Chapter 5
On the Possibility of Rice Green Revolution in Rainfed Areas in Northern Ghana: An Assessment of a Management Training Program

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Abstract This chapter investigates the impact of technical intervention on the adoption of a set of improved rice production technologies, as well as on productivity and profit for smallholders in rainfed lowland areas in Northern Ghana. The key finding is that productivity and profit are significantly enhanced when modern varieties (MVs) and chemical fertilizer are adopted, coupled with water control techniques. This is essentially the transfer of the Asian Green Revolution to sub-Saharan Africa. Such transfer, however, is not truly successful unless information about the use of MVs and fertilizer are directly disseminated by extension activities.

Keywords Rice technology • Impact assessment • Rainfed ecology • SSA • Asian Green Revolution

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5.1 Introduction

One management training program designed to realize an Asian rice Green Revolution (GR) is the Lowland Rice Development Project (LRDP), which was implemented in Northern Ghana (Mercer-Quarshie 2000). The project, which spanned from 1998 to 2003, was funded by the Agence Francaise de Development (AFD) of France in collaboration with the Ministry of Food and Agriculture (MOFA) of Ghana. The objective of the project was to enhance rice production through the adoption of improved technologies and management practices as well as to improve the processing and marketing of rice. In an effort to help smallholders overcome production challenges such as periodic droughts and poor soil quality, the project introduced to the farmers water and soil conservation techniques such as bunding and leveling.[1] The project also promoted the adoption of MVs, chemical fertilizer application and dibbling, which are designed to be yield enhancing.[2] These five technologies are referred to as improved technologies in this chapter. Since these technologies, except for dibbling, are core technologies of the Asian GR, this study amounts to assessing the transferability of the Asian rice GR to rainfed area in SSA, using micro-level data of 545 smallholder lowland rice farmers in Northern Ghana.[3]

It is well known from the experience in Asia that the dissemination of MVs was mainly limited to irrigated and favorable rainfed areas, even though the dissemination area expanded further to less favorable areas in later periods (David and Otsuka 1994; Estudillo and Otsuka 2006). In light of this, extensive studies have been conducted regarding the impact of improved technology adoption under irrigated conditions in SSA (Kajisa and Payongayong 2011; Nakano and Otsuka 2011). We extend the existing studies by examining the impact of the adoption of MVs, fertilizer and improved water management practices in rainfed areas.

The specific objectives of this chapter are (1) to explore how small-scale farmers in the project communities have responded to the promotion of improved technologies, (2) to examine how technology is disseminated to surrounding communities, and (3) to assess the effect of technology adoption on productivity and profitability in both the project and non-project communities under rainfed conditions.[4] Since

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[1] Bunding and leveling ensure that water stored on the field is evenly distributed, and this promotes the uniform growth of plants as well as controls the growth of weeds. Adoption of these technologies implies that less time will be spent on crop care management. Planting by dibbling, which is usually practiced in upland field, helps ensure the efficient use of seeds and facilitates weeding, the application of fertilizer and harvesting.

[2] Note that some farmers in the region may have had prior knowledge of some of these technologies due to the introduction to large-scale irrigation schemes such as the Tano, Vea and Botanga constructed during the 1970s (Kranjac-Berisavljevic et al. 2003; Namara et al. 2011). However, because the adoption rates were much lower prior to the project phase (Table 5.2), the LRDP introduced these technologies formally to the communities.

[3] Dibbling is seldom adopted in lowland rice farming in Asia.

[4] We are interested in the knowledge transfers between farmers, rather than through formal teaching intervention delivered by professional instructors/extension workers.

rainfed ecology is dominant in SSA, the empirical findings from this study would contribute to the design of future technology promotion projects of a similar nature.

The rest of the paper is organized as follows. Section 5.2 explains the survey design and sampling structure, and provides descriptive analyses of the improved technology adoption and its impact. Section 5.3 discusses the analytical framework for the improved technology adoption, and the estimation of yield and profit functions. The empirical results are presented in Sect. 5.4, while the conclusion and policy implications are presented in Sect. 5.5.

5.2 Data and Descriptive Statistics

5.2.1 Survey Design and Sampling Structure

The LRDP was implemented by MOFA in 58 communities (natural villages) in three selected districts around Tamale, the capital city of Northern region. For our study, we randomly selected 20 communities from the list of 58 project communities. Then, with the help of 1/50,000 scale topographic sheets, we randomly selected 20 non-project communities within a 20 km radius from any of the project communities, and another 20 non-project communities located beyond the 20 km radius, in order to assess how information is diffused across geographical peers. In this chapter, we designate the former as "nearby" communities and the latter as "remote" communities relative to the project sites. In this way, we selected 60 communities for our study (see Fig. 5.1). The survey was conducted in May 2010 and August 2011 in collaboration with Savanna Agricultural Development Institute (SARI) located in Nyankpala, 15 km away from Tamale. During the first survey in 2010, we
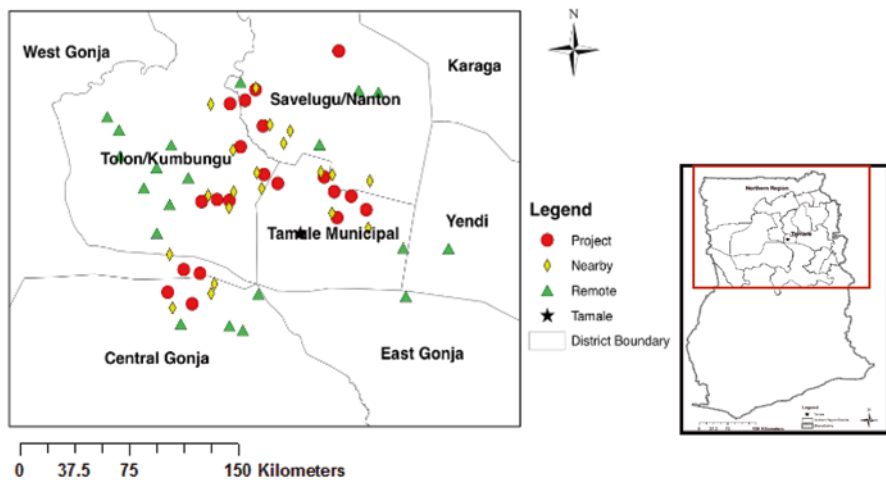

Fig. 5.1 Map of survey region – northern Ghana (Source: Survey data on rice production in 2010)

collected community-level information and applied a random sampling of 10 rice farmers in each of the 60 communities. Subsequently, the household survey in 2011 gathered data on a broad range of socioeconomic variables, farming practices, institutional factors, input use and rice production, and the history of technology adoption regarding the periods when the farmers first adopted the improved technology, whether they discontinued its use and if so whether they re-adopted after disadoption. Although the total number of sample households was 600, due to incomplete data and outliers only 545 households are used in this analysis.

5.2.2   Overview of Rice Production in Ghana and Study Area

Rice has become a major staple in Ghana and is currently the third most important grain after maize and sorghum. Rice accounts for about 15 % of the agricultural gross domestic product, and the per capita annual consumption of milled rice as of 2010–2011 was 24 kg per annum (Kranjac-Berisavljevic et al. 2003; MOFA 2010). The continuous growth in the consumption of rice, particularly among urban dwellers, is due to the ease of preservation and cooking and the effective marketing strategies of importers. However, the increasing growth in demand has not been backed by local production. As a result, the value of rice imports has increased from $65 million in 2000 to $201 million in 2010, amounting to 39.4 % of domestic consumption (MOFA 2010). Scarce foreign reserves are therefore channeled to rice importation instead of importing more productive capital goods and intermediate inputs. Interestingly, studies conducted by MOFA have shown that Ghana has a huge potential to increase its paddy rice production, under rainfed condition, from an average yield of 2.4 t/ha to 6.5 t/ha, with more effective extension and the use of recommended technologies (MOFA 2010).[5] The report by Asuming-Brempong (1998) also places Ghana at a comparative advantage compared to other countries in the sub-region in the production of paddy rice. Generally, rice can be grown in almost all parts of the country, but the major producing regions are Upper East region, Northern region and Volta region. Of the three, the Northern region produces the bulk of the nation's paddy rice. This study, therefore, focuses on lowland rice farming in Northern Ghana.

The study area is located in the northern part of Ghana, and Tamale is the regional capital.[6] The rainfall distribution in this region is uni-modal, and this results in a single growing season. The mean annual rainfall ranged from 880 mm in 2001 to 1,292 mm in 2010 with a 10-year average of 1,204 mm in the 2000s (MOFA 2010). Rice farming in the region is mostly carried out by small-scale farmers who depend entirely on rainfall for production. However, farming in the lowland areas is often

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[5] The target yield of 6.5 t/ha is too ambitious in view of the fact that the average yield in Asia is 4 t/ha.

[6] Northern region is the largest of the ten regions in Ghana and is a sparsely populated region.

hampered by frequent flooding from precipitation and ground water. The average monthly rainfall over the past decade (2001–2010) in Tamale and its environs varied from as low as 3.2 mm in January to as high as 228.2 mm in August according to the data gathered from the Ghana Meteorological Agency (GMET). The onset of the raining season in the region is usually from April to September/October with the maximum amount of rainfall is recorded in August. The rainfall data from the GMEt also showed that over the past decade the maximum rainfall amount recorded in August varied from as low as 88.1 mm in 2005 to as high as 334.6 mm in 2008 with an average of 228.2 mm. The variability of rainfall and periodic droughts often have a damaging effect on the rice harvest. In the quest to improve the productivity of the rice sector, the AFD, in collaboration with MOFA, implemented the Lowland Rice Development Project (LRDP) in parts of Tamale. The main objective of the project, which spanned from 1998 to 2003, was to increase rice productivity, by introducing the Asian-type modern rice varieties, chemical fertilizer and improved production management practices such as bunding and leveling, which are common in Asia.

5.2.3 Descriptive Analyses

5.2.3.1 Characteristics of Sampled Households and Survey Communities

First let us assess how well small-scale farmers have responded to the promotion of the five improved technologies and examine the rate of disadoption in the region. Table 5.1 shows the socioeconomic and plot characteristics of the surveyed communities. The project and nearby communities are quite homogenous in terms of household, plot and community characteristics. The soils in the surveyed region have a light to slightly heavier texture with various variations – sandy, loamy, laterite and clay. The only significant differences are that the project communities have relatively smaller farm sizes with good water retention capacity represented by clay soil. There are no significant differences among the three categories of communities in terms of formal education, age, family labor endowment and community paddy price. However, we observe a number of significant differences when we compare the project and nearby communities with the remote communities. In terms of the household characteristics, the farmers from the project and nearby communities have longer years of rice farming experience than those from the remote communities. In addition, the remote communities have relatively larger farm size, and the distance from homestead to these farms is much farther. In some instances, the farmer has to walk for over 4 h to visit the farm. The scarcity of labor relative to land in these communities could account for the significantly high community wage rates recorded for the remote communities, which is shown under the community characteristics in the table.

Table 5.1 Socioeconomic and plot characteristics of surveyed communities in Ghana

	Project communities		Non project communities			
	Project	Diff	Nearby	Diff	Remote	Diff
Number of households	178		181		186	
Household characteristics						
Formal education (%)	8.0		10.0		7.0	
Non-farm income (%)	25.0		30.0		37.0	c*
Member of local farmers group (%)	71.0		65.0		60.0	c*
Age of household head (years)	46.58		46.70		44.89	
	(16.08)		(15.99)		(15.84)	
Experience in rice farming (years)	9.47		8.59	b*	6.29	c*
	(7.21)		(7.60)		(5.97)	
Rice farming experience prior to LRDP (years)	1.88		1.77		0.66	c*
	(4.76)		(5.31)		(4.23)	
Family labor (15−65 years)	5.47		5.75		5.48	
	(2.79)		(2.98)		(3.48)	
Total farm size (ha)	2.81	a*	3.30	b*	4.36	c*
	(2.06)		(2.37)		(3.79)	
Rice cultivating area (ha)	0.99		1.19		1.41	c*
	(0.63)		(1.18)		(1.53)	
Maize cultivating area (ha)	1.34		1.31	b*	1.60	
	(1.18)		(0.97)		(1.27)	
Plot characteristics						
Soil with good water retention − clay (%)	69.0	a*	56.0	b*	68.0	
Land slope -flat slope dummy (%)	62.0		71.0	b*	82.0	c*
Walking from homestead to farm (min)	24.07		27.86	b*	48.71	c*
	(21.71)		(29.10)		(65.70)	
Community characteristics						
Distance from community to district capital (km)	21.55		20.63	b*	30.94	c*
	(8.80)		(7.34)		(8.60)	
Distance from non-project community to nearest project community	0.00		2.98	b*	12.42	c*
			(1.66)		(6.24)	
Community price for paddy (USD/kg)	0.22		0.23		0.20	
	(0.04)		(0.04)		(0.04)	
Community standard wage (USD/day)	1.29		1.46	b*	1.93	c*
	(0.46)		(0.42)		(0.62)	
Number of community	19		19		20	

Source: Survey data on rice production in 2010

a*Is the significant difference in means between project communities and nearby zones at the 5 % level

b*Is the significant difference in means between nearby communities and remote zones at the 5 % level

c*Is the significant difference in means between project communities and remote zones at the 5 % level

5.2.3.2   Adoption of Improved Technology

Now let us explore the technology adoption pattern based on the recall survey on the adoption history and the household's current adoption status.[7] To aid the analyses, the farmers were stratified into five groups. First, the early adopters (pre–LRDP) are farmers who adopted the technology before the LRDP phase (1997 and before) and are still using the technology. The second, the mid-adopters (LRDP) are those who adopted the technology during the LRDP phase (1998–2003) and are still using the technology. The third group, the late adopters (post–LRDP), are farmers who adopted the technology after the project phase (2004–2010) and are still using the technology. The fourth group, the disadopters are those who adopted the technology before and discontinued the use of the technology by 2010. Non-adopters, the last group, are those who have never used the technology as of 2010. In binary terms, the current users of the technology include the early adopters, mid-adopters and late adopters. The current non-users are the disadopters and the non-adopters.

Table 5.2 shows the means of the adoption classifications for each of the five technologies. As observed in column (1) of the table, fewer than 6 % of the farmers were using any of the technologies before the project intervention. The notable technologies are chemical fertilizer (5.1 %) and leveling (4.2 %). This group of early adopters might have realized the importance of these technologies through self-experimentation or from other farmers, since farmers often experiment on their own or learn from the experiences of others. The percentage of adopters increased moderately in the project communities during the project phase for all five technologies, especially for MVs. In column (3) of the table, we observe that many of the late-adopters (post–LRDP) of leveling, dibbling, MVs and fertilizer are from the nearby communities. The percentage for the late adoption of leveling, MVs and fertilizer increased in the remote communities. The increase in the number of adopters for the non-project communities could be due to information and knowledge obtained from the project communities.

Figure 5.2 displays the relative comparison of the adoption of the five technologies. Overall, the most widely adopted technologies are MVs and fertilizer. Bunding is the least popular, and less than 25 % of the farmers have adopted this technology. Table 5.3 shows the extent to which farmers have adopted improved technologies but subsequently discontinued their use. A relative comparison between the current adopters and farmers who have ever used the technology shows a generally low trend of disadoption with the exception of dibbling. We observe that the share of disadoption of dibbling among the ever-adopted is close to 42 %, which suggests that this technology might not be appropriate for the farming communities in this area. If that is the case, then further analysis needs to be conducted to explain why. According to our interviews, the major constraints on the continuous use of dibbling

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[7] Using farmer recall we obtained information regarding when the farmer first adopted the technology, whether the farmer discontinued the use of technology after adoption, and whether the farmer re-adopted after disadoption. We used the Lowland Rice Development Project (LRDP) as the reference period for the classification.

Table 5.2 Means of adoption classification for the five improved technologies in Ghana (%)

Improved practices	Current adopters			Current non-adopters		Total sample
	Pre-LRDP phase	LRDP phase	Post-LRDP phase	Dis-adopters	Non-adopters	
	(1)	(2)	(3)	(4)	(5)	
Bunding	(6)	(59)	(69)	(23)	(388)	(545)
Project	0.4	8.3	6.6	3.5	13.9	
Nearby	0.7	1.7	5.3	0.7	24.8	
Remote	0.0	0.9	0.7	0.0	32.5	
Total	1.1	10.8	12.7	4.2	71.2	100.0
Leveling	(23)	(76)	(189)	(51)	(206)	(545)
Project	1.7	7.7	8.3	3.9	11.2	
Nearby	1.8	3.3	14.5	4.8	8.8	
Remote	0.7	2.9	11.9	0.7	17.8	
Total	4.2	13.9	34.7	9.4	37.8	100.0
Dibbling	(14)	(42)	(82)	(100)	(307)	(545)
Project	0.7	4.6	5.3	8.3	13.8	
Nearby	1.5	1.8	6.8	7.3	15.8	
Remote	0.4	1.3	2.9	2.8	26.8	
Total	2.6	7.7	15.0	18.3	56.3	100.0
MV	(11)	(100)	(302)	(20)	(112)	(545)
Project	0.6	12.5	16.3	1.1	2.2	
Nearby	0.7	2.8	20.7	0.7	8.3	
Remote	0.7	3.1	18.3	1.8	10.1	
Total	2.0	18.3	55.4	3.7	20.6	100.0
Fertilizer	(28)	(105)	(269)	(50)	(93)	(545)
Project	2.8	11.4	16.1	1.3	1.1	
Nearby	1.7	4.6	18.3	3.5	5.1	
Remote	0.7	3.3	14.9	4.4	10.8	
Total	5.1	19.3	49.4	9.2	17.1	100.0

Source: Survey data on rice production in 2010
The number of observations is in parenthesis

technology include: the labor intensive nature of the technology (47 %), lack of cash to pay hired laborers (24 %), excessively large farm size (7 %), and flooded fields, which made dibbling impossible (22 %). We use regression analysis to investigate what led farmers to disadopt this technology in Sect. 5.3.2.

5.2.3.3 Impact of Technology Adoption

For the assessment of the introduction of any new technology it is informative to undertake a factor-share analysis and examine the possible factor use bias in the technology choice (David and Otsuka 1994; Kijima et al. 2008). For this analysis,
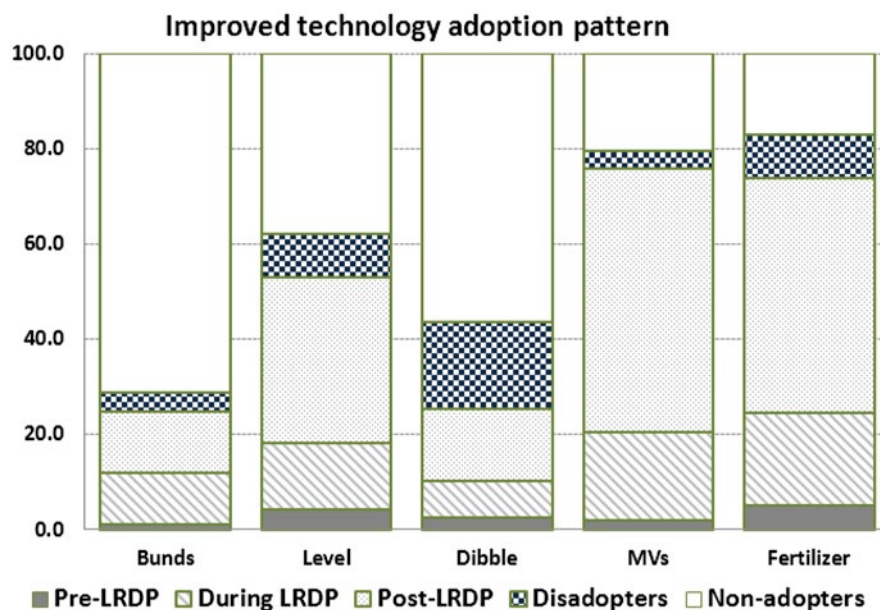
Fig. 5.2 Relative comparison of the adoption trend among the five technologies in Ghana (Source: Survey data on rice production in 2010)

Table 5.3 Rate of disadoption of the five improved technologies in Ghana (%)

	Improved technologies				
	Bunding	Leveling	Dibbling	MVs	Fertilizer
Farmers who have ever used the technology (by 2010)	28.8	62.2	43.7	79.4	82.9
Current adopters of the technology (in 2010)	24.6	52.8	25.3	75.8	73.8
Share of disadopters among those who ever adopted of which[a]	14.6	15.1	42.1	4.5	11.0
Project community	18.6	17.9	43.7	3.6	4.1
Nearby community	8.7	19.5	42.1	2.9	12.4
Remote community	0.0	4.5	37.5	7.6	18.9

Source: Survey data on rice production in 2010
[a]shows the share of disadopters in terms of the survey communities

we stratified the farmers into non-adopters, partial adopters and package adopters. Our earlier estimation, which is not reported here, showed that the most popular combination of technology choice in the region is MVs and fertilizer.[8] Hence, based on this finding we examine the impact of four possible combinations to investigate the potential gains from adopting a set of practices. These combinations include: (1) the adoption of only modern inputs (MVs and fertilizer), (2) the adoption of modern inputs and water control practices only (MVs, fertilizer, bunding, and leveling), (3) the adoption of at least modern inputs and water control practices, and (4) package adoption (MVs, fertilizer, bunding, leveling and dibbling). Table 5.4 summarizes the input and output relationship and factor shares. Rice income is calculated as the value of production per hectare minus the actual paid out cost per hectare, which includes the costs of current inputs (seeds and fertilizer cost), machinery services, and hired labor. The total cost is the sum of the actual paid out cost and the imputed cost of family labor days used in production. The cost of current inputs and machinery are computed using the prevailing prices at the time of the survey (August, 2011). For the imputed family labor we used the average wage rate observed in the community.[9] The profit (net return) is derived as the value of production less the total cost per hectare. Thus, the profit is expected to capture the returns to land and management ability.

The value of production per hectare for package adopters (column (5)) is significantly higher than that of the partial adopters (columns (2–4)) and almost twice that of the non-adopters (column (1)). The factor shares of labor, which is defined as the sum of the hired labor cost and the imputed cost of family labor divided by the value of production, are similar across the three cases, indicating that new technologies are largely factor neutral. We observe that although package adopters incur a higher cost of labor and current inputs due to the use of more labor intensive practices and cash intensive technologies, the net return for the package adopters is twice that of the partial and almost thrice that of the non-adopters. Another interesting finding is that the net return for the adoption of only modern inputs is much smaller than that of the non-adopters. This is due to the high input cost, especially of labor. The yield difference between the two groups is relatively small. This suggests that the adoption of modern inputs without water management practices requires more labor for crop care without increasing yields significantly under rainfed conditions. Hence, we can deduce from these observations that the net returns to technology adoption are much higher when all the technologies are adopted as a package. However, since the choice of technologies is endogenous, the simple comparison of the net returns can be biased. Therefore, we would like to confirm these findings more rigorously using regression analysis in Sect. 5.3.3. In terms of capital use, although a greater percentage of the farmers use tractors for land preparation, the factor share is relatively lower for package adopters (5.6 %).

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[8] We used the multivariate probit to examine the possible technology combination for the five technologies. The result of this estimation is not provided here.

[9] It should be noted that the wage rate used for the imputation of family labor cost is not activity-specific, as wage rates are similar across different tasks.

Table 5.4 Factor payments (USD/ha) and factor share (%) in terms of various technology combinations in Ghana

		Partial adopters			
	None	Modern inputs only	Modern inputs + bunding + leveling	At least modern inputs + bunding + leveling	Package
	(1)	(2)	(3)	(4)	(5)
Production					
Yield (tons/ha)	1.46	1.70	1.98	2.33	2.59
Value of production (USD/ha) (A)	304.07	377.04	444.90	524.26	586.73
Current input cost	56.86	112.10	120.73	135.93	147.90
	(18.7)	(29.7)	(27.1)	(25.9)	(25.2)
Seed cost	24.00	25.41	22.38	25.90	28.68
Fertilizer cost	0.00	53.77	70.81	79.49	86.32
Machinery services	32.86	32.92	27.54	30.54	32.90
	(10.8)	(8.7)	(6.2)	(5.8)	(5.6)
Labor cost	188.03	236.14	234.93	259.70	279.19
	(61.8)	(62.6)	(52.8)	(49.5)	(47.6)
Hired labor cost	19.39	52.74	85.67	73.74	64.35
Imputed family labor cost	168.64	183.40	149.26	185.95	214.84
Total paid-out cost (B)	76.25	164.84	206.40	209.67	212.25
Total cost (C)	244.89	348.24	355.66	395.63	427.09
	(80.5)	(92.4)	(79.9)	(75.5)	(72.8)
Income (A) − (B)	227.81	212.21	238.49	314.58	374.48
Profit (net return) (A) − (C)	59.18	28.81	89.24	128.63	159.64
	(19.5)	(7.6)	(20.1)	(24.5)	(27.2)
Labor share[a] (%)	61.8 %	62.6 %	52.8 %	49.5 %	47.6 %
Family labor (man-days/ha)	90.71	119.96	129.87	170.95	203.29
Hired labor (man-days/ha)	11.49	32.27	73.75	66.70	61.15
Number of observations	63	78	37	84	47

Source: Survey data on rice production in 2010
Numbers in parentheses are the factor shares in percentage terms
[a]Total labor cost divided by value of production

On the whole, the results suggest that there are net gains by the adoption of improved technology. Indeed, package adopters attain much higher yields and net profits (2.6 t/ha and 159.6 USD/ha) than partial adopters. It should be noted that this yield level is comparable to the yield in rainfed areas of Asia in the late 1980s when MVs were largely adopted, suggesting that comparable yields can be attained in SSA if new technologies are completely adopted (David and Otsuka 1994). It is also worth mentioning that the yield of 1.46 t/ha for the non-adopters is probably close

to the average yield of rice under rainfed condition in SSA at present and the average yield in Asia before the GR (Balasubramanian et al. 2007).

5.3 Methodology and Variable Construction

5.3.1 Determinants of Improved Technology Adoption

In this sub-section, we investigate the determinants of improved technology adoption using two logit regression functions. A major challenge in assessing new technology adoption is the presence of unobserved factors that may cause endogeneity in the estimation. The use of panel data in a randomized-control-and-trial setting is more preferable, but since we have cross-sectional data with historical data on adoption, we rely on logit regression, by separating the innovators and all current adopters. Here, the farmers who adopted the technology before and during the LRDP and continue to use the technology are considered as innovative farmers. In the first function, the dependent variable (adoption decision) is 1 if the farmer is an innovative farmer and zero otherwise. In the second function, the dependent variable is 1 if the farmer is currently using the technology and zero otherwise.[10] The current adopters in this case include the innovators and the post–LRDP adopters.

The community-level explanatory variables used in the models are the wage rate (USD/day), community paddy price (USD/kg) and the distance to the district capital, Tamale (km). The community wage rate is used as a proxy for the cost of hired labor as well as the opportunity cost of family labor. A higher wage rate may have a negative effect especially on the adoption of labor intensive technologies. The distance from the community to the district capital is used as a proxy for access and proximity to a central market. We control for the effects of the LRDP and of the dissemination of information across geographical communities by including the project community dummy and the distance from the non-project community to the nearest project community (km). We predict that the closer the non-project communities to the project communities, the higher the probability of obtaining information from the project community and, hence, the higher the likelihood of adoption. Although we recognize that the distance to the nearest project community may capture various effects other than technology information, we follow the convention in the technology adoption literature that uses distance to measure access to information (e.g., Amare et al. 2012). Moreover, as will be shown later, this variable is significant in several regression estimates. The project community dummy is predicted to capture the direct learning effect of the project.

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[10]The multinomial logit regression model is also used to check the robustness of our estimation method and to compare the significance of key variables. The dependent variable in this case has four categories (pre–LRDP adopter, during–LRDP adopter, post–LRDP adopter and non-adopter). The estimation result, which is found to be consistent with the logit regression models, is provided in the Appendix Tables 5.9, 5.10, 5.11, 5.12, and 5.13.

The plot characteristics are captured by the land slope, the soil type and the walking distance between the farm and the homestead (minutes). The farmers in the survey communities perceive clay soil to be of high quality and conducive to rice cultivation, and hence, a clay soil dummy is used as a proxy for soil of high quality. We also controlled for flooding, which is a serious problem in the region and possibly an important factor in deciding whether to adopt water control technologies. We do so by including the land slope dummy which takes a value of 1 if the plot is perceived to be flat and zero otherwise because flat land is more prone to flooding relative to steep land.

The household variables include education (formal level), age and experience of the household head, family labor endowment (the number of economically active members of the household between 15 and 65 years of age), and total farm size. Experience pertains to the household head's rice farming experience prior to the implementation of the LRDP.

5.3.2 Determinants of Dibbling Disadoption

Since the disadoption rate of dibbling is very high, the question raised is whether this technology is appropriate for Northern Ghana. Thus, we attempt to explore the determinants of dibbling disadoption using the multinomial logit regression model. Here, the dependent variable has three outcomes – disadopters, continuous adopters and non-adopters. The explanatory variables used are the same as earlier.

5.3.3 Determinants of Yield and Profit

To assess the impact of improved technology adoption on productivity and profitability, we estimate two regression function, the yield function and the profit function, using the same model specification. The dependent variable of the yield function is the paddy yield in tons per hectare, while the dependent variable of the profit is the residual profit in USD per hectare. The dependent variable in each case is expressed as a function of technology, input prices, and other exogenous factors such as socioeconomic and farm characteristics. However, since the technology variable of interest is considered as an endogenous binary choice variable, the estimation may suffer from the selection bias, i.e., those farmers achieving higher yields may have done so even without adopting the technology due to some unobserved factors. Experimental panel data would allow us to obtain unbiased estimates; however, it is not always available. Several methods are used in the evaluation literature to correct for this bias for cross-sectional data, such as the propensity-score matching method (e.g., Faltermeier and Abdulai 2009), the endogenous switching regression model (e.g., Amare et al. 2012), and the instrumental variable method. In our case, we applied the treatment effects model (TEM), which is a variant of the

Heckman two-step model and is essentially the same as the Roy model or endogenous switching regression model (Cameron and Trivedi 2005; Guo and Fraser 2009). The TEM models the selection bias specifically in the selection equation rather than assuming it random as explained below. We did not use the propensity-score matching method because it does not control the unobserved heterogeneity among the sample. We preferred the TEM over the IV as one of the conditions for an instrument for the IV method cannot be tested (i.e., the instrument is not correlated with the outcome equation) and thus it is difficult to guarantee the validity of the instrument (Guo and Fraser 2009).

The TEM is given as:

$$y_i = \beta_i X_i' + \delta T_i + \varepsilon_i,$$
$$i = 1, 2 \ldots 545,$$

(5.1)

where y_i is a dependent variable that represents an outcome (either yield or profit); X_i' represents a vector of explanatory factors; β_i is a vector of coefficients parameters for X_i'; T_i is the technology adoption status and represents the binary outcome of the probit model; δ is the coefficient estimator for the technology (the outcome of the probit model) and ε_i is the error term. To account for the endogeneity of technology (T_i), we introduce an unobserved latent variable (T_i^*) that determines whether technology is adopted or not $\left(i.e.\ T_i^* = 1\, or\, 0\right)$. The treatment ($T_i$) is modeled by a probit model and specified as:

$$T_i^* = \gamma W_i' + \upsilon_i,$$

(5.2)

where $T_i = \begin{cases} 1 & if\ T_i^* > 0 \text{ i.e. famer used technology} \\ 0 & otherwise \end{cases}$.

The adoption of improved technology in Eq. 5.2 is specified as a function of a set of explanatory factors (W_i'). Here, we include the walking time from the homestead to the farm, which proves to be a significant determinant of technology adoption in the technology function. γ is a vector of unknown parameters and υ_i is the error term. The assumption made here is that the error terms (ε_i, υ_i) are bivariate normal with mean zero and covariance given as $Cov\left(\varepsilon_i, \upsilon_i\right) = \rho\sigma^2$. If the correlation between the error terms (denoted as ρ) is zero, then there is no endogeneity problem and the two error terms are independent. The estimation of the treatment effects model is done using either a maximum likelihood (MLE) approach or the two-step estimation method. We use the MLE method since it estimates the technology adoption equation and the profit or yield equation jointly, and hence, enables us to test for endogeneity (Cameron and Trivedi 2009; Greene 2008).

Here, we consider a reduced form with specific technology combinations. That is, we focus only on the impact of technology adoption on yield and profit and do not consider explicitly the use of other inputs, such as labor or tractor use due to endogeneity problems. For the factor payment analysis in Sect. 5.2.3.3, we classify the status of technology adoption into four groups: adoption of modern inputs only (MVs and fertilizer), adoption of modern inputs and water control practices only

(MVs, fertilizer, bunding, leveling), adoption of at least modern inputs and water control practices, and package adoption (MVs, fertilizer, bunding, leveling and dibbling). However, for the regression analysis, the use of a dummy variable for the adoption of modern inputs only, as well as the use of dummy variables for the adoption of modern inputs and water control technology only, is not appropriate as the default group includes not only non-adopters, but also adopters of additional technologies. Therefore, we use the following two inclusive dummies: (1) at least modern inputs and water control technologies and (2) package adoption. In effect, the first specification is a subset of the second specification. As we observe that the disadoption rate of dibbling was quite high, the result in these models helps us analyze the effects of adopting dibbling technology on productivity and profit. The coefficient on the dummy for package adoption will be large if dibbling is complementary to the other technologies. The explanatory variables included in $X_i^{'}$ are the same as those used for technology adoption except for the walking time from the homestead to the farm.

5.4   Results

5.4.1   Determinants of Improved Technology Adoption

Table 5.5 shows the determinants of technology adoption. Columns (1–5) provide the results for the innovative farmers, while columns (6–10) show the results for all the current adopters (innovators and post–LRDP adopters). The displayed coefficients are the marginal effect on the probability of adoption, which are evaluated at the sample means. The project community dummy is found to be positive and highly significant for the adoption of modern inputs shown in columns (4–5), and (9–10), but generally not so for the other three technologies. These findings suggest that for technologies that require s ome level of technical know-how, such as the use of MVs and chemical fertilizer application, learning directly from project developers and extension agents increases the probability of adoption.[11] Similar results are reported in Amare et al. (2012) which found that contact with government and non-government extension agents increases the rate of technology adoption. The distance to the nearest project community was found to be negative and significant in the case of bunding and leveling (columns (1), (2), and (6)). One possible explanation for the

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[11] The application of chemical fertilizer requires some level of instruction in terms of the application timing and rate. The LRDP provided participating farmers with credit to purchase inputs such as seed and fertilizer. It may have contributed to the positive effect of the project community dummy on the adoption of the modern inputs. The dummy has a positive effect even after the project, implying that the learning through using such modern inputs has a long-lasting impact. Since the adoption of improved technologies might not be solely induced by LRDP, that some farmers rely on self-experimentation or learning from the experiences of other farmers, we try to interpret the regression results with caution.

Table 5.5 Estimation results of the determinants of improved technology adoption in Ghana (logit-model – marginal effects)

Explanatory variable	Innovative adopters					All current adopters (innovators and post-LRDP adopters)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Bunding	Leveling	Dibbling	MVs	Fertilizer	Bunding	Leveling	Dibbling	MVs	Fertilizer
Experience prior to LRDP (years)	0.001	0.012***	0.003***	0.008***	0.017***	−0.000	0.009	0.004	0.006	0.005
	(1.04)	(4.05)	(2.79)	(3.14)	(4.25)	(−0.11)	(1.61)	(1.30)	(1.21)	(1.06)
Age (years)	−0.000	0.000	0.000	−0.000	−0.001	0.001	0.001	0.002**	−0.002	−0.003**
	(−0.09)	(0.21)	(0.19)	(−0.02)	(−0.52)	(0.65)	(0.31)	(2.01)	(−1.53)	(−2.45)
Formal education (dummy)	−0.006	−0.023	−0.022	−0.055	−0.036	0.012	0.071	0.122*	−0.020	0.025
	(−0.32)	(−0.48)	(−1.39)	(−1.28)	(−0.63)	(0.24)	(0.85)	(1.65)	(−0.29)	(0.39)
Family labor (number)	0.001	0.007	0.002	0.012**	0.011	0.003	0.012	0.006	0.010	0.015**
	(0.38)	(1.32)	(1.00)	(2.15)	(1.64)	(0.56)	(1.35)	(0.86)	(1.52)	(2.12)
Total farm size (ha)	−0.001	−0.006	−0.005	−0.002	0.004	−0.004	−0.017*	−0.031***	−0.015**	−0.004
	(−0.15)	(−0.94)	(−1.41)	(−0.41)	(0.56)	(−0.58)	(−1.72)	(−2.93)	(−2.26)	(−0.52)
Soil with high water retention (dummy)	0.032**	0.003	0.020	−0.006	−0.025	−0.040	−0.182***	−0.052	−0.125***	0.013
	(2.07)	(0.09)	(1.50)	(−0.19)	(−0.62)	(−1.23)	(−3.62)	(−1.28)	*(−3.58)	(0.31)
Land slope (dummy)	−0.002	0.021	−0.021	−0.010	−0.044	−0.008	0.057	−0.045	0.082*	0.004
	(−0.19)	(0.67)	(−1.31)	(−0.31)	(−1.08)	(−0.25)	(1.05)	(−1.08)	(1.83)	(0.10)
Walking from homestead to farm (min)	−0.000	0.000	−0.001***	−0.001*	−0.001*	−0.001	0.000	0.000	0.001	0.000
	(−0.92)	(0.26)	(−2.60)	(−1.79)	(−1.72)	(−1.40)	(0.71)	(0.23)	(1.33)	(0.64)
Project community (dummy)	0.015	0.040	−0.007	0.206***	0.156***	0.053	−0.139**	−0.014	0.164***	0.201***
	(0.62)	(0.97)	(−0.44)	(3.75)	(2.81)	(1.18)	(−2.24)	(−0.31)	(4.26)	(4.88)

Nearest project community distance (km)	-0.011***	-0.008*	-0.001	0.002	-0.007	-0.027***	-0.006	-0.005	0.003	-0.007
	(-4.34)	(-1.92)	(-0.48)	(0.41)	(-1.24)	(-5.39)	(-0.96)	(-1.06)	(0.71)	(-1.62)
Community wage rate (USD/day)	-0.045*	-0.137***	-0.092***	-0.136***	-0.085**	-0.132***	-0.323***	-0.159***	-0.219***	-0.105***
	(-1.94)	(-3.95)	(-4.92)	(-3.87)	(-2.01)	(-3.19)	(-5.86)	(-3.73)	(-5.41)	(-2.79)
Distance to district capital (km)	0.001	0.006**	0.001	0.001	-0.001	0.008***	0.008**	0.004	0.010***	-0.000
	(1.29)	(2.41)	(1.09)	(0.40)	(-0.43)	(3.25)	(2.22)	(1.45)	(3.81)	(-0.08)
Community paddy price (USD/kg)	0.241	0.911**	0.163	0.183	0.950*	1.252***	2.348***	2.688***	2.673***	1.926***
	(1.28)	(2.10)	(0.92)	(0.42)	(1.82)	(2.78)	(3.37)	(5.10)	(5.04)	(3.39)
McFadden's R^2	0.211	0.143	0.199	0.190	0.184	0.217	0.123	0.145	0.223	0.178
Correctly predicted	88.073	83.119	89.908	83.486	79.633	75.963	68.440	74.495	80.734	76.514
Model X^2 – Chi²	83.870	74.113	71.701	104.457	111.611	131.990	92.711	89.521	134.433	111.753
Number of observations	545	545	545	545	545	545	545	545	545	545

The numbers in parentheses are *t*-statistics

***, **, and * indicate significance at 1, 5, and 10 %, respectively

distance effects on bunding and leveling is that since these technologies are observable, the farmers in close proximity can observe and imitate without coming into direct contact with the project developers.

Rice farming experience prior to LRDP has a positive and strong impact on the innovators' adoption decisions (columns (2–5)) but has no significant impact on the all current adoption decision (columns (6–10)). The lower importance of experience on the all current adoption decisions suggests that experience has only a short-run effect on adoption. Probably, the experienced farmer is able to better assess the impact of a new technology quickly, which influences the early adoption decision. The post–LRDP adopters with less experience, however, are able to realize the benefits of improved technology through the experience of adopting new technologies and learning from neighbors. What we deduce from this finding is that in the long-run, learning substitutes experience.

Total farm size does not significantly affect the adoption of improved technologies in the earlier periods. In columns (7), (8) and (9) of Table 5.5, however, we observe an inverse and significant relationship between farm size and the adoption of leveling, dibbling and MVs at present. One possible explanation is that since the technology is found to be labor intensive, having large farm units discourages adoption in later periods. This finding is critically important because it indicates that new technologies do not favor wealthy, large farmers, as in the case of the Asian GR (David and Otsuka 1994). Further, the cost of hired labor as well as the opportunity cost of family labor, which is proxied by the wage rate, affects negatively the adoption of all five technologies.

Unexpectedly, we did not find a generally significant impact of education on the technology adoption. This variable is only positive and significant in the case of the current adoption of dibbling. This insignificant impact of education is not typically observed in adoption studies in SSA (Abdulai and Huffmann 2005; Doss and Morris 2001; Amare et al. 2012). One possible explanation for the insignificant effect might be the generally low and similar level of education among the sample farmers.

5.4.2 Determinants of Dibbling Disadoption

Table 5.6 presents the estimated effects in the dibbling function in terms of the marginal effect evaluated at the sample means. Column (1) shows the results for the disadopters of dibbling, while the results for the continuous adopters and non-adopters are provided in columns (2) and (3). The possible constraints on the continuous adoption of dibbling technology are large farm size, high wage rate, low paddy prices, poor soil type, and close proximity to the nearest project community. These findings confirm the responses we received from farmers in our interviews that the high labor intensity of dibbling was the major constraints on continuous adoption (by 47 % of the farmers). The labor-intensive nature of dibbling seems to discourage large farm owners in communities with high wage rate from the continuous use of the technology. Since the rate of disadoption of dibbling is very high, this

Table 5.6 Determinants of the disadoption of dibbling technology in Ghana (multinomial logit – marginal effect)

	Dis-adopters	Continuous adopters	Non-adopters
Explanatory variables	(1)	(2)	(3)
Experience prior to LRDP (years)	0.005*	0.006*	−0.011**
	(1.66)	(1.65)	(−2.10)
Age (years)	0.002*	0.003**	−0.005***
	(1.69)	(2.21)	(−2.95)
Formal education (dummy)	0.111	0.138*	−0.249***
	(1.47)	(1.77)	(−2.89)
Family labor (number)	0.004	0.007	−0.010
	(0.62)	(0.92)	(−1.16)
Total farm size (ha)	0.011*	−0.032***	0.021*
	(1.72)	(−2.84)	(1.84)
Soil with high water retention (dummy)	−0.071**	−0.065	0.136***
	(−1.99)	(−1.48)	(2.64)
Land slope (dummy)	0.049	−0.043	−0.006
	(1.54)	(−0.97)	(−0.11)
Walking from homestead to farm (min)	0.001	0.000	−0.001
	(1.58)	(0.40)	(−1.24)
Project community (dummy)	−0.023	−0.001	0.025
	(−0.59)	(−0.02)	(0.41)
Nearest project community distance (km)	−0.024***	−0.006	0.030***
	(−5.17)	(−1.00)	(4.59)
Community wage rate (USD/day)	0.034	−0.169***	0.135**
	(0.85)	(−3.67)	(2.51)
Distance to district capital (km)	0.003	0.005	−0.008**
	(1.02)	(1.60)	(−2.01)
Community paddy price (USD/kg)	−1.670***	2.821***	−1.152
	(−3.03)	(4.97)	(−1.64)
Chi2	180.012	180.012	180.012
Pseudo R²	0.168	0.168	0.168
Number of observations	545	545	545

The numbers in parentheses are *t*-statistics
***, **, and * indicate significance at 1, 5, and 10 %, respectively

technology might not be desirable for the rainfed regions in Northern Ghana. An alternative to dibbling, which is more desirable, would be broadcasting (direct seedling) if proper water control technologies are adopted.[12] The finding that the nearest project community distance has a negative effect on the disadoption indicates that

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[12] This is based on personal interviews with agricultural scientists of the International Rice Research Institute who are familiar with lowland rainfed rice farming in West Africa.

farmers near the project communities temporarily adopted dibbling and abandoned it later. This may be taken to imply that dibbling is a seemingly useful technology, and thus, nearby farmers adopted it, but after implementation, they realized that it was too labor-intensive and thus was not profitable relative to its cost requirement. This finding is further examined in the impact assessment section.

5.4.3 Productivity and Efficiency

Tables 5.7 and 5.8 show the determinants of paddy yield in t/ha and profit in USD/ha, respectively. Column (1) shows the results for the combination of at least modern inputs and leveling and bunding and column (2) provides the results for package adopters. The chi-square test of independent equations $(\rho = 0)$, which is provided at the bottom of the table, shows that we can reject the null hypothesis of no endogeneity at the 5 % significance level. Overall, we observed a positive and highly significant relationship between technology adoption and productivity performance. This suggests that when controlling for other factors, the adoption of improved technology clearly results in increases in yield and profit per hectare.

In Table 5.7 we observe that the farmers who adopted the entire technological package obtained a higher yield than the partial adopters in column (1), which is supposed to reflect the contribution of dibbling (1.67 t/ha vs. 2.01 t/ha). Overall, the results indicate a positive relationship between yield and the number of technologies adopted, with package adopters realizing the highest gains. The project community dummy has a positive impact on yield, but it is weakly significant only in the case of package adoption (column (2)), which indicates that the project affected rice yield primarily through affecting the technology adoption rather than through providing additional technological information. The age of the household head and experience did not have much impact on yield while the experience prior to the project had significantly positive effects in both models.

Table 5.8 summarizes the findings of the profit function. Here, the result also indicates a positive and highly significant relationship between technology adoption and profit. Similar to the yield function, we observe that due to the strong complementary relationship among the five technologies, package adopters in column (2) realized a higher profit than partial adopters (column (1)). High soil quality, proxied by clay, has a positive impact on profit. The project community dummy and the nearest project community distance are found to have no additional impacts on profit. The farmer's human capital (age and education) had no impact on profit, but the experience did have positive and significant effect in column (1). Unexpectedly, family labor is found to impact negatively on profit, even though it has no impact on yield.[13] As predicted, community paddy prices have positive and very significant effect on the profit. Examining the difference in the magnitude of

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[13] This may be due to the over-estimation of the family labor cost, as the wage rate used for the imputation pertains to labor cost at peak seasons.

Table 5.7 Determinants of paddy yield in tons per hectare in Ghana (treatment effects model)

	At least modern inputs + bunding + leveling	Package adopters
	(1)	(2)
Experience prior to LRDP (years)	0.019**	0.015*
	(1.97)	(1.65)
Age (years)	0.001	0.003
	(0.49)	(1.08)
Formal education (dummy)	0.016	0.035
	(0.10)	(0.23)
Family labor (number)	−0.001	0.001
	(−0.09)	(0.04)
Total farm size (ha)	−0.011	−0.018
	(−0.64)	(−1.02)
Soil with high water retention (dummy)	0.138	0.135
	(1.38)	(1.40)
Land slope (dummy)	−0.043	−0.044
	(−0.43)	(−0.44)
Project community (dummy)	0.149	0.222*
	(1.24)	(1.93)
Nearest project community distance (km)	−0.004	−0.011
	(−0.40)	(−1.03)
Community wage rate (USD/day)	0.189*	0.123
	(1.90)	(1.31)
Distance to district capital (km)	0.007	0.015**
	(1.07)	(2.40)
Community paddy price (USD/kg)	0.278	1.139
	(0.22)	(0.93)
At least modern inputs + bunding + leveling (dummy)	1.663***	
	(8.35)	
Package adopters (dummy)		2.010***
		(9.28)
Constant	0.888**	0.637*
	(2.34)	(1.72)
Number of observations (N)	545	545
Wald (chi2)	103.983	122.400
Endogeneity test: prob > chi2	0.002	0.003

The numbers in parentheses are *t*-statistics

***, **, and * indicate significance at 1, 5, and 10 %, respectively

coefficients of technology adoption dummies across these models, the effect of dibbling is positive and significant, possibly because bunding and leveling are not complete, so that broadcasting leads to the uneven growth of rice plants and the failure of germination.

Table 5.8 Determinants of profit USD/hectare in Ghana (treatment effects model)

	At least modern inputs + bunding + leveling	Package adopters
	(1)	(2)
Experience prior to LRDP (years)	4.392*	3.701
	(1.67)	(1.41)
Age (years)	−0.192	0.129
	(−0.23)	(0.15)
Formal education (dummy)	−23.163	−20.110
	(−0.51)	(−0.45)
Family labor (number)	−10.246**	−9.924**
	(−2.16)	(−2.11)
Total farm size (ha)	7.469	6.353
	(1.48)	(1.27)
Soil with high water retention (dummy)	64.450**	64.711**
	(2.31)	(2.34)
Land slope (dummy)	−17.056	−17.607
	(−0.60)	(−0.63)
Project community (dummy)	35.434	48.956
	(1.06)	(1.49)
Nearest project community distance (km)	2.743	1.550
	(0.92)	(0.52)
Community wage rate (USD/day)	1.171	−10.216
	(0.04)	(−0.38)
Distance to district capital (km)	−0.630	0.933
	(−0.34)	(0.51)
Community paddy price (USD/kg)	942.025***	1099.277***
	(2.64)	(3.14)
At least modern inputs + bunding + leveling (dummy)	315.429***	
	(5.14)	
Package adopters (dummy)		394.452***
		(6.06)
Constant	−191.332*	−240.832**
	(−1.80)	(−2.27)
Number of observations (N)	545	545
Wald (chi2)	62.024	72.672
Endogeneity test: prob > chi2	0.001	0.002

The numbers in parentheses are *t*-statistics
***, **, and * indicate significance at 1, 5, and 10 %, respectively

5.5   Concluding Remarks

This chapter explored the determinants and impact of the adoption of modern inputs and proper water control technologies on the productivity and profitability of rice farming under a rainfed ecology in Ghana. As in the case of the Asian GR, our

findings suggest that new technologies do not favor wealthy large farmers in the rainfed regions, as small farmers are more likely to adopt labor-intensive technologies such as dibbling and MVs (David and Otsuka 1994; Otsuka and Larson 2013b).[14] We also observed that although the experience gained from rice farming prior to LRDP increases the early adoption decisions of the new technologies in the short-run, the effect of pre-project experience diminishes in the long run and is substituted by own learning. Our findings also suggest that learning directly from the project or extension services increases the probability of the continuous adoption of MVs and fertilizer. This finding implies that for technologies that require some level of technical know-how, having direct contact with extension services and projects increases the acquisition of relevant knowledge. This finding is consistent with the finding in Tanzania that farmers who have taken training directly achieve higher productivity than followers (see Chap. 3). For the adoption of observable technologies such as bunding and leveling, the distance to the nearest project community was negative and significant. These findings imply that there is a need to increase and strengthen the capacity of extension services for the adoption of modern inputs, while the construction of demonstration plots will be effective for the diffusion of observable technologies.

Another major finding of this study is that the Asian rice GR is directly transferable to rainfed areas in SSA and can result in yield gains similar to those in Asia and significantly higher profit. The gains realized are significantly enhanced if these technologies are adopted together due to the strong complementarities among them. Whether dibbling is an appropriate technology for Northern Ghana needs to be analyzed carefully as it was disadopted by many farmers, but we found the evidence of its positive impacts on both yield and profit. Although it will be possible to improve lowland rice technology further, we would like to argue that the fuller dissemination of the currently available technological package can bring about revolutionary changes in the productivity and profitability of rice farming in SSA.

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[14] MVs are also labor intensive because they require more crop care relative to traditional varieties.

Appendix

Table 5.9 Determinants of bunding adoption in Ghana (marginal effects – multinomial logit regression model)

Explanatory variables	(1) Pre-LRDP phase	(2) During LRDP phase	(3) Post-LRDP phase	(4) Non-adopters
Experience prior to LRDP (years)	0.000	−0.000	−0.003	0.003
	(0.01)	(−0.09)	(−1.02)	(0.94)
Age (years)	0.000	0.000	0.001	−0.001
	(0.01)	(0.05)	(0.95)	(−0.82)
Formal education (dummy)	0.000	−0.008	0.027	−0.019
	(0.01)	(−0.43)	(0.60)	(−0.39)
Family labor (number)	0.000	0.001	0.002	−0.003
	(−0.01)	(0.63)	(0.46)	(−0.68)
Total farm size (ha)	−0.000	0.001	−0.003	0.003
	(−0.01)	(0.21)	(−0.64)	(0.41)
Soil with high water retention (dummy)	−0.000	0.027*	−0.085***	0.058*
	(−0.01)	(1.87)	(−2.82)	(1.70)
Land slope (dummy)	0.002	−0.010	−0.008	0.017
	(0.64)	(−0.76)	(−0.34)	(1.50)
Walking from homestead to farm (min)	0.000	−0.000	−0.000	0.001
	(0.01)	(−1.19)	(−0.98)	(1.50)
Project community (dummy)	−0.000	0.027	0.016	−0.044
	(−0.01)	(0.93)	(0.54)	(−1.05)
Nearest project community distance (km)	−0.000	−0.009***	−0.014***	0.023***
	(−0.01)	(−3.79)	(−3.80)	(4.83)
Community wage rate (USD/day)	0.000	−0.047**	−0.063**	0.110***
	(0.01)	(−2.11)	(−2.11)	(2.97)
Distance to district capital (km)	−0.000	0.002	0.005***	−0.007***
	(−0.01)	(1.62)	(2.97)	(−3.36)
Community paddy price (USD/kg)	−0.001	0.345*	0.844**	−1.188***
	(−0.01)	(1.71)	(2.36)	(−2.82)
Chi2	187.793	187.793	187.793	187.793
Pseudo R^2	0.225	0.225	0.225	0.225
Number of observations	545	545	545	545

The numbers in parentheses are *t*-statistics

***, **, and * indicate significance at 1, 5, and 10 %, respectively

Table 5.10 Determinants of leveling adoption in Ghana (marginal effects – multinomial logit regression model)

Explanatory variables	(1) Pre-LRDP phase	(2) During LRDP phase	(3) Post-LRDP phase	(4) Non-adopters
Experience prior to LRDP (years)	0.003***	0.007***	−0.011	0.000
	(3.02)	(2.83)	(−1.50)	(0.03)
Age (years)	0.001	−0.000	0.000	−0.000
	(1.30)	(−0.44)	(0.12)	(−0.23)
Formal education (dummy)	0.021	−0.039	0.105	−0.087
	(0.68)	(−1.10)	(1.25)	(−1.02)
Family labor (number)	0.001	0.006	0.005	−0.012
	(0.55)	(1.26)	(0.59)	(−1.33)
Total farm size (ha)	−0.000	−0.005	−0.010	0.016
	(−0.15)	(−0.96)	(−1.05)	(1.60)
Soil with high water retention (dummy)	−0.017	0.017	−0.193***	0.193***
	(−1.08)	(0.64)	(−3.82)	(3.77)
Land slope (dummy)	0.022*	−0.003	0.035	−0.054
	(1.91)	(−0.09)	(0.67)	(−1.00)
Walking from homestead to farm (min)	0.000	−0.000	0.000	−0.000
	(1.53)	(−0.62)	(0.79)	(−0.54)
Project community (dummy)	0.003	0.018	−0.188***	0.166***
	(0.18)	(0.53)	(−3.53)	(2.69)
Nearest project community distance (km)	−0.001	−0.009**	0.002	0.007
	(−0.30)	(−2.34)	(0.36)	(1.20)
Community wage rate (USD/day)	−0.014	−0.127***	−0.193***	0.334***
	(−0.93)	(−4.12)	(−3.75)	(6.03)
Distance to district capital (km)	−0.000	0.007***	0.002	−0.008**
	(−0.07)	(3.21)	(0.48)	(−2.22)
Community paddy price (USD/kg)	−0.281	1.155***	1.525**	−2.399***
	(−1.27)	(3.07)	(2.28)	(−3.40)
Chi2	168.579	168.579	168.579	168.579
Pseudo R²	0.137	0.137	0.137	0.137
Number of observations	545	545	545	545

The numbers in parentheses are *t*-statistics
***, **, and * indicate significance at 1, 5, and 10 %, respectively

Table 5.11 Determinants of dibbling adoption in Ghana (marginal effects – multinomial logit regression model)

Explanatory variables	(1) Pre-LRDP phase	(2) During LRDP phase	(3) Post-LRDP phase	(4) Non-adopters
Experience prior to LRDP (years)	0.000	0.001	−0.004	0.002
	(0.91)	(1.00)	(4.04)	(0.63)
Age (years)	−0.000	0.000	0.002***	−0.003***
	(−0.47)	(0.61)	(2.62)	(−2.62)
Formal education (dummy)	0.002	−0.026**	0.166**	−0.142*
	(0.52)	(−2.08)	(2.31)	(−1.95)
Family labor (number)	0.000	0.001	0.002	−0.003
	(0.84)	(0.26)	(0.34)	(−0.47)
Total farm size (ha)	−0.000	−0.003	−0.022***	0.025***
	(−0.67)	(−0.88)	(−2.68)	(2.90)
Soil with high water retention (dummy)	0.001	0.014	−0.090**	0.075**
	(0.76)	(1.25)	(−2.57)	(2.04)
Land slope (dummy)	0.001	−0.024	−0.013	0.036
	(0.59)	(−1.59)	(−0.42)	(1.05)
Walking from homestead to farm (min)	0.000	−0.001***	0.000	0.001*
	(0.43)	(−3.29)	(1.01)	(1.82)
Project community (dummy)	−0.004	0.006	−0.019	0.017
	(−1.08S)	(0.42)	(−0.61)	(0.47)
Nearest project community distance (km)	−0.000	−0.000	−0.005	0.006
	(−1.09)	(−0.32)	(−1.17)	(1.30)
Community wage rate (USD/day)	−0.010	−0.057***	−0.035	0.103***
	(−1.12)	(−3.27)	(−1.06)	(2.72)
Distance to district capital (km)	0.000	0.001	0.002	−0.003
	(0.63)	(1.19)	(0.85)	(−1.26)
Community paddy price (USD/kg)	0.005	0.207	2.078***	−2.291***
	(0.31)	(1.31)	(5.13)	(−5.22)
Chi2	176.708	176.708	176.708	176.708
Pseudo R^2	0.204	0.204	0.204	0.204
Number of observations	545	545	545	545

The numbers in parentheses are t-statistics
***, **, and * indicate significance at 1, 5, and 10 %, respectively

Table 5.12 Determinants of MVs adoption in Ghana (marginal effects – multinomial logit regression model)

Explanatory variables	(1) Pre-LRDP phase	(2) During LRDP phase	(3) Post-LRDP phase	(4) Non-adopters
Experience prior to LRDP (years)	0.001*	0.006**	−0.003	−0.003
	(1.76)	(2.14)	(−0.61)	(−0.64)
Age (years)	0.000	−0.000	−0.002	0.002
	(0.32)	(−0.06)	(−1.32)	(1.52)
Formal education (dummy)	0.020	−0.071*	0.028	0.024
	(0.84)	(−1.90)	(0.35)	(0.31)
Family labor (number)	0.003*	0.007	−0.000	−0.009
	(1.91)	(1.25)	(−0.01)	(−1.27)
Total farm size (ha)	−0.001	−0.000	−0.015	0.016**
	(−0.83)	(−0.04)	(−1.62)	(2.10)
Soil with high water retention (dummy)	0.003	−0.011	−0.129***	0.137***
	(0.50)	(−0.34)	(−2.84)	(3.63)
Land slope (dummy)	0.001	−0.016	0.104**	−0.089*
	(0.11)	(−0.50)	(2.03)	(−1.84)
Walking from homestead to farm (min)	−0.000	−0.001	0.001**	−0.000
	(−0.80)	(−1.44)	(2.22)	(−0.98)
Project community (dummy)	−0.001	0.196***	−0.034	−0.161***
	(−0.09)	(3.45)	(−0.54)	(−3.85)
Nearest project community distance (km)	0.000	0.000	0.002	−0.002
	(0.31)	(0.11)	(0.28)	(−0.49)
Community wage rate (USD/day)	0.003	−0.157***	−0.089*	0.243***
	(0.37)	(−4.44)	(−1.78)	(5.54)
Distance to district capital (km)	−0.000	0.002	0.010***	−0.011***
	(−0.37)	(0.69)	(2.88)	(−3.85)
Community paddy price (USD/kg)	−0.212*	0.483	2.665***	−2.936***
	(−1.77)	(1.12)	(4.06)	(−5.06)
Chi2	240.421	240.421	240.421	240.421
Pseudo R^2	0.208	0.208	0.208	0.208
Number of observations	545	545	545	545

The numbers in parentheses are *t*-statistics
***, **, and * indicate significance at 1, 5, and 10 %, respectively

Table 5.13 Determinants of fertilizer adoption in Ghana (marginal effects – multinomial logit regression model)

Explanatory variables	(1) Pre-LRDP phase	(2) During LRDP phase	(3) Post-LRDP phase	(4) Non-adopters
Experience prior to LRDP (years)	0.004***	0.011***	−0.018**	0.003
	(3.11)	(2.59)	(−2.36)	(0.46)
Age (years)	0.000	−0.001	−0.002	0.003**
	(0.40)	(−0.80)	(−1.56)	(2.44)
Formal education (dummy)	0.013	−0.050	0.066	−0.029
	(0.50)	(−0.97)	(0.84)	(−0.42)
Family labor (number)	0.002	0.010	0.005	−0.016**
	(0.63)	(1.58)	(0.57)	(−2.15)
Total farm size (ha)	−0.006	0.007	−0.005	0.004
	(−1.46)	(1.08)	(−0.51)	(0.53)
Soil with high water retention (dummy)	−0.012	−0.009	0.035	−0.014
	(−0.79)	(−0.23)	(0.70)	(−0.33)
Land slope (dummy)	0.003	−0.047	0.048	−0.003
	(0.19)	(−1.20)	(0.94)	(−0.07)
Walking from homestead to farm (min)	−0.000	−0.001*	0.001**	−0.000
	(−0.22)	(−1.87)	(2.10)	(−0.13)
Project community (dummy)	0.031	0.148***	0.029	−0.208***
	(1.25)	(2.69)	(0.45)	(−4.67)
Nearest project community distance (km)	0.001	−0.006	−0.003	0.008*
	(0.42)	(−1.06)	(−0.52)	(1.75)
Community wage rate (USD/day)	−0.019	−0.062	−0.035	0.115***
	(−1.17)	(−1.52)	(−0.68)	(2.85)
Distance to district capital (km)	−0.000	−0.001	0.001	0.000
	(−0.24)	(−0.51)	(0.41)	(0.09)
Community paddy price (USD/kg)	0.190	0.911*	0.934	−2.035***
	(1.06)	(1.82)	(1.40)	(−3.35)
Chi2	209.971	209.971	209.971	209.971
Pseudo R2	0.165	0.165	0.165	0.165
Number of observations	545	545	545	545

The numbers in parentheses are t-statistics

***, **, and * indicate significance at 1, 5, and 10 %, respectively