information on prices, farmers know the best options to sell their produce and maximize profits from their agricultural crops; hence their agricultural income is higher.

Table 10 Impact of mobile phone use on output and income

Matching algorithm	Outcome indicator	Treated (N=163)	Control (N=169)	ATT T-statistics (.)	Critical value of hidden bias
Kernel-based	Output value	201,348	145,919	55,429* (1.66)	1.52-1.53
matching	Household income	419,680	333,801	85,878***(2.70)	1.16-1.17
Radius	Output value	201,348	141,680	60,135* (1.80)	1.41-1.42
matching	Household income	419,680	329,251	90,429***(2.86)	1.22-2.23

*, **, and *** indicate the statistical significance at 10, 5, and 1 percent, respectively. T-values are indicated between brackets, ATT is the average treatment effect of the treated.

We tested the conditional independence assumption (CA) after propensity score matching. Table 10 indicates a substantial reduction bias in propensity score covariates after matching (more than 50 percent in each). Except the education level of the head, the mean differences on covariates between the mobile phone users (treated) and non-users (control) after matching were not statistically different. The figure 2 shows that the mobile phone users and non-users were within the region of common support, indicating that all treated households (mobile phone users) have got corresponding untreated households (non-mobile phone users) with similar characteristics. The quality of matching is judged good as all individuals could be successfully matched and the bias reduction is far above the threshold of 20 percent (Rosenbaum & Rubin, 1983).

The sensitivity analysis results also presented in the last column of table 10 indicate that our propensity score matching results on output value are more robust to hidden bias than household income. The critical level of gamma (Γ), at which the causal inference of significant impact of use of mobile phone may be questionable is comprised between 1.52 and 1.53 meaning that, the significance of average treatment effect for output would be questionable only if the odds of mobile phone adoption for two households with similar characteristics differ by the factor of 53 percent. Likewise the significance of average treatment effect on household income will be questionable if the odds of mobile phone use between two households with the same vector of characteristics differ by the factor of 23 percent. Across two different matching algorithms, the lowest critical value on output ATT is 1.41 and the highest is 1.53 while for household income ATT, the small critical value is 1.16 and the highest is 1.23.

Table 11 Test of matching quality of covariates

Variable	Unmatched/ Matched	Mean Treated	Mean Control	%bias	% reduction bias	t-test
Head age	Unmatched	42.12	47.91	-35.5		-3.23***
	Matched	42.12	43.01	-5.2	85.3	1.46
Gender	Unmatched	0.82	0.75	18.6		1.69*
	Matched	0.82	0.80	4.2	77.6	-0.88
Off-farm job	Unmatched	0.56	0.45	23.0		2.10**
	Matched	0.56	0.53	6.3	72.8	-1.13
Institutional membership	Unmatched	0.72	0.67	10.7		0.98
	Matched	0.72	0.73	-1.8	83.2	-0.38
Log asset	Unmatched	11.94	11.43	38.7		3.52***
	Matched	11.94	11.79	11.4	70.5	-1.43
Log land	Unmatched	-1.34	-1.49	13.6		1.24
	Matched	-1.34	-1.41	6.7	50.9	-0.48
Education	Unmatched	5.41	4.09	45.4		4.14 ***
	Matched	5.41	5.06	12.3	73.0	-1.97**

*, **, and *** indicate the statistical significance at 10, 5, and 1 percent, respectively. Results presented in this table are based on Kernel-based matching algorithm

The results suggest that large amount of hidden heterogeneity will not alter the inference about the estimated treatment effects on output, while the treatment effects on household income are sensible to large amounts of hidden bias.

However, A. Ali and Abdulai (2010) pointed out that the main purpose of propensity score matching is to balance the distribution of relevant variables between the groups (here mobile phone uses and non-users) rather than obtaining a precise prediction of selection into treatment. In this regards, the overall indicators of matching before and after matching presented in table 12 confirmed the results presented above that the large absolute mean reduction was obtained after matching indicating the balancing power of our estimates.

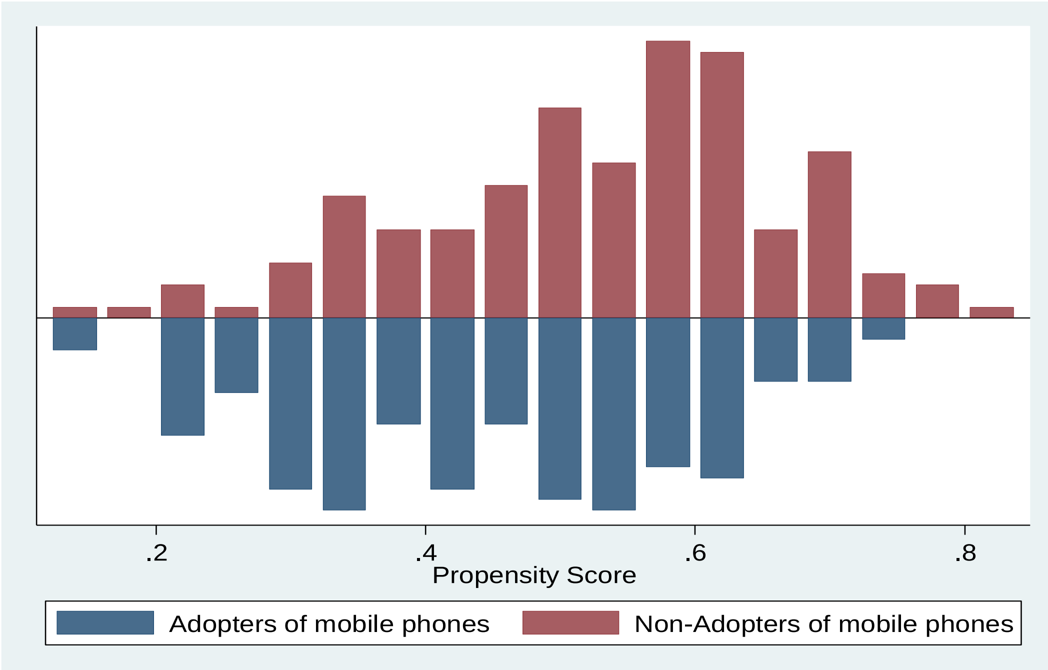

Figure 2 Distribution of propensity score

Table 12 Indicators of matching quality before matching and after matching

Matching algorithm	Outcome	Mean absolute bias (unmatched)	Mean absolute bias (matched)	Absolute bias reduction (%)	Pseudo R2 (unmatched)	PseudoR2 (matched)	LR p-value (unmatched)	LR p-value (matched)
KBM	Output	26.2	8.3	68.3	0.061	0.015	0.000	0.454
	Income	28.2	9.8	65.2	0.074	0.027	0.000	0.134
RM	Output	26.2	10.9	58.4	0.064	0.007	0.000	0.924
	Income	28.2	12.4	56	0.074	0.016	0.000	0.521

KBM: Kernel-based matching; RM: Radius matching

The pseudo R-squared is lower after matching and the likelihood ratio tests before and after matching indicate that the joint significance of regressors is always rejected after matching, while it couldn't be rejected before. We conclude that, for the two outcomes of interest (output value and household income); there is no systematic difference in covariate distribution between mobile phone users and non-users after matching.

4. CONCLUSION

This paper analyzed the long-term drivers of agricultural output in the densely populated area of Nyabihu District in Rwanda. Analyses are based on a unique panel dataset that spans for a 26-year period, constructed from two surveys on randomly selected households. We link the split-off households to the original households to construct an extended family dataset in the second wave of panel. The findings suggest that factors such as labor, capital, land, and land quality are the key driver of output growth in the study area. The 10 percent increase in land, labor and capital results in respective 1, 5, and 2 percent increase in gross output, other things being equal. This result is consistent with other previous findings on agricultural production relationships in the same area of study (D. A. Ali & Deininger, 2014; Clay et al., 1996; von Braun et al., 1991) and other developing countries (Cornia, 1985; Deininger & Okidi, 1999; Koffi-Tessio, 2004; Mundlak, Butzer, & Larson, 2012; Rasmussen, 2011; Tripathi & Prasad, 2009). Over the past two and a half decades, agriculture has been characterized by decreasing return to scales, with a substantial decrease in land and capital elasticities; whereas the elasticity of labor has multiplied three-fold over the same study period. This effect is attributed to high population growth in the sample area (88 percent increase) and the continuing land scarcity over time.

However, the increasing productivity of labor over time does not mean that agricultural output will continue to increase, considering the law of marginal productivity of labor in the long run. Within decreasing return to scale economies, it would be less profitable if all excess labor is affected on farm. Pathways to less labor intensive agricultural innovations and off-farm employment are required in the area, accompanied by sound population policy to check on the prevailing population growth.

The paper also investigated the role of ICT as a driver of agricultural output, with a focus on the recently cellular phone adoption by smallholder farmers. Our findings suggest that households who use mobile phones in their daily activities have performed better on farm than non-users. Cellular phone adopters achieved 38 and 26 percent more of agricultural output and household income respectively. However, access to mobile phone is itself driven by education level of the household head and household wealth. Relatively richer households are likely to acquire and use mobile phone, other things remaining unchanged. The maximum from ICT will be obtained if not only necessary ICT infrastructure is expanded rural area, but also if community illiteracy is high. More importantly, facilitating access to credit markets will enhance asset acquisition at household level and, hence provide means to ICT adoptions in rural area.

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Appendices

Appendix 1

Comparison of output regression coefficients between original sample and non-attriting sample

Explanatory Variables (in Log)	(1) Original Sample	(2) Non-attriting Sample	(3) Difference Prob>chi2 in (.)
Farm size	0.513***	0.529***	-0.016
	(8.699)	(8.446)	(0.658)
Labor	0.227**	0.197 *	0.03
	(2.217)	(1.757)	(0.556)
Capital	0.201***	0.191** *	0.01
	(3.365)	(3.259)	(0.636)
Land quality	-0.181**	-0.164**	-0.017
	(-2.329)	(-2.064)	(0.708)
Constant	7.458***	7.694***	-0.236
	(10.695)	(10.007)	(0.543)
Adjusted R-squared	0.508	0.522	
Number of observation	190	164	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Reported are Cobb-Douglas output elasticities and t-values between brackets.