

Aus dem Institut für Ernährungswirtschaft und Verbrauchslehre
der Christian-Albrechts-Universität zu Kiel

**Adoption and Economic Impact of Water Conservation and Intensification Methods on
Input Demand, Output Supply, and Net Returns in Lowland Rice Production of
Northern Ghana**

Dissertation
zur Erlangung des Doktorgrades
der Agrar- und Ernährungswissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von
Dipl. Volkswirtin Andrea **Liane** Linda Faltermeier
aus Regensburg

Kiel, Dezember 2008

Dekan:	Prof. Dr. Uwe Latacz-Lohmann
1. Berichterstatter:	Prof. Dr. Awudu Abdulai
2. Berichterstatter:	Prof. Dr. R.A.E. Mueller
Tag der mündlichen Prüfung:	12. Februar 2009

Gedruckt mit der Genehmigung der
Agrar- und Ernährungswissenschaftlichen Fakultät der
Christian-Albrechts-Universität

Diese Arbeit kann als pdf-Dokument unter
<http://e-diss.uni-kiel/agrар-fak.html>
aus dem Internet geladen werden.

Acknowledgement

The present study could not have been accomplished without the support of several individuals and institutions, who have contributed directly or indirectly to this thesis. In this limited space, I have to resist the urge to individually thank all of them. However, I want to unreservedly thank all of them for their support.

I want to thank my advisor Professor Dr. Awudu Abdulai, Chair of Food Economics at the Department of Food Economics and Consumption Studies, Christian Albrecht's University, Kiel, Germany, for support and approving my thesis as well as funding of field-work. Thanks also to members of my doctoral thesis examining committee, Professor Dr. R.A.E. Müller and Professor Dr. Dr. Christian Henning.

I want to express my sincere gratitude to the Savannah Agricultural Research Institute, Nyankpala, for support. I also must mention the valuable support of the Ministry of Food and Agriculture.

I am deeply grateful to all those numerous individuals who made my time in Ghana fruitful, enjoyable and a great experience. I owe my deepest gratitude to Dr. James Kombiok and his wife for their support and their warm-hearted and wonderful hospitality. I wish to express my warm and sincere thanks to Marie-Aude Even, project coordinator of the FSRPOP, for her help in organizing field work and her valuable comments. Thanks to her and Peter Anaadumba also for their great friendship and help. Appreciation is also extended to the several enumerators who assisted in data collection, as well as the rice farmers in the various sites who spared the time to be interviewed. I very much hope that the results of this work improve their standard of living.

I also wish to acknowledge the contribution of friends and colleagues at the Department of Agricultural Economics and the Department of Food Economics and Consumption Studies at the Christian Albrecht's University: I especially wish to express my gratitude towards Dr. Hendrik Tietje for his advice and numerous helpful comments. I am also very thankful to Dr. Thomas Herzfeld and Dr. Gunnar Breustedt for their constructive comments during the developmental stage of this thesis. I wish to express my warm and sincere thanks to Dr. Emily Ouma for her excellent advice regarding my field-work and her encouragement. I am also deeply grateful to my colleague Dr. Javier Becerril-García for his wonderful friendship and his serenity. I warmly thank Andrea Bieberstein for her moral support and friendship. Thanks also to Dr. Silke Schmitz for the friendly social support during my work.

I am very thankful to Dr. Girma Tesfahun Kassie and Klaus Edenhoffer for proof-reading parts of the manuscript.

Summary

The adoption of new agricultural technologies still plays a key role in increasing agricultural productivity and food security in developing countries and in stimulating overall economic growth through intersectoral linkages (e.g. Haggblade and Hazell, 1989; Hazell and Hoijati, 1995; de Janvry and Sadoulet, 2002).

Rice is an important cereal to Ghana's economy and agriculture, particularly as major cash crop in rice producing communities. There has been a remarkable increase in the demand for rice and in rice imports. Due to relatively high rainfall and large lowland area that is not yet cultivated, there is a huge potential for lowland rice cultivation in northern Ghana, which has been the major rice-producing sector of the country. However, lowland rice production continues to be characterised by low input use and productivity. The key constraints to rain-fed lowland rice production remain the erratic rainfall and the low and degrading soil fertility. The need to develop and disseminate water and soil conservation methods, as well as intensification methods has been repeatedly emphasized to increase productivity in the Ghanaian rice sector (MoFA, 2001). Soil bunds for water and soil conservation and dibbling as seed sowing and fertilizer application method have been introduced in smallholder lowland rice cultivation in the study region as part of a project to increase productivity.

Few studies have analyzed the economic impact of agricultural technology adoption on farm outcomes considering selection bias that may occur due to self-selection of farmers into adoption status. Without controlling for selection bias, the estimated technology effect may be biased and result in wrong policy implications. The present study employs an endogenous switching regression model and the non-parametric method of propensity score matching and contributes to the literature by analyzing the impact of bund technology and dibbling method on fertilizer demand, output supply, and net returns by explicitly taking account of selection bias. Determinants of adoption are analyzed in a first step. The cross-sectional data set refers to the cropping season 2005 and consists of 342 smallholder farmers cultivating lowland rice. Data was collected in 24 communities across three river valleys within a 50 km radius around the regional capital Tamale.

The adoption decisions of dibbling and bund technology are estimated employing a seemingly unrelated bivariate probit model. The results suggest that the adoption decisions

should be estimated jointly. Adoption decisions are found to be related to economic constraints, particularly of labour and capital. However, off-farm income appears to decrease the adoption of labour-intensive technologies due to increasing opportunity costs. Furthermore, adoption seems to be strongly related to the perception of technologies, and the participation in technology-related projects and farmer groups. In addition, the use of interrelated technologies such as the use of improved varieties, plot-level characteristics, and the geographic location appear to be significant factors. Results suggest that bunds are more likely constructed on marginal land as a preventive technology, while dibbling method seems to be used complementary to good soil productivity.

While most empirical studies use matching approaches that are based only on the propensity score, this study applies Mahalanobis metric matching with calipers and the propensity score as additional variable. This method has been rarely used in agricultural economics. However, it is particularly useful in the present analysis with multiple treatments. To check for the robustness of results, kernel based matching and nearest neighbour matching are applied in addition. Balancing tests were conducted by checking the reduction of the mean standardized absolute bias. To control for hidden bias due to selection on unobservables, sensitivity analysis was done by employing the Rosenbaum (2002) bounding approach. Results indicate the significance of matching in reducing bias in the distribution of relevant variables between the treatment and control group and that the estimates are quite insensitive to hidden bias. Results of the Mahalanobis metric matching indicate that the adoption of bund technology has a positive and significant effect on fertilizer demand, as well as a positive, but insignificant impact on output supply and net returns. Adopters of dibbling technology appear to have higher rice yields, while no statistically significant difference in net returns and fertilizer demand was found. However, data reveal a positive and significant effect on output supply and net returns when dibbling method is combined with intensified weeding. Furthermore, when dibbling is not only used as seed sowing but also as fertilizer application method, nitrogen demand is significantly higher.

The endogenous switching regression model identifies the factors determining net returns, fertilizer demand, and output supply for adopters and non-adopters. Estimates suggest that self-selection occurs and that different variables influence the adoption and outcomes. Furthermore, different variables are found to be significant in explaining the behaviour of adopters and non-adopters. Labour and capital constraints appear to be important factors in determining farm outcomes. In addition, the use of interrelated technologies and the timely availability of land preparation equipment reveal to be important factors. Furthermore, social networks such as farmer groups, education, as well as learning effects through the dissemination and the use of interrelated technologies turn out to impact on fertilizer demand, output supply, and net returns. However, the effects vary in the level and significance according to the type of technology and outcome.

Zusammenfassung

Neuen landwirtschaftlichen Technologien wird eine Hauptrolle bei der Steigerung der landwirtschaftlichen Produktivität und der Ernährungssicherheit in Entwicklungsländern zugeschrieben. Darüber hinaus tragen sie durch eine Vielzahl intersektoraler Verknüpfungen auch zur Stimulation des gesamtwirtschaftlichen Wachstums bei (z.B. Hazell und Hoijati, 1995; de Janvry and Sadoulet, 2002).

Der Reisanbau ist für Ghana sowohl ökonomisch als auch ernährungswirtschaftlich bedeutsam. Die seit den 70er Jahren stark steigende Nachfrage nach Reis hat aufgrund der weiterhin niedrigen Produktivität und dem niedrigem Faktoreinsatz zu einer stetig steigenden Importmenge geführt. Die großen, bisher ungenutzten *lowlands* im Norden Ghanas und die im regionalen Vergleich relativ hohe Jahresniederschlagsmenge stellen ein großes Potential für eine Ausweitung der regenabhängigen Reisproduktion dar. Die wichtigsten Produktionshemmnisse sind dabei die Unbeständigkeit der Niederschläge sowie die abnehmende Bodenfruchtbarkeit. Die Bedeutung wasser- und bodenerhaltender Maßnahmen sowie einer Intensivierung des Reisanbaus wurde auch vom ghanaischen Ministerium für Ernährung und Landwirtschaft unterstrichen (MoFA, 2001). Die Einführung und Verbreitung von *soil bunds* als wasser- und bodenerhaltende Maßnahme und *dibbling* als Methode der manuellen Reihenaussaat und der Düngemittelausbringung in Reihe waren in der Studienregion Bestandteil eines Projekts für Kleinbauern von 1999 bis 2003.

Die vorliegende Arbeit untersucht die ökonomische Auswirkung von *soil bunds* und *dibbling* auf den Nettoerlös, die Düngemittelnachfrage und Produktivität, sowie die Determinanten der Technologieannahme im regenabhängigen Reisanbau. Da die Wahl der Technologie im Zusammenhang mit anderen Charakteristika der Kleinbauern stehen kann, können Anwender und Nichtanwender bei der Evaluation der Technologien nicht als vergleichbare Gruppen angesehen werden. Bei Nichtberücksichtigung dieses selectivity bias können die geschätzten Technologieeffekte verzerrt sein. Da bisher keine Untersuchung der Auswirkung von *soil bunds* und *dibbling* auf Nettoerlös, Produktivität und Düngemittelnachfrage unter Berücksichtigung dieses methodischen Problems bekannt ist, soll die vorliegende Arbeit diese Lücke schließen. Dazu werden statistische Verfahren angewendet, die das Problem des *selectivity bias* explizit berücksichtigen. Dies geschieht zum einen durch die Anwendung parametrischer Verfahren (*endogenous switching regression*) sowie nicht-parametrischer

Verfahren (Matching-Methode). Die vorliegende Untersuchung basiert auf einer Befragung von 342 Kleinbauern bezogen auf die Anbausaison 2005. Die Daten wurden in 24 Dörfern in drei Flusstälern in einem Radius von etwa 50 km um die Distrikthauptstadt der Northern Region, Tamale, erhoben.

Die Determinanten der Technologieannahme beider Technologien wurden mittels eines bivariaten *seemingly-unrelated* Probitmodells geschätzt. Die Ergebnisse zeigen, dass die Annahmeentscheidungen beider Technologien nicht unabhängig voneinander sind. Die Technologieannahme scheint stark mit ökonomischen Beschränkungen, insbesondere von Arbeit und Kapital, verbunden zu sein. Außerbetriebliches Einkommen dagegen scheint die Annahme von arbeitsintensiven Techniken zu reduzieren. Zusätzlich ist die Technologieannahme mit der Wahrnehmung der Technologie und der Teilnahme in technologiebezogenen Projekten und Gruppen verbunden. Auch die Verwendung weiterer Technologien (wie verbesserte Reissorten) und die Eigenschaften der Anbaufläche sind signifikante Faktoren. Während *bunds* als präventive Technik eher auf qualitativ schlechteren Anbauflächen eingesetzt werden um regenabhängigen Anbau zu ermöglichen, scheint die Verwendung von *dibbling* komplementär zu einer guten Bodenqualität zu erfolgen.

Während die in den meisten empirischen Studien angewandten Matchingverfahren nur auf dem *propensity score* beruhen, wird in dieser Studie das multivariate Verfahren des *Mahalanobis metric matching* angewendet. Dabei können neben dem *propensity score* weitere Variablen aufgenommen werden, um Determinanten, die stark mit dem Ergebnis korreliert sein können, explizit zu berücksichtigen. Dieses Verfahren ist insbesondere im vorliegenden Fall von *multiple treatments* sinnvoll, wurde aber im Bereich agrarökonomischer Fragestellungen bisher nur wenig eingesetzt. Um die Sensitivität der Ergebnisse bezüglich des Matchingalgorithmus abzuschätzen, wurden zusätzlich das *kernel based matching* und das *nearest neighbour matching* durchgeführt. Balancing-Tests wie die Reduktion des *standardized mean absolute bias* zeigen eine starke Reduktion des *bias* in der Verteilung der relevanten Variablen zwischen den Gruppen der Anwendern und Nichtanwendern und bestätigen den Erfolg der Matching Methode. Mit dem Ansatz von Rosenbaum (2002) ergab sich zudem, dass die Ergebnisse als relativ robust gegenüber einer *hidden bias* gelten können. Die Ergebnisse des *Mahalanobis metric matching* ergeben, dass die Verwendung von *bunds* einen positiven und signifikanten Effekt auf die Düngemittelnachfrage, jedoch einen insignifikanten (positiven) Effekt auf Produktivität und Nettoerlös hat. Die Anwender des *dibbling* scheinen einen höheren Ertrag, aber keinen signifikant unterschiedlichen Nettoerlös, zu erzielen. Dagegen zeigt sich ein positiver und signifikanter Effekt auf Produktivität und Nettoerlös für die Kombination von *dibbling* mit verstärkter manueller Unkrautbekämpfung. Wenn *dibbling* nicht nur zur Aussaat, sondern auch zur Düngemittelausbringung verwendet wird, ist ebenfalls eine Erhöhung der Düngemittelnachfrage festzustellen.

Die Ergebnisse des *endogenous switching regression* Modells zeigen die Relevanz des *selection bias* und die unterschiedlichen Determinanten von Nettoerlös, Düngemittelnachfrage und Produktivität für Anwender und Nichtanwender. Beschränkungen von Kapital und Arbeitskraft konnten als wichtige Faktoren identifiziert werden. Zudem wirken soziale Netzwerke wie Farmergruppen, die Verwendung von verbundenen Technologien und die daraus entstehenden Lerneffekte auf die untersuchten Indikatoren. Des Weiteren ist die Verfügbarkeit von Traktoren und Ochsen zur Bodenbearbeitung ein starker Einflussfaktor. Die Stärke und Signifikanz der Effekte variiert dabei bezüglich Technologie und Ergebnisparameter.

Table of Contents

SUMMARY	I
ZUSAMMENFASSUNG	III
TABLE OF CONTENTS	VII
LIST OF TABLES	XI
LIST OF FIGURES	XV
LIST OF APPENDICES	XVII
ACRONYMS.....	XIX
CHAPTER 1 INTRODUCTION	1
1.1 Problem Setting and Motivation	1
1.2 Objectives of the Study	3
1.3 Significance of the Study	3
1.4 Outline of the Thesis.....	4
CHAPTER 2 RICE PRODUCTION IN GHANA.....	5
2.1 Background Information	5
2.1.1 Geography and Population	5
2.1.2 Nutrition and Social Indicators	8
2.1.3 Economic Situation and Macro-economic Environment for Agriculture.....	9
2.1.3.1 History of Economic Reforms and Agricultural Policy	9
2.1.3.2 Economic Situation Today.....	14
2.1.4 Situation of Agriculture Today.....	17
2.2 Rice Production and Rice Market in Ghana	21
2.2.1 Rice Ecologies and Varieties	21
2.2.2 Economics of Rice Production in Ghana	22
2.2.3 Potential of Rice Production in Ghana.....	30

2.2.4	Improved Lowland Rice Production in Northern Ghana	31
CHAPTER 3	LITERATURE REVIEW	35
3.1	Concepts of Innovation and Adoption.....	35
3.2	Theories of the Adoption and Diffusion of Innovation	36
3.3	Review of Literature on the Adoption of Agricultural Technologies on Micro-level	42
3.4	Review of Economic Impact Studies on Agricultural Technologies.....	55
3.5	Concluding Remarks and Contribution of the Analysis.....	61
CHAPTER 4	THEORETICAL MODEL	63
CHAPTER 5	ADOPTION SURVEY	69
5.1	Background and Working Definitions	69
5.2	Data Collection	71
5.2.1	Sampling Procedure	72
5.2.2	Survey Instruments and Implementation	72
5.3	Descriptive Analysis	73
5.3.1	Sample Structure and Adoption Pattern	73
5.3.2	Household Characteristics	76
5.3.3	Production System and Farm Characteristics	78
5.3.4	Plot-level Characteristics	83
5.3.5	Credit and Market Access and Information Sources	84
5.3.6	Input Demand, Output and Net returns.....	86
5.3.7	Perception of Technology and Constraints in Lowland Rice Production.....	89
5.3.8	Reasons for Use and Non-use of Bund Construction and Dibbling Method ..	91
5.3.9	Bund Construction Equipment and Maintenance Measures	96
5.3.10	Concluding Remarks.....	97
CHAPTER 6	ECONOMETRIC MODEL	99
6.1	Adoption Decision	99
6.2	Impact Assessment of Technology Adoption on Farm Outcomes	102
6.2.1	The Problem of Selection Bias and Non-experimental Solutions	103
6.2.2	The Endogenous Switching-regression Model	106
6.2.3	The Matching Estimation Approach	108
6.2.3.1	<i>The Counterfactual Framework.....</i>	<i>108</i>
6.2.3.2	<i>Matching Algorithms</i>	<i>113</i>
6.2.3.3	<i>Assessing the Matching Quality</i>	<i>118</i>
6.2.3.4	<i>Sensitivity Analysis</i>	<i>120</i>

CHAPTER 7	ECONOMETRIC RESULTS	123
7.1	Determinants of the Adoption Decision of Bunds and Dibbling	123
7.1.1	Variables Included in the Model.....	123
7.1.2	Results of Bivariate Adoption Model.....	133
7.1.3	Concluding Remarks.....	140
7.2	Determinants of Input Demand, Output Supply, and Net Returns in the Endogenous Switching-regression Framework.....	142
7.2.1	Variables Included in the Model.....	142
7.2.2	Results of the Endogenous Switching-regression Model	143
7.2.3	Concluding Remarks.....	160
7.3	Non-parametric Impact Assessment	160
7.3.1	Variables Included in the Matching Process.....	161
7.3.2	Results of Matching Procedure.....	164
7.3.3	Summary of Results and Concluding Remarks.....	185
CHAPTER 8	SUMMARY AND POLICY IMPLICATIONS.....	187
8.1	Summary of Results	187
8.2	Policy Implications.....	189
REFERENCES		191
APPENDICES		217
CURRICULUM VITAE.....		253

List of Tables

Table 5-1: Sample structure72

Table 5-2: Adoption pattern in the sample74

Table 5-3: Adoption pattern and technology use of adopters and non-adopters76

Table 5-4: Household characteristics of adopters and non-adopters78

Table 5-5: Farm characteristics of adopters and non-adopters80

Table 5-6: Frequency of other crops cultivated81

Table 5-7: Rice varieties cultivated (plot-level).....82

Table 5-8: Equipment for land preparation.....83

Table 5-9: Differences in plot-level characteristics84

Table 5-10: Credit source of non-project credits85

Table 5-11: Ranking of sources of knowledge of bunds and dibbling.....86

Table 5-12: Outcomes of adopters and non-adopters.....87

Table 5-13: Difference in outcomes between adopters and non-adopters89

Table 5-14: Perception of adopters and non-adopters90

Table 5-15: Perception of bunds and dibbling among adopters and non-adopters.....90

Table 5-16: Ranking of reasons to use intermediary bunds according importance
(% of responses)91

Table 5-17: Ranking of reasons for dibbling seed (% of responses)92

Table 5-18: Percentage distribution of reasons given for not using bund technology93

Table 5-19: Percentage distribution of reasons given for not dibble seed95

Table 5-20: Main construction equipment (% of responses)96

Table 5-21: Maintenance measures (% of responses).....96

Table 7-1: Expected impact of determinants on adoption probability of dibbling and
bund technology 124

Table 7-2: Variable names, definitions, and selected descriptive statistics for the
sample.....126

Table 7-3: Estimated coefficients and marginal effects at the mean for the seemingly
unrelated bivariate probit model of adopting bund technology and dibbling
method 135

Table 7-4:	Univariate probit model of the adoption decision of bund construction.....	145
Table 7-5:	Univariate probit model of the adoption decision of seed dibbling	146
Table 7-6:	Switching-regression model of input demand for adopters and non-adopters of bund construction.....	148
Table 7-7:	Switching-regression model of rice yields for adopters and non-adopters of bund construction	149
Table 7-8:	Switching-regression model of net returns for adopters and non-adopters of bund construction	150
Table 7-9:	Switching-regression model of input demand for adopters and non-adopters of dibbling	151
Table 7-10:	Switching-regression model of rice yields for adopters and non-adopters of dibbling	152
Table 7-11:	Switching-regression model of net returns for adopters and non-adopters of dibbling.....	153
Table 7-12:	Average treatment effects for adopters of bund technology and critical levels of hidden bias	173
Table 7-13:	Indicators of covariate balancing, before and after matching (bund technology).....	174
Table 7-14:	Average treatment effects for adopters of seed dibbling and critical level of hidden bias	175
Table 7-15:	Indicators of covariate balancing, before and after matching (dibbling seed technology).....	176
Table 7-16:	Average treatment effects for adopters of both dibbling seed and fertilizer and critical value of hidden bias	177
Table 7-17:	Indicators of covariate balancing, before and after matching (dibbling seed and fertilizer).....	178
Table 7-18:	Average treatment effects for adopters of intensified technology package...	179
Table 7-19:	Indicators of covariate balancing, before and after matching (impact of intensified technology package).....	180
Table A. 1:	Ghana's post-independence regimes.....	219
Table A. 2:	Estimation of propensity scores: treatment effects of bund adoption on net returns	220
Table A. 3:	Estimation of propensity scores: treatment effects of bund adoption on output supply	221
Table A. 4:	Estimation of propensity scores: treatment effects of bund adoption on input demand.....	222
Table A. 5:	Estimation of propensity scores: treatment effects of dibbling seed on input demand.....	223
Table A. 6:	Estimation of propensity scores: treatment effects of dibbling seed on output supply	224

Table A. 7:	Estimation of propensity score: treatment effects of dibbling seed on net returns	225
Table A. 8:	Estimation of propensity score: treatment effects of dibbling seed and fertilizer on input demand	226
Table A. 9:	Estimation of propensity score: treatment effect of intensified package on net returns	227
Table A. 10:	Estimation of propensity score: treatment effect of intensified package on output	228
Table A. 11:	Rice cropping calendar	230

List of Figures

Figure 2-1:	Map of Ghana.....	6
Figure 2-2:	Rainfall and temperature distribution of Northern Region’s capital Tamale, Ghana	7
Figure 2-3:	Sectoral contribution to the GDP (value added) in 2005	15
Figure 2-4:	Contribution of agricultural sub-sectors to the agricultural GDP	18
Figure 2-5:	Per capita rice consumption trends (index) selected West-African countries: 1960-2005	23
Figure 2-6:	Production of main staple crops in Ghana (1960-2007) in Mt.....	24
Figure 2-7:	Rice production in SSA, Nigeria, and Ghana (1960-2007)	25
Figure 2-8:	Rice area harvested and rice yield (1960-2007).....	26
Figure 2-9:	Total consumption and production of rice in Ghana (1960-2007).....	27
Figure 2-10:	Total rice imports in Ghana (1960-2007).....	28
Figure 2-11:	Rice price development 2000-2008: paddy rice and 200 TGL (\$ per hundredweight, CBoT).....	29
Figure 5-1:	Location of river valleys covered by the survey.....	69
Figure 6-1:	Trade-off in terms of bias and variance in matching methods	113
Figure 7-1:	Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of bund technology	165
Figure 7-2:	Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed	167
Figure 7-3:	Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed and fertilizer	169
Figure 7-4:	Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed and fertilizer	170
Figure A. 1:	Cropping calendar of principal food crops.....	229

List of Appendices

Appendix 1: Background information219

Appendix 2: Econometric Estimations220

Appendix 3: Calendar of Cropping Activities, Northern Region Ghana229

Appendix 4: Farmer-level Questionnaire231

Appendix 5: Compound Section of the Farmer-level Questionnaire.....248

Appendix 6: Village-level Questionnaire251

Acronyms

AAGDS	Accelerated Agricultural Growth and Development Strategy
ACP	Africa Caribbean and Pacific
AEA	Agricultural Extension Agents of the Ministry of Food and Agriculture of Ghana
AGDP	Agricultural GDP
AIC	Akaike Information Criterion
ATT	Average Treatment Effect on the Treated
AU	African Union
CIA	Conditional Independence Assumption
CRI	Crops Research Institute
ECOWAS	Economic Community of West African States
ERP	Economic Recovery Program
FAO	Food and Agriculture Organization of the United Nations
FASDP	Food and Agriculture Sector Development Policy
FSRPOP	Food Security and Rice Producers' Organizations Project
GDP	Gross Domestic Product
GHC	Ghanaian Cedi
GHS	New Ghanaian Cedi
GNI	Gross National Income
GoG	Government of Ghana
GPRS	Ghana Poverty Reduction Strategy
Ha	Hectares
HIPC	Highly indebted poor countries
IMF	International Monetary Fund

IRRI	International Rice Research Institute
KBM	Kernel based matching
LRDP	Lowland Rice Development Project
MMM	Mahalanobis Metric Matching
MoFA	Ministry of Food and Agriculture, Ghana
Mt	Metric tons
MTADP	Medium Term Agricultural Development Programme
MTDP	Medium Term Development Plan
NERICA	New Rice for Africa
NLC	National Liberation Council
NNM	Nearest Neighbour Matching
NPK	Compound fertilizer containing nitrogen, phosphate, and potash
NRC	National Redemption Council
PNP	Peoples' National Party
PRA	Participatory rural appraisal
PRGF	Poverty Reduction and Growth Facility
PRSP	Poverty Reduction Strategy Paper
PSM	Propensity score matching
SAP	Structural Adjustment Programme
SARI	Savannah Agricultural Research Institute (Tamale, Ghana)
SMC	Supreme Military Council
SSA	Sub-Saharan Africa
SUTVA	Stable Unit Treatment Value Assumption
SWC	Soil and water conservation
UDS	University of Development Studies (Tamale, Ghana)
UNCTAD	United Nations Conference on Trade and Development
UNDP	United Nations Development Programme
USDA	United States Department of Agriculture
WARDA	West African Rice Development Association
WTO	World Trade Organization

Chapter 1

Introduction

1.1 Problem Setting and Motivation

The direct contribution of the agricultural sector to the national development is obvious for many developing countries looking at its contribution to the GDP and the foreign exchange earnings. Agricultural growth is considered to be closely linked with rural development and poverty alleviation (see, e.g., Pinstруп-Andersen and Pandya-Lorch, 1995; DeJanvry and Sadoulet, 2002; Minten and Barrett, 2008). Empirical evidence shows that the largest growth in poverty reduction has resulted from agricultural growth, while urban-led development does not appear to trickle down to the poor rural areas (Ravallion and Datt, 1996). Moreover, agricultural sector growth may exert significant multiplier effects on the growth of other sectors in the economy. Based on the work of Adelman and Morris (1973) and Mellor (1976), much empirical work has been done that shows that the agricultural sector is linked to the national economy via several production and consumption linkages (e.g. Bell and Hazell, 1980; Delgado et al., 1998, on sub-Saharan Africa). Beyond that, Falcon and Naylor (2005) concluded from empirical evidence that food security, poverty alleviation, and broad-based economic growth could also be linked with democratization and national security.

Given the importance of agricultural growth there is urgent need for a sustainable increase in agricultural productivity in developing countries to improve food security, alleviate poverty, and to stimulate economic growth. Efforts have been made by governments of developing countries and NGOs to introduce and disseminate new farming technologies by alleviating economic constraints of technology adoption aimed at increasing agricultural productivity. However, these efforts have only been of partial success as measured by observed rates of adoption, even if the technologies were found to be beneficiary in agronomic experiment stations and in on-farm trials (Just and Zilberman, 1985; Abdulai and Huffmann, 2005). This observation continues to generate increased interest in issues related to innovation and dissemination of improved agricultural technologies (e.g. Johnson et al., 2007, Marenja and Barrett; 2007; Abdulai et al., 2008).

Rice is an important cereal to Ghana's economy, agriculture, and nutrition that accounts for nearly 15% of the agricultural Gross Domestic Product (Kranjac-Berislavjevic, 2000). Particularly in the northern sector regions of Ghana, where the poverty levels are highest in the country, rice is the major cash crop. Due to a remarkable dietary shift towards rice consumption in West African countries, rice consumption increased from 7.4 kg/capita/year in the period 1982-1985 to 25 kg/capita/year. It is even predicted to increase further. On the supply side, rice production is characterized by low yields (2.0 Mt/ha under rain-fed conditions in 2003 compared with 6.5 Mt/ha found to be achievable). Thus, domestic rice supply has been constantly less than consumption needs (MoFA, 2004a; Lançon and Benz, 2007). Therefore, imports of rice have been steadily increasing since the 1970s and weight heavily on the country's foreign currency reserves (Asubonteng et al., 2006).

However, there is great potential to increase rice production in northern Ghana. Ghana was found to have a comparative advantage in rice production in the sub-region due to a relatively high annual rainfall of 1100 mm and vast inland valleys exceeding 400,000 ha, of which only a small proportion is currently under cultivation and with the majority of this in northern Ghana (Senayah and Dedzoe, 1997; Asuming-Brempong, 1998; Mercer-Quarshie, 2000). Northern Region has been a major rice producer, with rice being a major cash crop for rice producing communities. However, rice production is hampered by the key problem of erratic rainfall and poor soil quality. Thus, there is urgent need for water conservation and yield-increasing methods in the rain-fed lowland rice production in northern Ghana where poverty rates and malnutrition are highest, to boost productivity and total output in order to improve food security and alleviate poverty. In this context, the Ministry of Food and Agriculture of Ghana (MoFA) recommended the construction of bunds as water conservation method in rain-fed lowland rice production to increase rice output in order to cut rice imports. The construction of earthen bunds as water conservation method and dibbling as yield-increasing seed sowing and fertilizer application method in lowland rice production were introduced in the study area as part of the Lowland Rice Development Project (LRDP) in the period 1999–2003. Despite the fact that bund creation was found to be yield-increasing by the LRDP and the efforts put in by the project to encourage the adoption of bund technology, dissemination has been quite low among the farmers. However, the reasons for the low adoption rate, particular of bund technology, remain unclear and need to be investigated. Thus, empirical investigations of the micro-economic adoption behaviour and economic impact studies of the technology adoption under actual farm conditions are required to fully understand the adoption behaviour.

1.2 Objectives of the Study

This thesis aims to evaluate the economic impact of the adoption of bund technology and dibbling method under farm conditions. Specifically, it aims at evaluating the impact of these technologies on farm outcomes such as output supply, net returns, and input demand, which are of major interest to the farmers and policy-makers. To analyze the impact of technology adoption on farm outcomes, the non-parametric propensity score matching method is employed, while the parametric selection correction model within the framework of the endogenous switching-regression model is used to identify differing determinants of the farm outcomes for adopters and non-adopters.

Empirical literature on agricultural technology adoption underlines that determinants of adoption vary according to the stage in the diffusion process, region, and characteristics of the technology. For this reason, region and technology specific studies are necessary to understand the adoption decision process. Thus, in a first step, the determinants explaining the adoption decision of bund technology and dibbling method are investigated by employing a seemingly-unrelated bivariate probit model of the joint adoption decision.

1.3 Significance of the Study

Much empirical work has been done to analyze the adoption decision of a single agricultural technology in developing countries. In the beginning, the focus of adoption literature was on technologies related with the Green revolution (improved high-yielding varieties, fertiliser, and pesticides). Recently, empirical work has been setting increasing priority on sustainable and low-input farming techniques and soil conservation methods. However, most adoption studies did not assess the impact of adoption decisions on farm outcomes, which are of primary interest to the farmers and policy-makers. Among impact assessment studies of technology adoption, majority do not consider that technology choice is not randomly assigned but endogenous due to self-selection of farmers into adoption status (with some exceptions, see, e.g., Abdulai and Binder, 2006). Self-selection bias arises if factors determining the adoption decision also influence farmers' outcomes (such as net return, yield, and input demand). Self-selection may therefore result in systematic differences between adopters and non-adopters. The main challenge of impact studies is then to estimate the missing counterfactual outcome for adopters properly. Ignoring the issue of self-selection would result in biased estimates of the technology impact and thus in misleading policy implications.

A propensity-score matching model is used to control for self-selection bias due to differences in observables. Most evaluation studies that have applied matching methods have used kernel based matching and nearest neighbour matching that are based on the single index of propensity score. This study employs the multivariate Mahalanobis metric matching approach that provides perfect matches on variables that may be strongly related with the outcome. This approach has been rarely used in agricultural economics, but is especially useful in the present analysis with multiple treatments. Furthermore, a sensitivity analysis is conducted using the Rosenbaum bound approach (Rosenbaum, 2002) to check for hidden bias due to the selection of unobservables.

The endogenous switching-regression model is a generalization of the Heckman selection correction method that also accounts for selection on unobservables. It is employed to explore not only the technology effect but also the effect of other determinants explaining farm outcomes such as net returns, output, and fertilizer demand separately for adopters and non-adopters.

1.4 *Outline of the Thesis*

The remainder of the thesis is structured as follows: In chapter 2, concise geographical and demographic description of Ghana and the study area is presented. Chapter 2 then gives an overview of the general economic situation and the macro-economic environment as related to agriculture and rice production in the study region. After that, the agricultural sector and the rice production in Ghana specifically will be outlined in further detail. In chapter 3, a review of the literature on technology adoption and impact assessment of agricultural technologies is presented. In chapter 4, the theoretical model for the analysis of the technology impact on net returns, input demand, and output supply is given. Chapter 5 provides the data collection procedures and descriptive statistics of the data generated in the survey. Chapter 6 presents the econometric model that is employed for the modelling of the adoption decision behaviour and for the evaluation of the impact of technology use. Chapter 7 then reports and discusses the results of the econometric estimations. Finally, chapter 8 concludes the thesis with policy recommendations.

Chapter 2

Rice Production in Ghana

This chapter aims at introducing geographical background information about Ghana and the study region. Furthermore, an overview of economic and agricultural policies in the country is given. After that, the chapter provides an overview of the rice production in Ghana, and the constraints and the potential of lowland rice cultivation in the Northern Region of Ghana.

2.1 Background Information

Ghana is a democratic country since the presidential and parliamentary elections in 2000 and it is currently reputed to be one of the most stable countries in West Africa and a leader in the democratization of the sub-region. Ghana is – amongst others – a member of international organizations such as the United Nations (since 1957) and African Union (AU), the World Trade Organization (WTO), the ACP-EU Agreement, the International Monetary Fund (IMF), and the Economic Community of West African States (ECOWAS).

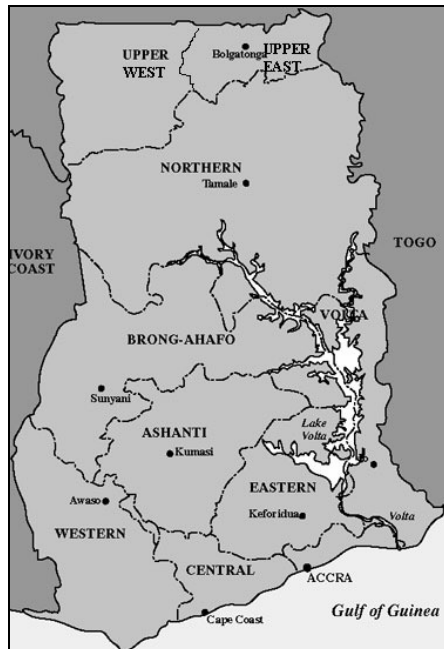
2.1.1 Geography and Population

Ghana is located on the west coast of Africa, about 750 km north of the equator. The country is 230 940 km² wide and shares borders with Burkina Faso in the north, Côte d'Ivoire in the east and Togo in the west. Most of the country is flat and the altitude varies between 500 m and 2000 metres above sea level.

The south has an extensive rain forest and has a tropical climate with two main rainy seasons. Northern Ghana extends from approximately 8°N to lat. 11°N and 0°-3°W longitude and consists of three administrative regions: Northern, Upper East, and Upper West (see figure 2-1). Northern Region is the largest region of Ghana and comprises 41% of Ghana's land area. In the same time, it has the lowest population density of all ten regions in Ghana,

which is about 20% of the country's population (MoFA, 1991). It lies in the agro-ecological Interior Savannah zone, comprising sub-humid to sub-arid Guinea and Sudan savannah.

Figure 2-1: Map of Ghana



Source: Ministry of Information and National Orientation (2007)

Ghana is endowed with relatively high levels of natural resources (including arable land, mineral deposits of diamonds, gold, manganese and bauxite and forests).

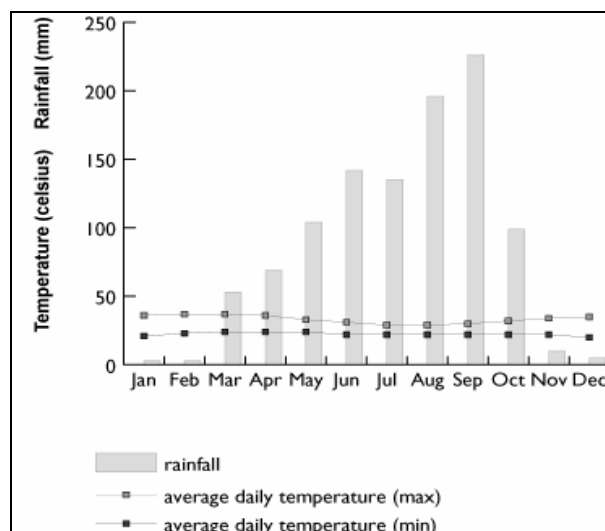
The population was estimated to be about 22,409,572 million in 2006 (CIA, 2006). The national population density is about 90 persons per km², with the lowest density being 26 inhabitants per km² in the Northern Region (FAO, 2005a). Population growth rate was estimated to be about 2.07% in 2006 (CIA, 2006). The fertility rate was 4.20 per woman in 2000, which is a significant decline from 6.50 in 1980 (The World Bank, 2003). This was also lower than the Sub-Saharan African average that was at 5.20 in 2000 (McKay and Areetey, 2004). Ghana's population is quite young, due to the higher fertility rate in the past. In 2005, 39% of the population was 14 years or younger (WTO, 2007). Furthermore, a high percentage of the population is rural: in 2004, it was about 54% of total population (FAO, 2005a).

Northern Region consists of 18 administrative districts and has a human population of about 1.9 million (referring to the 2000 population census) (MoFA, 2005b). Tamale is the administrative headquarters of the Northern Region and by far the biggest town in Northern Ghana. Northern Region has a total landmass of seven million hectares (which is 30% of the country's total landmass), of which 735,000 ha is under crop production. This equals 15% of

land available for agricultural production in Northern Region (MoFA, 2005b). About 75% of population in Northern Region was rural in 1995, which was even higher than the national average of 68% (MoFA, 2001). Furthermore, nearly 75% of the population in Northern Ghana depends on smallholdings and livestock (FAO, 2002).

The study region is located in the Guinea Savannah agro-ecological zone, which is characterized as tropical continental with two distinct seasons with almost equal duration. The unimodal rainy season begins in April and ends in September (Seini and Nyanteng, 2003). As it can be observed from figure 2-2, three-quarters of the annual total rainfall fall between May and September. Rainy season starts with small rains in March/April and gradually builds up to a maximum in September, then the rains decline and completely stop in October/November. In mid-November, the dry-Saharan winds usher in the Harmattan season. In the dry season, the weather is very hot and dry. From December until February, the relative humidity drops to 15-26%, while it varies from 78% to 83% during the months of June to September. Mean annual rainfall totals about 1100 mm and falls in the range of 900-1200 mm. This rainfall allows a length of 180-200 days of growing season (Seini and Nyanteng, 2003). However, the rainfall is unpredictable and erratic with periods of excessively heavy rainfall, as well as long periods (more than 10 days) of dry spells that often occur at critical stages of plant growth thus resulting in considerable drought risks.

Figure 2-2: Rainfall and temperature distribution of Northern Region's capital Tamale, Ghana



Source: BBC Weather

Soils in the study region are predominantly lateritic, and the texture is mainly silt or sandy loam. It therefore becomes waterlogged in the rainy season but dries out completely during the dry season due to generally shallow depths below the surface of a more cemented layer

of iron pan, through which rainwater does not penetrate easily. Soils are mostly shallow with low fertility. Thus, fertility is a major constraint for agricultural production (Runge-Metzger and Diehl, 1993).

2.1.2 Nutrition and Social Indicators

Ghana is not self-sufficient in food production and there is variability in the availability of food from season to season and from year to year depending upon rainfall amount and its distribution in space and time. Food insecurity is particularly severe in the rural areas of northern Ghana. With its single cropping season, unreliable rainfall, and mostly shallow soils of low fertility, the Interior Savannah (Guinea and Sudan) agro-ecological zone is regarded as marginal as far as the sufficiency of its own crop production is concerned. Due to unreliable rainfall, complete crop failures can be expected in most northern areas in about one out of every five years (FAO, 2005a).

Food insecurity is manifested in low anthropometric measurements and the incidence of certain diseases. Protein Energy Malnutrition is the most widespread and serious nutritional disorder in Ghana, especially among children (FAO, 2005a).

Ghana has made remarkable achievements in poverty reduction, showing improvements in most social indicators between 1997 and 2003 (such as access to education, basic health services, and water) (WTO, 2007). Per capita income increased to about US\$450 in 2005 from about US\$320 in 2000 supported by GDP growth rates that continuously exceeded population growth rates (WTO, 2007). Nonetheless, Ghana is still among the countries at the lower edge among the 55 countries classified as low-income countries (UNDP, 2007)¹. According to UNDP's Human Development Index for the year 2007/2008, Ghana ranks 135th out of 177 countries, thus being in the range of 'medium human development' (UNDP, 2007). Although this represents a slight increase from position 138 in 2003, this is still below Ghana's position as 119th in 1999 (UNDP, 2001; UNDP, 2005).

Poverty remains widespread, particularly among rural areas and among women (WTO, 2007). According to the UNDP's Human Development Index Report of the year 2005, about 50% of the population lives on under 1 \$US per day, and 75% of the population on under 2 US\$ per day (UNDP, 2005). A recent survey even shows a rise in child and infant mortality rates (The World Bank, 2005a). Infant mortality among the 20% poorest was 89 per 1000 live

¹ In 2005, low-income countries are defined as countries with a GNI per capita of US\$875 or less (UNDP, 2007).

births and mortality among under five years of age was even 125 per 1000 live births among the 20% poorest in 2006 (UNDP, 2007). Among children under five, 22% are underweight (UNDP, 2007), 16% of infants still had a low birth weight, and 11% of the whole population was still undernourished (on average between 2002 and 2004). However, this represents some improvement over 37% of population on average being undernourished between 1990 and 1992 (UNDP, 2005).

There are still significant disparities in the poverty distribution reflecting the imbalance between north and south, whereby the south has a significantly higher level of development. Poverty is still pervasive in many parts of Ghana, especially in the rural areas, the northern part of the country and among non-cocoa farmers. According to Ghana Living Standards Survey (GLSS) IV in 1998/1999, 54% of Ghana's poor were food crop farmers (MoFA, 2001). This survey also shows regional differences: rural poverty was estimated at almost 50 percent, while urban poverty was estimated at 19 percent (The World Bank, 2003). Poverty levels are highest in Upper East, Upper West and Northern Regions, with 88%, 84% and 69% in 1998/99, respectively (FAO, 2005a). Levels of malnutrition are estimated at more than double the nation average in Northern, Upper East, and Upper West Regions (FAO, 2002). While national indicators for underweight and stunting among children below the age of five are 22 and 30 percent respectively, these indicators are 33 and 48 percent in the north of Ghana (WFP, 2008)

2.1.3 Economic Situation and Macro-economic Environment for Agriculture

2.1.3.1 History of Economic Reforms and Agricultural Policy

Ghana is generally regarded as one of the more successful examples of an economic turnaround in sub-Saharan Africa. After independence in 1957, Ghana had one of the highest per capita incomes in Africa that would have placed it among the middle-income countries by today's standards. The growth rates were relatively high between 1960 and 1964 but they gave way to economic mismanagement with macroeconomic instability and poor growth performance from 1965 to 1983, with the worst period between 1977 to 1983 (McKay and Aryeetey, 2004). After major changes since 1983, Ghana's economy bounced back. Since 2001, macroeconomic fundamentals have improved considerably (WTO, 2007). Generally, after economic growth showed considerable unevenness and volatility in the first two decades after independence, but this was followed by much more even and stable

growth in the last two decades, following substantial policy reforms accompanied by large inflows of external aid.

During the late 1970s and early 1980s, real wages and employment, as well as production levels declined and poverty and income inequality increased. Food self-sufficiency ratio declined from 83% in 1984 to 71% in 1978-1980 and 60% in 1982 (Asuming-Brempong, 2003a). Domestic savings and investment fell, while the government deficit increased. Similarly, annual inflation rate peaked at 122% in 1983 (Asuming-Brempong, 2003a; Agbola, 2005). Between 1970 and 1980, the average per capita income growth rate declined from 2.1% in the 1950s to 0.5% in the 1960s and -1.2% between 1970 and 1980. Similarly, in this time the average growth rate in agriculture was -1.2% per annum. Due to the population growth rate of 2.6% per annum, this resulted in a 28% decline in food production per capita between 1970 and 1984 (Dapaah, 1995).

The socialist-oriented policy of the government of Nkrumah (1957-1966) focused on industrialization and heavy state interventions. The policies aimed at speeding up industrialization and economic development by the use of state enterprises in production, foreign exchange licensing, and internal price controls. Between 1959 and 1965, the world market price of cocoa collapsed and deteriorating terms of trade compounded the impact of these policies. Because of all these factors, large fiscal deficits emerged, the balance of payments deteriorated significantly, and the economy went to crisis (Tsikata, 1999).

A major policy focus under Nkrumah was the modernization of agriculture. The basic development strategy was to concentrate on a selected number of commodities and to apply to them all technological knowledge. Extensive bush clearing was undertaken to maximize the acreage under cultivation (Asuming-Brempong, 2003a). The adoption of new farming techniques was supported by establishing the Extension Service as an integral part of agricultural policy. Ghana attempted to transform the agricultural production by state interventions in production and distribution of agricultural produce (Beckman, 1981). The government focused on large-scale mechanized farming, on public ownership in form of state farms, and on massive government investments while private farmers were encouraged to organize into co-operatives (Seini and Nyanteng, 2003). However, the performance of socialist-oriented agriculture was rather disappointing and state-farms could not be sustained (Asuming-Brempong, 2003a).

The two regimes following Nkrumah (the National Liberation Council (NLC) in 1966-1969 and the Government under Busia in 1969-1972) adopted a capitalist oriented policy strategy focusing on liberalization of the economy and private sector led growth. While both regimes made substantial investments in rural development schemes, this policy was not sustained in

the 1970s (Asuming-Brempong, 2003a). Political turmoil and short-lived reforms followed in 1966-1972 while the economic decline continued and the balance of payments slipped into crisis in 1971 (Asuming-Brempong, 2003a). However, shortly after implementation of IMF conditionalities involving the devaluation of the overvalued Ghanaian Cedi by 44 percent in late 1971, the government was overthrown in 1972 (Agbola, 2005).

Under Acheampong and his National Redemption Council (NRC) (1972-1975) and later the Supreme Military Council (SMC) (1975-1979), the earlier misplaced socialist policies under the First Republic were reintroduced and even intensified, leading into economic chaos. Particularly by 1974, economic decline and perishing had begun to set in and Ghana experienced currency collapse in the 1970s and continued stagflation in the second half of the seventies (Tsikata, 1999). Until 1977, when a five-year development plan was launched, the NRC governed without the guidance of any development plan. This plan aimed at reaching an independent economy through self-reliance with significant government participation in direct production (Asuming-Brempong, 2003a). The NRC revalued the currency by 26 percent and imposed stringent import controls, introduced additional price controls, and unilaterally suspended foreign debt servicing. Consumer price inflation skyrocketed, rising to 77.2 percent by 1977. As the exchange rate continued to be fixed, the GHC was increasingly overvalued, discouraging exports. Government expenditures rose and were financed by a complex and high tax rate on imports, goods, services, and exports. Additionally, widespread corruption emerged during the rest of the decade resulting from the system of import licenses, high tax rates for goods, and other reasons (Tsikata, 1999). When Akuffo overtook, the SMC II introduced structural adjustment programmes advised by the IMF in 1978 (Agbola, 2005).

Under Acheampong, in 1972-1974, the 'Operation Feed Yourself' and the 'Operation Feed Your Industries' were launched to increase agricultural production and to provide raw materials for industries. Price controls for manufactured goods and guaranteed minimum prices were set for major agricultural commodities, such as cocoa, maize, and rice (Asuming-Brempong, 2003a). However, due to various reasons (such as heavy taxes on agriculture, adverse weather conditions, and low commodity prices), agricultural production declined (Asuming-Brempong, 2003a). Towards the end of the 1970s, small-scale programmes were initiated to increase agricultural production particularly of small-scale farmers by providing improved agricultural inputs and services. Most of these projects were largely successful as long as funding from the sponsors was available. However, mostly they could not be sustained when sponsorship had ended (Seini and Nyanteng, 2003).

The civilian administration of the Peoples' National Party (PNP) led by Liman (1979-1981) faced a massive economic decline. As the government was not able to pull the economy out of the economic malaise, macro-economic crisis prevailed in 1981 followed by a coup by Rawlings in December 1981 (Tsikata, 1999). After taking power for a second time in 1982, Rawlings harmonised the national economic policy in accordance with the concepts of the World Bank and the IMF in 1983 to reverse the economic downturn in the 1970s and early 1980s. Accordingly, Ghana launched the Economic Recovery Program (ERP) and the related Structural Adjustment Programme (SAP) with the assistance of the Bretton Woods institutions and managed to reverse the declining trend. The program was supported by a stand-by arrangement with the IMF and a multi-sector rehabilitation credit from the World Bank (Tsikata, 1999).

The economic reforms undertaken in Ghana can be grouped into the stabilization period by the Economic Recovery Program (ERP) from 1983 to 1986 and the Structural Adjustment Programme (SAP, also known as ERP II) as a follow-up focusing on structural issues from 1986 to 1991. The stabilization policies in the early phase (1983-1986) were implemented to create incentives through realigning relative prices (including exchange rates and interest rates) in favour of domestic production of import-substitutes and exports with the objective to stabilise the inflation rate, budget position, to rehabilitate social and economic infrastructure, and to eliminate smuggling and black market activities (Tsikata, 1999). The adjustment phase began in 1986 and aimed at removing structural impediments from the economy to bring it back to the growth path. This phase involved foreign exchange reforms, fiscal and monetary policies and trade liberalizations. The major goals of the third phase (1989-1995) included deregulation of commodity and service markets, as well as liberalization of export and import markets (Dapaah, 1995; Seini and Nyanteng, 2003). As structural adjustment measures were implemented, the exchange rate of the Ghanaian Cedi (GHC) was liberalised, state-owned assets were privatised, and a substantial part of the labour force in the public sector was retrenched (Herbst, 1993). Due to the importance of the agricultural sector for overall economic growth, the agricultural sector was the focus in all phases of the reforms. Under the ERP/SAP, a major policy focus was the deregulation of the input and output markets. Guaranteed prices were discontinued, subsidies for inputs were gradually removed, and the importation and sale were privatized to promote efficiency (Asuming-Brempong, 2003a). First, incentives for the production of food, as well as industrial raw materials and export commodities were restored. In the second phase, special emphasis was given to increase productivity and to internal price stability. In the third phase of adjustment, the guaranteed minimum prices for maize and rice were abolished and all subsidies for agricultural inputs (particularly fertilizer and insecticides) were removed (Seini and Nyanteng,

2003). Because of the reforms in the agricultural sector, the prices of most agricultural chemicals used in cereal production increased in excess of 40 percent on average per annum between 1986 and 1992. Before the reforms, the subsidies on fertilizer have been in the range of 40 to 80 percent (Seini, 2002b). The liberalization of food imports has made imported food commodities compete strongly with domestic food commodities, particularly rice (Seini, 2002a). In addition, government spending in the agricultural sector was significantly reduced (Fan and Rao, 2003). The share of agriculture in total government expenditures dropped from about 12% prior to the reforms in 1980/1981 to 2% in the 1990s. This resulted in huge cuts in formal credits, input supply programs, animal traction equipment, and subsidies for fertilizer (Reardon et al., 1994).

The policy strategy of the post-structural adjustment phase implemented in 1992 relied strongly on the private sector to lead investment and economic growth. The period between 1992 and 1996 under the new civilian government of Rawlings starting in 1992 is characterized by 'oscillating policy reforms' (Tsikata, 1999). In this period, a loss of fiscal control, macroeconomic instability, and difficulties between the government and the Bretton Woods institutions due to policy slippage, occurred. The rather successful adjustment was partially derailed in 1992 partly due to an election-related wage increase (Tsikata, 1999). In 1995, the Government of Ghana (GoG) launched the Vision 2020 document ('Ghana Vision 2020: The First Step'), which is a 25 year perspective plan for national development, to fulfil the requirements of the 1992 constitution. It identifies basic objectives to increase employment and average incomes and to reduce poverty and inequities to transform Ghana into a middle-income country by the year 2020 (MoFA, 2001). For the implementation of the Ghana-Vision 2020 a series of 5-year medium-term development plans was expected to be undertaken. The first Medium Term Development Plan (MTDP) (1997-2000) under Ghana Vision 2020 has been replaced by the Ghana Poverty Reduction Strategy I (GPRS I) (2002-2005). This was extended by the Growth and Poverty Reduction Strategy II (GPRS II) as the national policy framework for the period from 2006 to 2009. While the emphasis of GPRS I was on macroeconomic stability, poverty reduction programs and projects, the emphasis of GPRS II (2006-2009) is on the implementation of growth inducing policies and programmes which have the potential to support wealth creation and sustainable poverty reduction so that Ghana can achieve middle-income status within a measurable planning period (IMF, 2006). Thereby, the implementation of the GPRS is part of the macroeconomic requirements of the

IMF Poverty Reduction and Growth Facility (PRGF) credits of 2003 (McKay and Aryeetey, 2004)².

In the post-structural adjustment era, government intervention in the agricultural sector has been restrained as much as possible. However, the private supply of goods and services is still below socially optimal levels (Seini, 2002a). In 1991, the MoFA in cooperation with the World Bank prepared the Medium Term Agricultural Development Programme (MTADP). The MTADP served as a strategy for food and agricultural development in the years 1991 to 2000. It acknowledged the importance of the private sector to boost economic growth in the agricultural sector, proposed a more free market pricing, and the liberalization of supply of seed, fertilizer, and other agricultural inputs (Asuming-Brempong, 2003b). Building on the achievement of MTADP, the Government of Ghana developed the Accelerated Agricultural Growth and Development Strategy (AAGDS) as a follow-up in 1996 to support the Vision 2020 goals in the agricultural sector (MoFA, 2001). This strategy was designed to increase the sector's annual growth rate from 2-3 percent in 1990 to 1996, to 5-6 percent as programmed for in the Vision 2020 document. Subsequently, the Food and Agriculture Sector Development Policy (FASDP) was formulated in 2002 as the main policy document of the MoFA, which provides a broad framework for agricultural development. In 2007, the FASDEP II (Revised Food and Agricultural Sector Development Policy) was developed as a continuation of these agricultural strategy plans (WTO, 2007). Additionally, the Kufuor government initiated some commodity specific programs in 2001 (President's Specials Initiatives (PSI's)) to boost exports of starch from cassava, garments, and textiles.

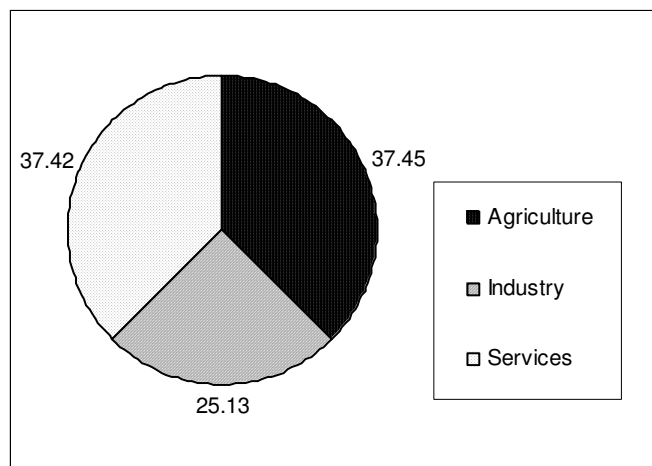
2.1.3.2 Economic Situation Today

The sectoral contributions to the GDP have been relatively stable in the last years. Figure 2-3 presents the sectoral contribution to the GDP in 2005. The agricultural sector (crops and livestock) developed well in 2005 and contributed 37.45% to the national GDP (value added), compared to 35.27% in 2000. The industrial sector contributed 25.13% of the GDP in 2005,

² The PRGF is the IMF's low-interest lending facility for low-income countries. PRGF-supported programs are framed around comprehensive, country-owned Poverty Reduction Strategy Papers (PRSPs) to make the objectives of poverty reduction and growth more central to lending operations in its poorest member countries. PRSPs are considered by IMF and World Bank as the basis for concessional lending from each institution and debt relief under the joint Heavily Indebted Poor Countries (HIPC) Initiative (IMF, 2008a).

while in 2000 the contribution was 25.40%. Services accounted for 37.33% of GDP in 2005 starting from 39.32% in 2000 (The World Bank, 2007a)³.

Figure 2-3: Sectoral contribution to the GDP (value added) in 2005



Source: The World Bank (2007a)

Since 2001, the macroeconomic fundamentals have improved considerably (WTO, 2007). Real GDP has been increasing annually in the range of 4% to 6% (ISSER, 2006). Average annual growth rate was 5.1% between 2000 and 2006, compared to 4.4% between 1995 and 1999. In 2005, it reached 5.8% and even 6.2% in 2006 (WTO, 2007). This expansion was mainly driven by the growth in the agricultural sector supported by productivity increases and favourable cocoa prices (WTO, 2007). However, these relatively high growth rates over the last few years could not be translated into increasing real per capita output growth (ISSER, 2006).

Inflation declined from 40.5% in 2000 to 10.9% in 2006 (MoFA, 2005a; WTO, 2007). Furthermore, the fiscal situation has improved significantly since 2000. Compared to a deficit of about 8.8% of GDP in 1999 and 2000, budget deficit reduced to 2.2% of GDP in 2006 (FAO 2002; Deutsche Botschaft 2006). Domestic debt as ratio of GDP decreased from 26.81% in 2001 to 19.5% in 2005 (ISSER, 2006). However, in absolute terms, domestic debt stock increased by 10% as compared to that of 2004 (ISSER, 2006). As foreign direct investments and private capital flow have been falling steadily, Ghana has been highly dependent on official international credits, with external debt rose by 5% in 2005 (ISSER, 2006). Ghana is one of the most heavily indebted countries in sub-Saharan Africa, with

³ In comparison, the contribution of agriculture to GDP in SSA was 16.20% on average in 2005, industry accounted on average for 32.54% and services contributed on average 51.20% (The World Bank, 2007a).

external debts of US\$8 billion in 2003 (Deutsche Botschaft 2006, ISSER, 2006). After reaching the completion point in 2004 under the HIPC initiative, foreign indebtedness reduced to US\$6.7 billion in 2005 after debt relieves⁴. This corresponds to 64.5% of GDP compared to 157.3% of GDP in 2000 (ISSER, 2006).

Despite diversification of the economy, Ghana remains over-dependent on cocoa and gold, which are the most important export items, followed by timber in the third position (Deutsche Botschaft, 2006). Other main export items are mining products (diamonds, bauxite, and manganese), coffee, tuna, and textiles (WTO, 2007). Various non-traditional exports have increased their share significantly in total exports (MoFA, 2001)⁵. The foreign exchange contribution of the agricultural sector (crops and livestock) through non-traditional export was US\$151.9 million in 2005, while total exports (fob) in 2005 were US\$2,802 million (MoFA, 2006b; The World Bank, 2007b).

Main import items are petroleum, consumer durables, foods and capital equipment (FAO, 2002). Increases in merchandise imports were triggered by domestic growth and rising oil prices. The structure of imports remained stable between 2000 and 2006, with manufactured products accounting for about 70% and agricultural goods and fuel each accounting for about 15% of imports in 2006 (WTO, 2007). Despite Ghana's export-led growth strategy, during 2000 to 2005 Ghana's total import bill strongly rose by about 90% outpacing increasing exports that rose by 41 percent only, widening the trade gap by more than 20 percent (ISSER, 2006). Merchandise exports-to-GDP ratio declined sharply from 50% in 2000 to 26% in 2005 (ISSER, 2006). Thus, the trade deficit remains growing enormously with about US\$2.5 billion in 2005, which represents an increase of 57.7% against 2004 (ISSER, 2006). Permanent trade deficit also put pressure on the foreign exchange reserves, even with declining depreciation of the Cedi against the US dollar from 49.8% in 2000 to 2.2% in 2004 (GoG, 2005). Foreign exchange reserves were equivalent to 3.8 months of imports in 2004 and increased from 0.9 months in 2000 (MoFA, 2005a). This trend of the trade deficit is

⁴ The HIPC initiative was launched in 1996 by the IMF and the World Bank and enhanced in 1999 to provide debt relief to the world's poorest and most heavily indebted countries pursuing IMF- and World Bank-supported adjustment and reform programs. Under HIPC, Ghana has experienced a relief of US\$2.2 billion (net present value or US\$3.2 billion in nominal terms) to bring the NPV of the debt-to-government-revenue ratio down to the HIPC threshold of 250% (The World Bank, 2005b). Debt relief and bilateral assistance beyond HIPC relief lowered Ghana's debt-to-export ratio to 84% and its debt-to-government revenue ratio to 130% in 2004 (levels that are 66 and 120 percentage points respectively below the HIPC threshold). In 2005, the HIPC Initiative was supplemented by the Multilateral Debt Relief Initiative (IMF, 2008b). To reach completion point, countries must maintain macroeconomic stability under a PRGF-supported program, carry out key structural and social reforms, and implement a Poverty Reduction Strategy satisfactorily for one year (IMF, 2008a).

⁵ Traditional exports are gold, diamonds, bauxite, manganese, cocoa beans, coffee, timber, and electricity. Non-traditional export items include processed forms of the above products and all other products (e.g. bananas, textiles, footwear) (WTO, 2007).

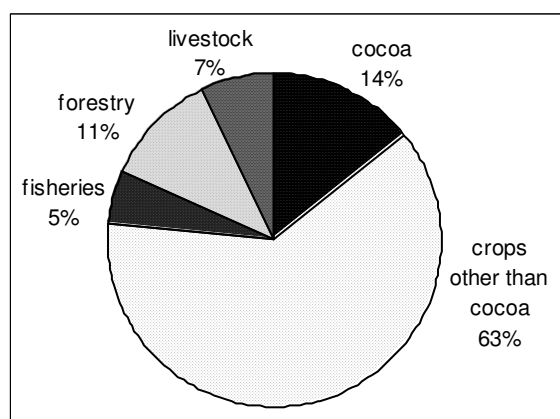
reflected in a significant deficit of the current account of US\$758 million in 2005, which was highest since 2000 and twice the deficit of US\$316 million in 2004 (ISSER, 2006). However, Ghana's overall balance reduced from a deficit of US\$1.16 billion to a deficit of US\$10.5 million in 2004, reaching a surplus of US\$110 million in 2005. This surplus was mainly driven by payments on the capital account that is largely due to private capital inflow (ISSER, 2006).

2.1.4 Situation of Agriculture Today

The agricultural sector still maintains a leading role and is important in terms of contribution to GDP, employment and export earnings. The agricultural sector consistently accounted for the highest proportion of the GDP over the last years (ISSER, 2006). Agriculture employed around 60% of the population and accounted for about 40% of merchandise exports (with cocoa being the main cash crop) in 2006 (MoFA, 2006a; WTO, 2007). Over 80% of the rural population depends on agriculture as the mainstay of life (FAO, 2006). However, public spending in agriculture as percentage of GDP declined in the post-structural adjustment era from 57.9% in 1980 to 44.8% in 1990 and 36.0% of GDP in 2002. In terms of the percentage of government spending, the decline is even more obvious. Public expenditure for agriculture started with 12.2% of government spending in 1980, but has decreased to only 4.1% in 1990 and 1.0% in 2002 (Fan and Saurkar, 2006).

According to MoFA (2001), the contribution of agricultural sub-sectors to the agricultural GDP is essentially composed of cocoa (14% of agricultural GDP), crops other than cocoa (61%), livestock (7%), fisheries (5%), and forestry (11%) (see figure 2-4).

Figure 2-4: Contribution of agricultural sub-sectors to the agricultural GDP



Source: MOFA (2001)

Agricultural growth traditionally lagged behind other sectors of the economy and was highly unpredictable, as most farming is reliant on rainfall. In recent years, however, agricultural growth has improved. In 2005, the agricultural sector in total grew at a rate of 6.5% (2004: 7.5%) compared to 4.4% in 2002 and 4.0% in 2001 (GoG, 2005, MoFA, 2006a). The good performance of the sector in the recent years virtually emanates from high growth rates in cocoa production and marketing (16.4% in 2003 and 29.4% in 2004), while the GDP shares of other agricultural sub-sectors remained either constant (forestry) or have even declined (fishing, livestock, other crops) (WTO, 2007). The growth rates of the sub-sector of crops and livestock are relatively stable with 5.3% in 2004 and 2003 (GoG, 2005). The annual growth rates of forestry and fishing in the years 1998 to 2004 are in the range of 5.0% to 5.8% and 2.0% to 3.5%, respectively.

Under the Vision 2020 programme, the agricultural sector is targeted to grow at an annual rate of 5-6%. This is to fuel an increase in Ghana's annual GDP growth rate to 8% in order to ensure food security and adequate nutrition for all Ghanaians, to supply raw materials and other inputs to other sectors of the economy and to contribute to an improvement in balance of payment and to provide producers with income comparable to earnings outside agriculture (MoFA, 2001).

Maize, rice, millet, sorghum, cassava, yam, cocoyam, and plantains are the main staple food crops. The country's most preferred cereal staple is maize with an annual per capita consumption of about 40 kg/head/year followed by rice with 25 kg/head/year (FAO, 2006; Lançon and Benz, 2007). In terms of production volume over the last 30 years, the major cereal crop produced has been maize followed by sorghum. Until 1989, millet ranked persistently in the third position, but since 1990, rice has overtaken millet's position (Seini and Nyanteng, 2003). Ghana has been self-sufficient (or nearly) in the production of several food commodities such as some cereals, roots, tubers, plantain, fruits, vegetables and eggs.

Industrial raw materials include cotton, oil palm, tobacco, and bast fibre. Cocoa has been the main agricultural export crop in the country. Furthermore, pineapples, vegetables, and fish are the major non-traditional agricultural export products (MoFA, 2001).

The total area cultivated for the major staples (maize, rice, cowpea, groundnut, cocoyam, yam, plantain, sorghum, millet, cassava, and soybean) in 2005 was about 3.6 million hectare. Approximately 40 percent of the total cereal production is concentrated in the northern part of Ghana (Northern, Upper East and Upper West Regions), thus being the dominant food production region of the country (FAO, 2002). The value of major staples production (cereal, starch and legumes) increased by 28% to GHC 29,617.2 billion in 2005 compared to GHC 21,310 billion in 2004 (MoFA, 2006b)⁶.

Actual yield levels are much below the potential yields with considerable variation even under comparable production systems (MOFA, 2004a). The gap reflects deficiencies arising primarily from inadequate crop, nutrient, and water management practices, limitations that are closely interlinked. There is urgent need to increase agricultural productivity. This is underscored by the fact that the population is expected to increase from 17.7 million in 1996 up to 36 million by 2020, resulting in a decline of the agricultural land available per capita from 0.77 hectare to 0.38 hectare (MoFA, 2001).

Despite advances in agricultural technology, the traditional crop farming system still prevails particularly in the production of food. Agricultural production is essentially rural and dominated by smallholders. Food production is the primary occupation of most rural farmers and the predominant production system of cereals is the traditional subsistence type (Al-Hassan and Jatoo, 2002). In the north of Ghana, more than 75% of the population depends on smallholdings and livestock (FAO, 2002). Smallholder farms account for about 80% of the total agricultural production (FAO, 2005a). Agriculture is mainly rain-fed and thus primarily determined, among other things, by the intensity and distribution of rainfall within the year. Rain-fed agriculture is predominant in the Northern Region, while the potential for irrigation is limited. Increasing population, limited fertile area for crop production and erratic rainfall characterize agriculture in northern Ghana. Land productivity measured by yield per hectare is generally very low in Ghana, especially in the 1970s and 1980s (Seini and Nyanteng, 2003).

⁶ Cereals include rice, maize, sorghum, and millet. Starchy include cassava, yam, cocoyam, plantain, while legumes include groundnut and cowpea.

The average fertilizer use is 6 kg/ha with a wide variation across crops and is one of the lowest in Sub-Saharan Africa (MoFA, 2001)⁷. The available amount of fertilizer is mainly applied for the cultivation of rice, cotton, pineapple, and vegetables (particularly tomatoes) (Seini and Nyanteng, 2003). Ghana lacks the means to produce fertilizers and therefore imports all its requirements (Seini and Nyanteng, 2003). Since 1987, subsidies of fertiliser were gradually removed and stopped (completely) in 1989 (FAO, 2005b). Since 1990, the importation and distribution of fertilizers have been privatized. This have been associated with a manifold increase in fertilizer prices and a decline in fertilizer use between the 1980s and 2000s (Seini and Nyanteng, 2003). The annual imported volume of fertilizer is inadequate and fluctuates widely, having reached a peak of 63,239 Mt in 1989 and then dropped to 19,840 Mt in 1996. In 1997, the total imported quantity rose again to 56,163 Mt per annum and 66,400 Mt in 2005 (MoFA, 2001; Seini and Nyanteng, 2003).

Tariffs are the main trade policy instrument in the agricultural sector. Ghana became a member of the World Trade Organization (WTO) in 1995 and is bound by the Agreement on Agriculture that was negotiated in the 1986 – 1994 Uruguay Round. In the 1980s and 1990s, tariffs were drastically reduced, particularly on agricultural products such as tomato, poultry, and rice. Since 1992, the applied tariff on agricultural products such as tomato, poultry, and rice is 20 percent, far below the ceiling of 99 percent⁸. In its 'Food and Agricultural Sector Development Policy' (FASDEP 1) of 2002, the government of Ghana declared its intention to reduce imports of rice by 30 percent by the year 2004. However, an increase in tariff within the WTO rules on poultry and rice from 20 to 40 percent and 20 to 25 percent, respectively, was suspended after consultation with the IMF in 2004 (Issah, 2007). On the export side, Ghana was not granting export subsidies to agricultural products according to Ghana's notification to the WTO Committee on Agriculture, submitted in 2001 (WTO, 2001). In 2007, Ghana had initialled the Interim Economic Partnership Agreement (EPA) with the EU, covering trade in goods, which will further liberalize Ghana's agricultural trade between ECOWAS and the EU. A first step in this direction is the creation of a Common External Tariff (CET) for ECOWAS.

⁷ Fertilizer application rate in SSA is about 8.9 kg/ha arable land and in total Africa 21.4 kg/ha arable land, which is still very low compared to developing countries with 111.6 kg/ha arable land in 1998-2000 (FAO, 2003).

⁸ The applied tariff is even higher than in neighbour countries (Cote d'Ivoire (12.5%), Togo and Benin (14%)) (USDA, 2008).

2.2 Rice Production and Rice Market in Ghana

2.2.1 Rice Ecologies and Varieties

In Ghana, the following four main rice ecology systems can be identified (MoFA, 1999):

- Irrigation schemes: cultivation depends on intensive and often large-scale water management and is capital intensive with mechanised irrigation systems. The average yield is about 4.5 Mt/ha.
- Midland/hydromorphic system: cultivation depends on precipitation and groundwater, with periodic flooding of the field. Water management is limited to field flooding. The average rice yield is 1.8 Mt/ha.
- Lowland/inland valley swamps/flood plains system: cultivation depends on precipitation, ground water, and flooding from simple water management interventions such as bunds and canals. The average rice yield is 1.8 Mt/ha and ranges between 1.5 Mt/ha and 3.5 Mt/ha.
- Upland rice systems: cultivation depends on precipitation without flooding of the fields and achieves an average yield of 1.2 Mt/ha.

A survey undertaken in 1997 shows that the irrigated schemes contribute about 18% of the total national rice production covering 7% of land under rice cultivation. Upland system cultivation accounts for 7% of total rice output covering 10% of rice area. Hydromorphic systems cover 63% of total rice area and constitute 54% of total rice output. Lowland, inland valleys, and flood plain systems cover 20% of rice area and account for 21% of total rice production (MoFA, 1999). In northern Ghana, irrigated and lowland valley cultivation systems are the dominant rice cropping systems. Upland rice production was once important, but is declining (estimated to cover only 1000 ha in 1998) (Kranjac-Berislavjevic et al., 2003).

In northern Ghana, rice was traditionally grown under rainfall (lowland) conditions in the inland valleys of the White Volta and its tributaries in this region (Ibrahim, 1982; Kranjac-Berislavjevic, 2000). Volta Region is the only region in Ghana where upland hill rice of *Glaberrima* origin (African rice) can still be found. In the inland valleys, mixtures of *Glaberrima* and improved types, mostly *Sativa* origin (Asian rice) are grown (Donya, 2000)⁹.

⁹ Asian rice (*Oryza sativa*) was already brought in the country during the 16th century. Genetic analyses of traditionally grown *O. Sativa* types show that they are from *O. Sativa indica* and *O. Sativa japonica* type.

Over the last 30 years, agricultural research by the Savannah Agricultural Research Institute (SARI), partly in collaboration with the Crops Research Institute (CRI), the International Rice Research Institute (IRRI) and the West African Rice Development Association (WARDA) brought several improved high-yielding rice varieties additionally to local varieties (Langyintuo et al., 2002).

Most rice production is still in the hands of smallholder farmers, with most of them holding less than one hectare. The 2000-2001 national survey showed that the level of technological knowledge of rice producers is low. The entire process of rice cultivation is still largely a manual activity (Kranjac-Berislavjevic et al., 2003). Hence, rice cultivation is still a very labour-intensive agricultural activity.

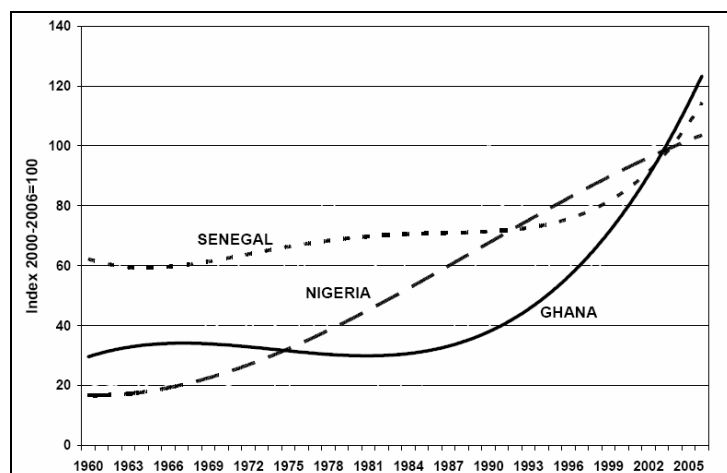
2.2.2 Economics of Rice Production in Ghana

Rice production in SSA increased by more than four times between 1961 and 2001 from 3 Mt to 13 Mt (Nwanze et al., 2006). However, this remarkable increase in rice production has not been able to keep pace with the strong increase in the demand for rice. Since the 1970s, the demand for rice has increased drastically in West African countries but also to a lesser extent in whole SSA (Nwanze et al., 2006). In West African countries, the consumption of rice rose from 1.7 million tons in the 1960s to 7.2 million tons in the 1990s. Per capita, this is a per year consumption of 35.4 kg/head/year compared to a per capita consumption of 19.1 kg/head/year (FAO, 2005d). Demand for rice is growing at a rate of about 6% annually – the highest rate in the world. Thus, rice is the fastest-growing food source in Africa (Nwanze et al., 2006). However, the average rice yield in SSA is the lowest in the world with 1.4 Mt/ha compared to an average of 4 Mt/ha in Asia and an average of 6 Mt/ha in China (Nwanze et al., 2006). Imports in the region thus showed a significant increase by about 700% from 2.4 million tons in the 1960s to 170 million tons in the 1990s. Sub-Saharan Africa accounts for 20% of total world rice imports and spends more than US\$1.2 billion annually on rice imports, restricting possible foreign earnings (FAO, 2005d). The trend of substitution of local products (grains, tubers and pulses) with imported rice and wheat is not only particular to West Africa, but has also long been observed in Asia (e.g. Senauer et al., 1986) and elsewhere in Africa (Pearce, 1990) (Diagana et al., 2005).

This general trend of increasing demand and imports of rice in West and Sub-Saharan countries can also be found in Ghana. As figure 2-5 shows, Ghanaian consumers started shifting to rice lately compared to Senegal, or Nigeria, but experienced a faster per capita consumption growth after 2000 (Lançon and Benz, 2007). Rice is an important cereal to

Ghana's agriculture and economy and is estimated to account for nearly 15% of the Agricultural Gross Domestic Product (AGDP) and to cover 45% of the total area planted with cereals in Ghana (Kranjac-Berislavjevic, 2003).

Figure 2-5: Per capita rice consumption trends (index) selected West-African countries: 1960-2005



Source: Lançon and Benz (2007)

Ghana experienced a rapid dietary shift to rice, particularly in the urban centres. This trend can be attributed to rapid urbanization, increased income, favourable government pricing policies, and factors of convenience such as good storability of rice and ease of cooking (Nyanteng, 1987)¹⁰. Per capita rice consumption has increased by more than 35% over the last ten years (FAO, 2006). It has rose up to 25 kg/head/year (Lançon and Benz, 2007), with 14.5 kg/head/year in 2000 starting from 7.4 kg/head/year between 1982 and 1985 (WARDA, 1986; MOFA, 2004a).

According to the Japan International Cooperation Agency (as cited by Garbers et al., 2007), rice consumption is particularly high and increasing in cities (38 kg per head per year in 2003, compared to 9 kg per head per year in rural areas in 2003). The per capita consumption of rice nationwide is second to maize with 40 kg/head/year among cereals (FAO, 2006). However, while maize accounts for 62 percent of grain output, rice accounts for 16% (sorghum: 14%, millet: 8%) (USDA, 2008a).

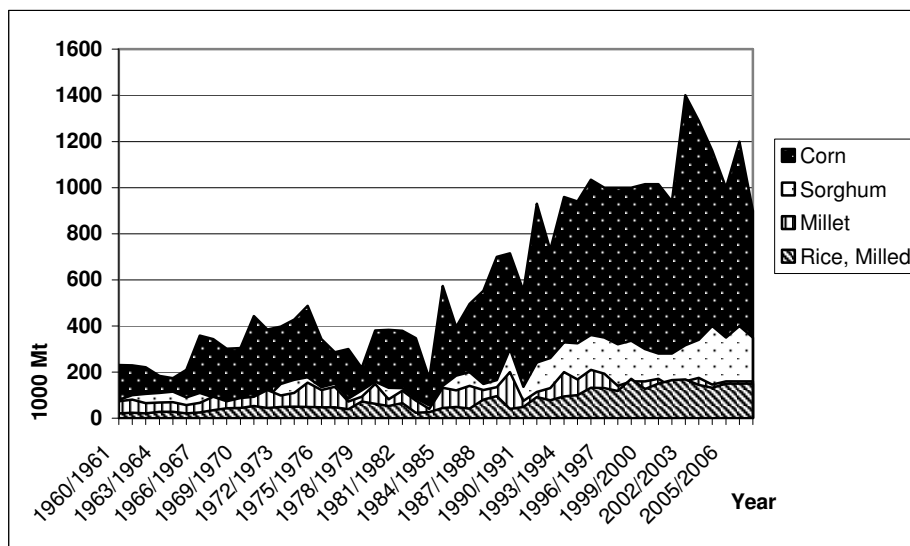
Rice consumption is even predicted to increase further. An estimated population growth rate of 2.8% will result in a population-driven increase in food demand of 2.2% to 2020 (MoFA, 2001). Additionally, further income-driven expansion in food demand is expected to shift

¹⁰ Nationwide, the percentage of urban population in 2003 was 47.8%. Between 2000 and 2005, the urban annual growth rate was 3.90% (UN, 2007).

demand from low value to high value staples such as from cassava to maize, or from maize to rice (MoFA, 2001). This is underlined by the finding that rice exhibits a high income-elasticity of demand (FAO, 2006).

On the supply side, the output of rice in Ghana increased from 49,000 Mt in 1970 to 236,500 Mt in 2005 (Seini and Nyanteng, 2003). However, the production is nearly stagnating since 1995 (221,300 Mt) reaching 241,810 Mt in 2004 and 236,540 Mt in 2005 after a production peak in 1998 and 2002 with about 280,000 Mt (Garbers, 2007). Local output of milled rice equivalent has stagnated at around 150,000 tonnes per year between 1998 and 2003 (FAO, 2006). As indicated by figure 2-6, increases in the production of rice remain relatively small compared to that of other main staples such as corn, sorghum, and millet in Ghana.

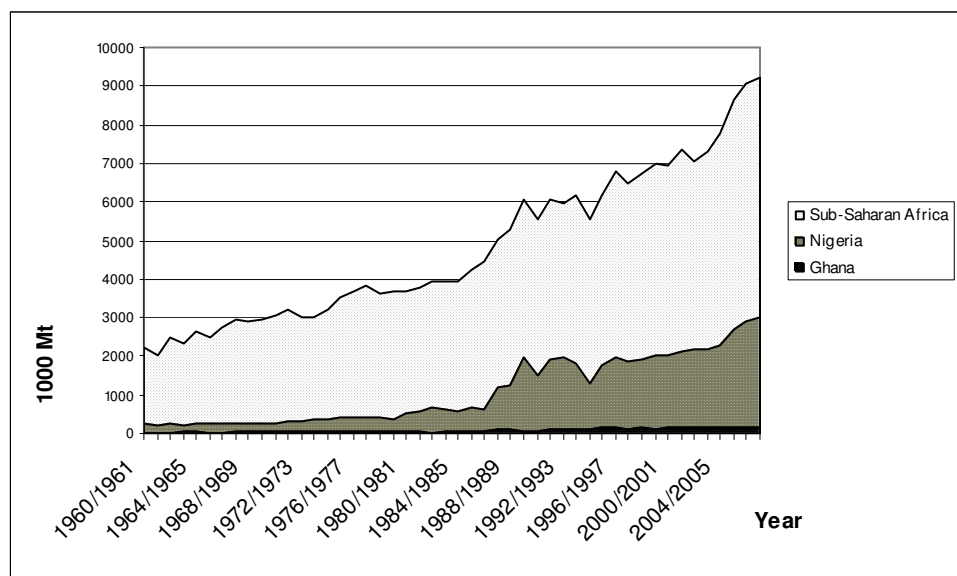
Figure 2-6: Production of main staple crops in Ghana (1960-2007) in Mt



Source: PS&D online, USDA, FAS

The increases in rice production in Ghana also appear small when compared with the development of rice production in sub-Saharan countries and Nigeria where output of rice has been increased remarkably (see figure 2-7).

Figure 2-7: Rice production in SSA, Nigeria, and Ghana (1960-2007)



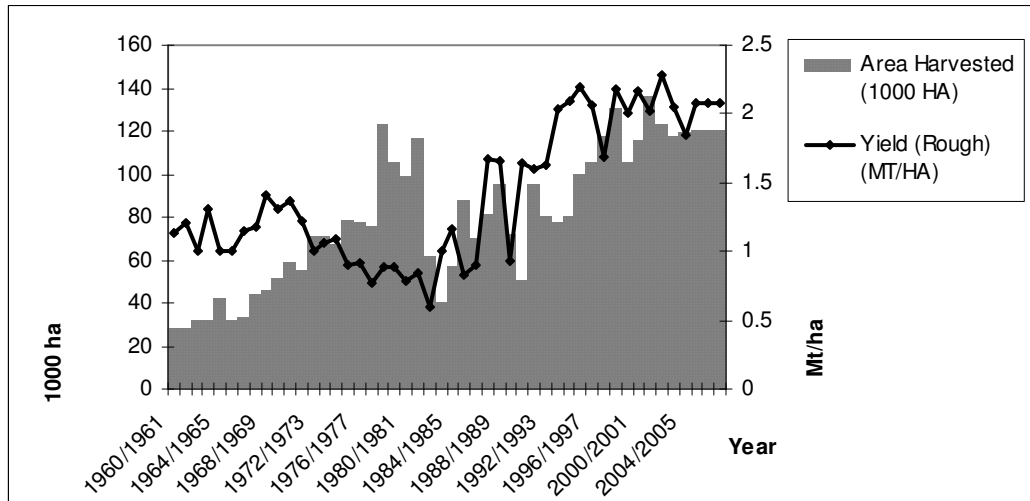
Source: PS&D online, USDA, FAS

In the 1970s and 1980s, rice was grown mainly by commercial farmers. Between 1974 and 1983, prices of imported rice were controlled by the Food Distribution Corporation and official prices for domestic rice were set (Abdulai and Huffman, 2000). The years between 1972 and 1982 can be considered the boom years of rice industry in Ghana (Kranjac-Berisavljevic et al., 2003). Protection of the sector decreased substantially in 1984 and again in 1985 when the exchange rate was successfully devalued. The erosion of rice profitability began in the mid- to late 1980s, when the liberalization of food trade and imports of agricultural inputs such as fertilizer, pesticides, and tractors was effected and the domestic rice sector was exposed to competition with imported rice. As subsidies were gradually removed, rice profitability has shrunken, due to increasing prices of agricultural inputs relative to nominal prices of rice. In effect, liberalization policy negatively affected farmers' incentives to produce rice in Ghana (Asuming-Brempong, 1998). The ratio of input price to the wholesale output price shows that in the late 1980s a farmer only required 0.2 kg of rice to purchase one kg of fertilizer, while in the 1990s that ratio has increased to about 0.8 kg (Gerken et al., 2001).

Total rice area in Ghana is shown in figure 2-8. In 2005, 120,000 ha of rice were cultivated (MoFA, 2006b). Production growth has mainly been due to area expansion while yield gains have played a minor role (see figure 2-8) (MOFA, 2004a). Accordingly, average yield of paddy rice under rain-fed conditions increased from 0.9 Mt/ha in 1970 to 1.97 Mt/ha in 2005 (Seini and Nyanteng, 2003; MoFA, 2006b). Yields per ha were particularly low in the 1970s and 1980s, with an average of 1.0 Mt/ha in the 70s and 0.9 Mt/ha in the 1980s, reaching 1.8 Mt/ha in the 1990s (Seini and Nyanteng, 2003). Yields of 3.3 Mt/ha have been already

reported for on-farm trials in rain-fed lowland ecologies in Ghana (Oladele and Sakagami, 2004)¹¹. However, according to the MOFA, even higher potential yields of 6.5 Mt/ha could be achieved under more effective extension and use of recommended technologies (MOFA, 2004a; MoFA, 2006a).

Figure 2-8: Rice area harvested and rice yield (1960-2007)

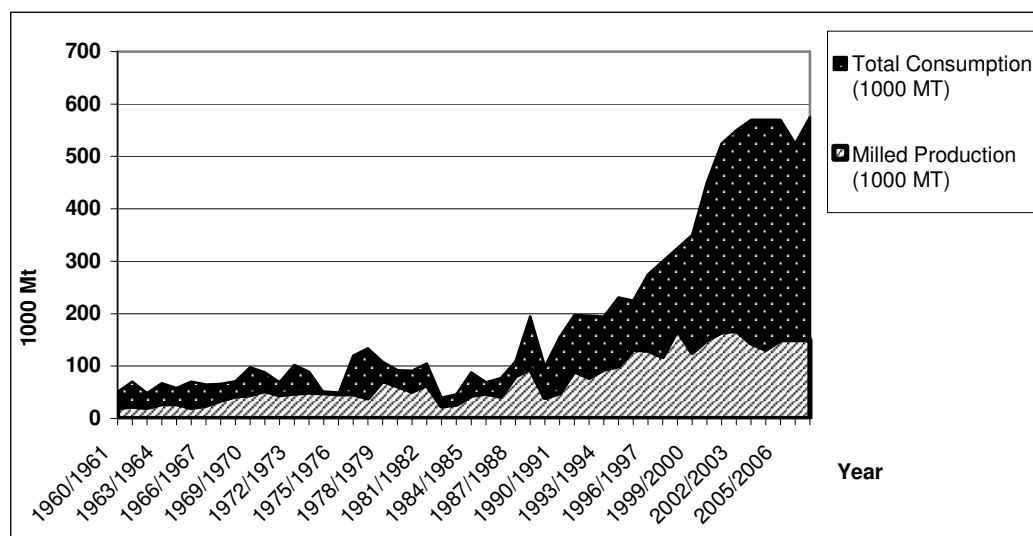


Source: PS&D online, USDA, FAS

As a result, domestic rice production in Ghana has been consistently less than its consumption needs (see figure 2-9). According to Norman and Otoo (2002), self-sufficiency in rice production has declined from 29.8% in 1960-64, 48.3% in 1970-74, 41.2% in 1980-84 to 15.1% in 1989-1996, but recently improved to 40% in 2001 and 45% in 2004.

¹¹ Compared to a yield of 5.2 Mt/ha for rice under irrigation on-farm trials (Oladele and Sakagami, 2004).

Figure 2-9: Total consumption and production of rice in Ghana (1960-2007)



Source: PS&D online, USDA, FAS

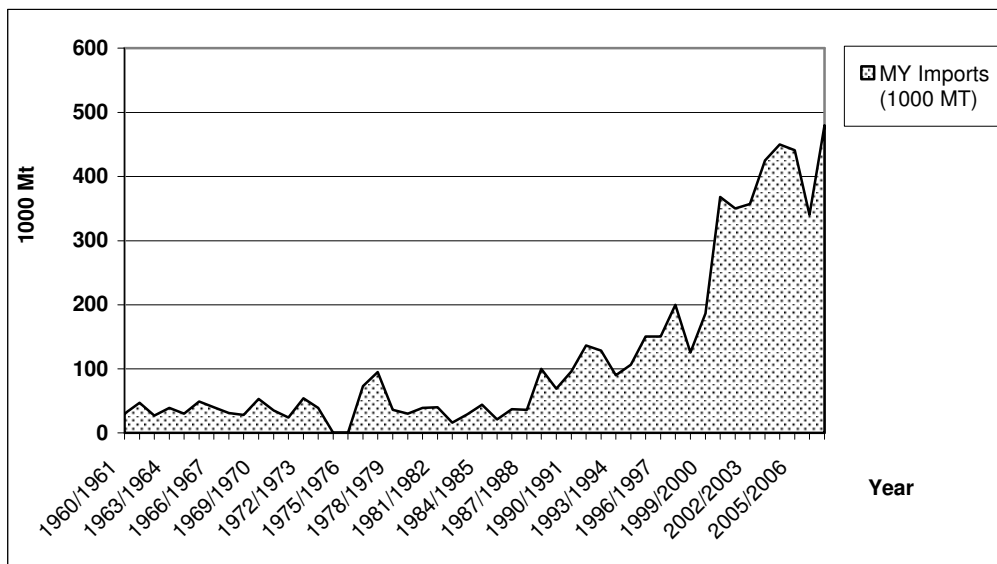
As it can be observed from figure 2-10, imports of rice have been increasing steadily since the 1970s reaching 415,150 Mt in 2005 (FAO, 2006)¹². The rice sector experienced a relatively free trade regime in the 1950s and 1960s. In the 1970s, import restrictions had been imposed to encourage domestic production. Imports of rice fell to zero in 1975 from 28,000 Mt in 1960 (Goody, 1980). Between the 1970s and the 1990s (except four years in between) the annual amount of imports normally did not exceed the annual domestic rough production. However, during the 1990s imports increased and accounted for the major part of rice supply in Ghana. Ghana's rice imports specifically picked up at the beginning of the 21st century, with five import surges occurring between 1990 and 2006 (Lançon and Benz, 2007)¹³. At the same time, rice production growth slowed down to a stagnant level of production starting from 10% annual growth rate in the 1990s (Lançon and Benz, 2007). In 2003, when the imported amount increased by 154% over that of 2002, the domestic (rough) production decreased from 280,000 Mt to 239,000 Mt. Likewise, the area of rice cultivation decreased from 130,400 ha in 1998 to 120,300 ha in 2005 (Garbers, 2007). Country case studies undertaken under the FAO Import Surge Project confirmed that since the mid-1990s import surges for rice took place mainly during the period of low world market prices, which were particularly low between 2000 and 2003 (FAO, 2007). Currently, Ghana

¹² Data is according to the Ghana's Ports and Harbour Authority. The FAO (2006) notes that import data of various sources differ significantly.

¹³ 'Import surges' as defined by De Nigris (2005) occur if the import volume for a given year is 30% higher than the average volume recorded in the previous three years.

ranks fourth among the rice importing countries in West Africa (after Nigeria, Senegal and Cote d'Ivoire) (Lançon and Benz, 2007)¹⁴.

Figure 2-10: Total rice imports in Ghana (1960-2007)

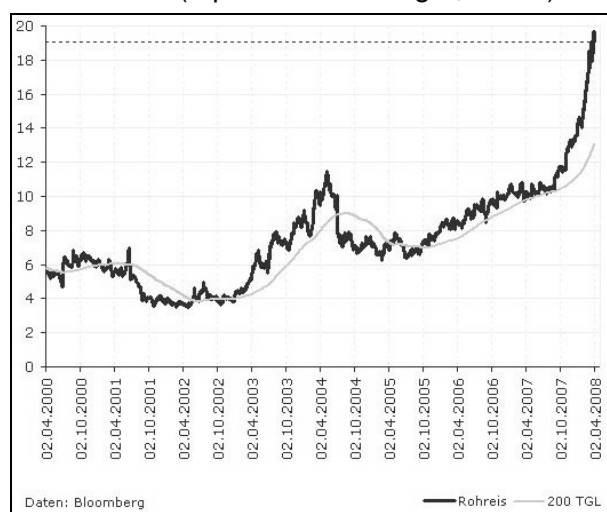


Source: PS&D online, USDA, FAS

Rice imports weight heavily on the country's hard currency reserve with an expenditure of US\$120 million in 2006 when 64% of Ghana's need had to be imported (Asubonteng et al., 2006). Costs of imports are influenced by world market prices and the depreciation of Cedi. The world market prices have increased remarkably between 2000 and 2008 (see figure 2-11). Depreciation of the Cedi increases costs of rice imports and thus discourages import demand, even counteracting the decrease of the world market price. The GHC experienced a depreciation against the US dollar by 67% between 1999 and 2007, which means that the price of imported rice in local currency increased by the same magnitude (Lançon and Benz, 2007). However, empirical studies, such as Diagona et al. (1999) found a rather low sensitivity of consumers in West African countries to imported rice price. This is due to the common feature of the rice market in West African countries (such as Ghana, Nigeria, and Senegal) that a higher value is attributed to imported rice compared to local rice (Diagona et al., 1999).

¹⁴ USA is the primary supplier for Ghana accounting for about 30% of Ghana's total rice imports. Ghana is also the largest market for U.S. rice in Africa. Other suppliers for Ghana's rice imports are Thailand, Vietnam, China, Pakistan, India, and Korea (USDA, 2008). Import business of rice is highly concentrated with only five major importers accounting for more than 75% of imports (FAO, 2006). The imported rice quality is in a broad range from mores expensive Thai rice, U.S. rice, Chinese parboiled to cheaper 70% broken rice (USDA, 2008).

Figure 2-11: Rice price development 2000-2008: paddy rice and 200 TGL (\$ per hundredweight, CBoT)



Source: Bloomberg (2008)

Furthermore, there is some evidence that the rate of yield increase of irrigated rice in Asian countries has stagnated (Nwanze et al., 2006). As Western and Eastern Asia account for more than 90 percent of world supply, there is some concern about the ability of global rice production to meet demand in the near future (Nwanze et al., 2006; UNCTAD, 2008)¹⁵. According to a report of the USDA, global rice prices were projected in 2008 to increase by 2.5 to 3 percent per year, exceeding US\$10.50 per hundredweight (rough basis) in 2017. These price increases largely reflect tightening global stocks due to slow yield growth and little ability to expand production area in most producing countries. However, this effect is expected to be partially offset by declining global per capita consumption, largely due to dietary diversification away from staple foods in Asia with rising incomes (USDA, 2008b).

Since 2001, the Government of Ghana has stressed the importance to cut rice imports by 30% and has prioritized increasing the domestic rice production. As a measure to reach this aim, rice was selected by the MoFA to be among the seventeen commodities for promotion in the National Agricultural Research Strategic Plan (NARSP) (1996-200) (MoFA, 2001)¹⁶.

¹⁵ The international rice market is a relatively thin market (only about 6% of the total rice produced globally) (Nwanze et al., 2006) and heterogeneous with relatively high product differentiation (Cramer et al., 1993). The U.S. Department of Agriculture (USDA) estimates a modest increase in global rice trade from 2008 to 2017 by 2.2 percent per year (compared to 8% growth between 1995 and 2002) due to large and steady growth in demand and in the incapability of rice importing countries to boost rice production (USDA, 2008b). Weaker global trade growth is predicted to reduce the upward price pressure in international markets (USDA, 2008b).

¹⁶ The NARSP was launched under the MTADP to prioritise the research programs and define the long-term strategy for agricultural research in Ghana (MoFA, 2001).

However, as the FAO point out, the investment in domestic rice industry is still very limited (FAO, 2006).

2.2.3 Potential of Rice Production in Ghana

However, Ghana has a higher average rainfall compared to other areas in the sub-region, such as Northern Nigeria and Mali (Kebbeh et al., 2004)¹⁷. Studies by Asuming-Brempong (1998), and Seini and Asante (1998) found Ghana to have a comparative advantage in the production of paddy rice over the other countries in West Africa. Rice production in rain-fed lowland areas has been found to have a high potential for intensification and high gains in productivity. In contrast, cropping of irrigated rice under the prevailing macro-economic climate of Ghana has proved to be economically non-competitive and further expansion of upland rice production is limited due to soil degradation caused by reduced fallow periods and weed problems (MOFA, 2001; Sakurai, 2002). The potential land for the development of lowland rice in inland valleys exceeds 400,000 ha, with only a small proportion of this being currently under cultivation, and a majority of these in northern Ghana (Senayah and Dedzoe, 1997; Mercer-Quarshie, 2000).

However, according to Asuming-Brempong (1998), Ghana has a disadvantage in the processing and distribution of rice, due to the high costs of processing and poor transportation systems and a lack of well-established distribution channels and of quality standards. Ghana therefore is found to be uncompetitive in the market when compared with imported rice. According to the FAO (2006), the domestic production costs have been on average 140% higher than farm gate prices in Thailand between 2002 and 2004.

According to the Deutsche Botschaft (2006) and Action-Aid, the CIF-price of imported rice is lower than the wholesale price of local rice in Ghana (Garbers, 2007). According to the U.S. Department of Agriculture, the prices of high quality U.S. rice are found to be relatively high but consistent while local rice is considered as low quality substitute for imported rice (USDA, 2008). In the study region, the prices of imported rice average over the prices of local rice. According to the LRDP Feasibility Report, the price of local rice is on average 30% lower than the price of imported rice (MoFA, 1997).

¹⁷ Rainfall in semi-arid and arid areas of neighbouring countries such as Senegal, Mali, Mauritania, Burkina Faso, Gambia is characterized by erratic pattern and low level (below 400 mm per year) (Kebbeh et al., 2004).

2.2.4 Improved Lowland Rice Production in Northern Ghana

Improving domestic rice production has become a high priority of the government, reflecting the key objectives of Ghana's agricultural policy. These objectives are first, to ensure food security and adequate nutrition for the population, second, to contribute to export earnings, third, to increase employment opportunities and income of the rural population and fourth, to generate resources for general economic development (FAO, 2005a).

As already noted, there is high potential for rain-fed lowland cultivation in the northern part of Ghana due to large uncultivated inland valleys. Furthermore, the Northern Region has been a main producer of paddy rice¹⁸. WARDA (1986) states that in the 1970s, 75% of rice produced in Ghana came from the northern section of the country, with Northern Region accounting for about 60% (WARDA, 1986; Kranjac-Berisavljevic, 2001). Northern Region became a major exporter to the rest of the country and beyond in the 1970s. Under the 'Operation Feed Yourself' programme launched in 1972, large-scale rice farming was encouraged by the government in northern Ghana favouring large-scale mechanized farming (MoFA, 1999). In this time, Northern Region produced 170,000 Mt in three years (1978-1980), while the production was only 31.0 Mt in 1986. However, production increased again to 73.0 Mt in 2000 (Kranjac-Berisavljevic, 2003; Seini and Nyanteng, 2003). In 2005, the northern sector regions still contributed about 70% of the national rice output (MoFA, 2005b).

Rice is a major cash crop in the Northern Region and thus the mainstay for rice-producing communities. Thus, to alleviate poverty and to improve food security in the northern part of Ghana, where poverty rates and malnutrition are highest in the country, it is particularly important to increase productivity and profitability in the lowland rice cultivation.

Increasing local rice production in Northern Ghana faces two key constraints: erratic rainfall, and poor soil conditions (Rhodes, 1995). Rice cultivation was found most profitable in years with normal rainfall. However, yields can drop dramatically in unfavourable years and in one out of five years rainfall is deficient (MoFA, 1997). As an economical option for promoting rice production in the country, the MoFA recommends the cropping of rice on the flood plains using simple engineering methods for effective water control, through the construction of structures such as bunds to facilitate water control in valley bottoms and areas inundated

¹⁸ Paddy rice has to be differentiated from milled rice. Usually, the term 'paddy rice' or 'rough rice' is used to attribute to rice as it comes from the field, before milling. Rice milling conversion rate was 61% in 2002 (FAO, 2002).

during the rainy season (MoFA, 2001)¹⁹. An economic analysis conducted for the LRDP Feasibility Report shows that the economic performance of inland valley rice cultivation can considerably be improved through water control systems and improved farming techniques with an achievable yield of 3.5 to 4.7 Mt/ha (MoFA, 1997). The need to develop and spread water conservation and yield-increasing methods for lowland rice cultivation in the region has repeatedly emphasized (MoFA, 2004a). One measure was undertaken by the MoFA from 1990 to 1993 when a MoFA project called the 'Valley Bottom Rice Development Project' financed by the World Bank was put in place. Its objective was to study and develop lowland rice farming in four sites, stretching from the Forest zone to the Savannah zone (MoFA, 2002). In 1993, the MoFA of the Northern Region set up the 'Low Risk Water Harvesting Project' assisted by the 'Agricultural Sector Rehabilitation Project' of the World Bank in some districts of Northern Region targeting on medium and large-scale farmers in order to intensify the rice production in Northern Region. Bund construction was carried out with heavy machinery, being out of the reach for small-scale farmers. Due to various problems most farmers abandoned farms after two or three growing seasons and the project was not sustainable (Kranjac-Berislavjevic, 2003).

More recently, in 1999, the MoFA implemented the 'Lowland Rice Development Project' (LRDP) in the Northern Region of Ghana to develop a profitable and sustainable intensive rice production system addressing smallholder farmers. The project essentially aimed at increasing the local supply of rice by alleviating the main constraints of the development of inland valley rice and promoting an improved production system. The LRDP was funded by the French Government's Agence Francaise de Developpment (AFD) from 1999 to 2003 after an economic feasibility study was carried out and completed in 1997. The project area extends over three valleys in four districts within a radius of 50 km from Tamale. It expanded its operations from about 250 ha to 1151 ha and 2,500 participating farmers (MoFA, 2002). The Food Security and Rice Producers' Organizations Project (FSRPOP), funded by the French Ministry of Foreign Affairs, took off in November 2002 (up to 2005) with the objective to sustain the rice intensive cropping scheme by building the capacities of farmer based organizations to fulfil and sustain some of the tasks ensured previously by the LRDP. The strategies of the LRDP to improve and increase local rice production and to improve harvesting, processing and marketing of inland valley rice consisted of the implementation of water management systems, the introduction of an improved technical package, as well as improved harvesting, post harvesting and processing techniques to match the quality and

¹⁹ Bund construction was found to remarkable increase yields in agronomic experiments (WARDA, 1997).

prices of imported rice (storage possibilities). This was supplemented by extension services to farmers, credits for seasonal farm inputs and equipment and support to create and operate local farmer organisations. The implemented improved technical package included the use of fertilizer and improved seed and improved agronomic practices such as intensified weeding, disease and insect control, dibbling, the removal of seed admixtures and improved land preparation. The main features of the project to improve production were the use of water regulatory structures to retain runoff water on the fields instead of traditional irrigation, as well as dibbling method. The two water management structures selected to improve the valleys were contour bunds and intermediary bunds. This water conservation method is much cheaper than full-scale irrigation, but can be used to produce rice only once in a year. Contour bunds are big earth ridges constructed along contours of the block. Since they are constructed against the direction of the water flow in the valley, bunds trap both surface runoff and precipitation thus improving infiltration into the soil and storage of the excess water on the soil surface. Bunds do not only extend growing season as water conservation method, but also conserve soil fertility and fertilizer²⁰. Contrary to the original planning of the contour bunds it was realized that manual construction of bunds was not feasible and thus LRDP contour bunds were made by motor graders. These bunds could last at least 5 years before being reshaped, while manually constructed bunds would not be that large and robust. Thus, manually constructed bunds may be not strong enough to withstand the force of the huge flows that pass through the valleys with high velocities particularly at the peak of the season. The contour bunds made by motor grader are on averagely 0.5 m high, 0.3 m wide and 1:1 sloped. Within the LRDP contour bunds, plots of one-acre size were distributed to the farmers (MoFA, 2004b). Without levelling, there is still the tendency for water to pond in one section in between the bunds, especially in larger plots. To improve the distribution of water within the plot, farmers were requested to construct mini bunds (or intermediary bunds) at intervals between the micro-catchments in between the two contour bunds. These mini bunds are constructed manually by the farmers after land preparation using hoes and are roughly 30 cm high, 15-20 cm wide and 1:1 sloped. These bunds are not permanent bunds and have normally to be re-constructed every year since tractors would destroy them during land preparation. Thus, bund construction is labour intensive especially during the peak

²⁰ Soil bunds fall in the category of sustainable agricultural technologies. According to the definition of the FAO, sustainable agriculture has five attributes: resource conserving (e.g. land, water, plant, genetic resources), environmental non-degrading, technically appropriate, economically and socially acceptable (Lee, 2005).

labour demand period²¹. Dibbling method can be used as seeding method and as application method for the first fertilizer. The LRDP encouraged the farmers to dibble seed or to transplant seedlings in lines if necessary due to the unpredictability of rainfall at the time of land preparation. To dibble seed a stick or a hoe is used to make a depression of about 2 cm depth into which about 4-6 seeds are dropped and covered with soil by pressing lightly with the foot²². Dibbling seed balances the population densities as uneven population densities make weeding very difficult, and compels farmers to broadcast fertilizer on surface of the soil leading to attendant losses (MoFA, 2004b). The method of fertilizer application is also crucial to increase its effective uptake. Two rounds of fertilizer application were recommended. The first fertilizer is given within 3 weeks after planting. Broadcasting fertilizer (as usually done by the farmers) leads to 60% loss of fertilizer as the fertilizer tends to vaporise. LRDP farmers were taught to dibble the basal fertilizer, a procedure usually undertaken when there is no flood in the fields. The fertilizer is then placed in between the seeded lines in larger intervals of 40 cm to cover the seeds equally. Summing up, dibbling technology enhances manual weeding, saves seed, and improves plant growing. Furthermore, dibbling fertilizer improves the uptake of fertilizer by the rice plants and prevents the fertilizer to be washed away. Additionally, at least two times manual weeding is recommended by the project, with the first weeding three weeks after planting and the second four weeks later. If herbicide is applied, a light manual weeding may be required six weeks later. Before the LRDP, farmers did not weed or only some rough hand weeding (MoFA, 1997).

Despite the efforts put in by the LRDP to encourage the construction of bunds, it appears that the dissemination of the dibbling method has been more successful than the dissemination of bund construction among the farmers. However, as underlined by the FSRPOP (2005), the reasons for the low adoption rate of bund technology remain unclear and need to be investigated. The MoFA as well explicitly states the need for adoption and economic impact studies (MoFA, 2001).

²¹ The most critical working periods in terms of labour requirement are land preparation which has to take place for all crops immediately after the first downfall of rain (up to a maximum of 3 to 4 weeks) and harvesting to a lesser extent.

²² The seeding space is 20 cm x 20 cm for TOX 3107 and GR 18 (= seeding rate of 100 kg/ha).

Chapter 3

Literature Review

This chapter first presents an overview of the concept of innovation and the concepts of the adoption and the diffusion of new agricultural technologies (section 3.1). In section 3.2, theories of adoption and diffusion of innovations are provided. Section 3.3 gives an overview of selected studies carried out to analyze the adoption of agricultural technologies on individual level in developing countries. After that, selected studies on the impact of soil and water conservation, as well as intensification methods on micro-level are presented in section 3.4. Finally, section 3.5 concludes the literature review and exposes the contribution of the present analysis to the empirical literature.

3.1 Concepts of Innovation and Adoption

Innovation

There are different definitions of the concept of innovation in the literature. Schumpeter (1934) defines innovation as the introduction of new combinations of methods for supplying commodities in the economy. Ellis (1988) regards innovation as the first practical use of a new, more productive technique. According to Rogers (1995), an innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption. Thus, as Rogers (1995) underlines, it does not matter whether the idea is objectively new as measured by the lapse of time since its first use or discovery, but only the perceived newness of the idea. If the idea is new to the individual, it is an innovation. The important factor for defining innovation is the perceived newness of the idea for the individual. Feder et al. (1985) specify individual adoption (at the level of an individual unit) as the degree of use of a new technology in the long-run equilibrium when the farmer (or firm) has full information about the new technology and its potential. Under these circumstances, the non-use is a clear rejection of the new technology by a fully aware individual in the long-run.

Adoption and diffusion

Schultz (1975) notes that the introduction of a new technology represents a state of disequilibrium with inefficient resource allocation by the individual farm until learning and experimentation lead the farmer to a new equilibrium. Technology adoption process can be viewed from the micro and macro perspective. The macro-level analysis examines the aggregate adoption pattern over time to identify specific trends in the diffusion cycle of a specific technology (within a specific region or population) across a large number of adoption decisions (Feder and Umali, 1993; Feder et al., 1995). At the aggregate level, the diffusion process is defined as “the process of spread of a new technology within a region” (Feder et al., 1995). According to Rogers (1995), diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system. At the micro level, each decision unit have to choose whether to adopt, as well as the intensity to adopt. Rogers (1962) defines the adoption process as “the mental process an individual passes from first hearing about an innovation to final adoption” (p.17).

3.2 Theories of the Adoption and Diffusion of Innovation

The main questions of research in the area of adoption and diffusion of innovations are how innovations diffuse and why some innovations diffuse more quickly, if, and when individuals adopt an innovation and why some individuals adopt more quickly than others do. An overview of diffusion models is given in this subsection²³.

Economic theories of technology diffusion:

The time path of the usage of new technologies usually follows an S-curve on the rate of technology diffusion with respect to time. Early work on the diffusion of new technologies tended to focus on the epidemic theory of diffusion (Mansfield, 1961) that is the most popular explanation of the S-curve. This theory considers the spread of information about a new technology as the key of explaining diffusion. Initially, potential adopters have little or no information about the new technology, but as the number of adopters grows, the dissemination of information accelerates as the information spreads from adopters to non-adopters. The ‘infectiousness’ of a technology, however, depends on the characteristics of the technology, while this model assumes that all potential adopters have the same chance

²³ An excellent review on diffusion modelling in economics is given by Stoneman (2002).

of becoming infected (Blackman, 1999). Thus, this model omits important aspects of technology diffusion that are explicitly involved in later diffusion models (Forman and Goldfarb, 2006).

The essential prediction of the theories of diffusion is that potential adopters of a new technology have different preferred adoption dates and that at any given date only some of the potential adopters wish to be (or are sufficiently informed to be) actual users. Karshenas and Stoneman (1993) mention three different mechanisms that have been suggested by the recent theoretical literature to result in such an outcome. These mechanisms include rank, stock, and order effects.

While epidemic models abstract from differences between individuals, such differences may affect the profitability of adopting the new technology, and may thus play an important role in explaining pattern of diffusion. Rank (or probit) models emphasize population heterogeneity. They result from the assumption that potential adopters of a technology are heterogeneous and thus obtain different (gross) returns from adopting the new technology. Relevant factors that may differ between potential adopters may be the firm or farm size, costs (such as search, switching, and opportunity costs), input prices, factor productivity, capital and the belief in the returns on the new technology (Blackman, 1999; Geroski, 2000). The different returns from the use of the new technology generate different preferred adoption dates. The potential adopters can then be ranked in terms of their returns from adoption (from highest to lowest). The net returns on adoption are assumed to increase over time due a number of reasons. A distribution of reservation acquisition costs can be derived from the benefit distribution (Karshenas and Stoneman, 1993). Potential adopters adopt the new technology when acquisition costs fall below the reservation acquisition costs. As the acquisition costs are assumed to fall over time, the cumulative benefit distribution is mapped out as a diffusion path (Karshenas and Stoneman, 1993). To analyze the adoption decision on individual level most commonly probit models are used (Geroski, 2000).

In addition to epidemic and rank models, Karshenas and Stoneman (1993) mention two ways, in which the behaviour of other potential users may influence adoption. They consider these effects as 'stock effects' and 'order effects'. These effects are negative network externalities, as the benefit from adoption declines with the number of users (Forman and Goldfarb, 2006).

Stock effects are based on the assumption that the benefits to the marginal adopter from acquisition decrease as the number of previous adopters increases. Then, net returns on adoption depend on the total stock of adopters. If new technologies are cost reducing, they

will increase the output that is produced (Forman and Goldfarb, 2006). As a result, increasing adoption will then eventually decrease profits of adopters and non-adopters alike. Under certain conditions, the difference in profits between adopters and non-adopters declines over time, resulting in decreasing net benefits from adoption (Reinganum, 1981). Stock models assume that the profit among all adopters is identical, and correspondingly, the profit among all non-adopters (Forman and Goldfarb, 2006).

Contrarily, order effects assume that the benefit from adopting a new technology decreases monotonically with the number of previous adopters (Forman and Goldfarb, 2006). Thus, the returns from adoption depend on the position of potential adopter in the order of adoption, where earlier adopters continue to achieve disproportionately greater returns from adoption than later adopters do, due to potential first-mover advantages (Forman and Goldfarb, 2006). The order effect arises from the existence of a fixed critical input into production (Blackman, 1999). The model is made operational by arguing that the firm's adoption decision will take into account how waiting will affect its profits. For any given cost of acquisition, it will be profitable only for some firms to actually adopt. As the costs of acquisition are assumed to fall over time the number of adopter increases.

Summarizing the factors emphasized in the theoretical models, information and learning, as well as the characteristics of the technology are critical factors in each of the four models (epidemic, rank, order, and stock model). In contrast, differences in the characteristics of potential adopters that affect the return on the new and old technology drive diffusion in the rank model. Limitations on the supply of a critical input for the new technology determine diffusion in order models. The effect of adoption on reductions in average production costs and on output prices ("general equilibrium" effects) explains diffusion in stock models (Forman and Goldfarb, 2006).

The four models do not necessarily offer competing explanations of diffusion but may be some combination of epidemic, rank, order, stock and supply-side effects. Empirical evidence by Karshenas and Stoneman (1993) however suggest that epidemic and rank effects appear to explain the observed diffusion patterns in a better way than order and stock effects.

Sociological models of technology diffusion:

The main review of diffusion research in other fields than economic is Rogers (1995). The sociological theories of adoption of innovations are rooted in the model of Rogers and Shoemaker (1971). Rogers focuses on the role of information and communication networks, analogous to the importance of the role of information transmission in epidemic models of

diffusion (Forman and Goldfarb, 2006). The innovation-diffusion paradigm as elaborated by Rogers takes the appropriateness of the innovation as evident and the problem of technology adoption is then seen as problem of access to information (i.e. education, training, access to extension services) about the innovation (Negatu and Parikh, 1999). Thus, the traditional diffusion model argues that access to information will accelerate adoption of technologies because individuals are made aware of the potential benefits of technology adoption.

Rogers (1995) mentions four main elements that influence the adoption of innovations. These factors are i) the innovation itself, ii) the communication channels, iii) time, and iv) the nature of the society to which it is introduced. Based on these factors, four major theories aim to explain adoption and diffusion of innovations. These theories are the innovation decision process, the theory of individual innovativeness, the concept of the rate of adoption and the concept of perceived attributes (Rogers, 1995). In the following, these interrelated concepts are briefly introduced.

Innovation

According to the ***theory of perceived attributes***, five perceived attributes of the innovation contribute to explaining different rates of adoption. The relative advantage is the degree to which an innovation is perceived as better than the current technique (in economic terms but also in terms of social prestige or convenience). The attribute of compatibility refers to the degree to which an innovation is regarded as consistent with existing values, past experiences, and needs. Complexity is the degree to which an innovation is perceived as difficult to understand and use. Trialability is the degree to which an innovation may be experimented with on a limited base, while observability is the degree to which the results of an innovation are visible to others (Rogers, 1995). Thus, the easier it is for individuals to see the results of an innovation, the more likely they adopt the innovation. Innovations that are less complex or easier to try on limited base and thus reduce uncertainty about the innovation, as well as innovations that have a higher relative advantage against the current practice or that are more compatible, are more likely to be adopted. Particularly, relative advantage and compatibility are found to be important factors in determining the rate of adoption (Rogers, 1995).

Communication

Diffusion of innovation is a social process that involves interpersonal communication. Communication can then be defined as the process by which individuals create and share information with each other in order to reach a mutual understanding. Communication is particularly effective if individuals are homophilous (e.g. in terms of share the same beliefs or

interests, education, socioeconomic status and so on). Furthermore, according to Rogers (1995) most individuals mainly depend on a subjective evaluation of an innovation given from other individuals who have already adopted the innovation. A main factor of the diffusion process seems to consist of the modelling and imitation by potential adopters of their network partners that have previously adopted (Rogers, 1995).

Time

The time dimension evolves in the diffusion research in i) the innovation-decision process by which an individual passes from of an innovation to the formation of an attitude towards the decision to adopt or reject, implementation and the confirmation of the decision ii) the innovativeness of an individual and iii) and the rate of adoption. The **innovation-decision process** consists of five steps that usually occur in the following time-based sequence of 1) knowledge of an innovation, 2) persuasion by forming a favourable or unfavourable attitude towards the innovation, 3) decision to adopt or reject, 4) implementation and use of the innovation, and 5) confirmation of the innovation decision. The innovation decision process is mainly characterized by information seeking and information processing in order to reduce uncertainty about the innovation. Individuals then vary in the time required to pass through the innovation-decision process (Rogers, 1995). The measure of **innovativeness of an individual** and the classification into adopter categories of 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards is based upon the relative time at which an innovation is adopted (Rogers, 1995). The **rate of adoption** defined as the relative speed with which an innovation is diffused through the system. While diffusion process of most innovations can be characterised by a S-shaped curve as the diffusion starts slowly and stabilizes or even declines after a period of rapid growth, the slope of the S-shape varies across innovations (Rogers, 1995).

Nature of society

The social system constitutes boundaries within which diffusion of an innovation occurs. Social and communication structure may facilitate or impede the diffusion of innovations within the system. Aspects of social structures that affect diffusion of innovations are norms, the role of opinion leaders and change agents, types of innovation-decisions and the consequences of innovation. Opinion leadership is the degree to which an individual is able to influence the attitude or behaviour of other individuals informally. Change agents are individuals attempting to influence the innovation-decision of clients in a direction that is found to be desirable to the change agent. Types of innovation decision are i) optional decisions, which may be made by individuals independently of other members in the system,

ii) collective innovation-decision, that are made by consensus among the members in the system and iii) authority innovation-decisions, that are made by few individuals who possess power, status or technical expertise in the system. The consequences that occur to an individual as result of adoption or rejection of an innovation influence the diffusion process (Rogers, 1995).

Economic models of individual adoption decision:

Beginning with the seminal work of Griliches (1957), economists have attempted to explain the process of technology diffusion in agriculture. Economic theory explaining adoption of innovations originates from the neo-classical theory (Griliches, 1957). The basic assumption of the economic constraint model (or factor endowment model) (Aikens, 1975) is that the distribution of resource endowment among potential users determines the pattern of adoption of a technological innovation (Negatu and Parikh, 1999). Thus, existing economic constraints (such as limited access to capital or land) prevent the traditional diffusion model from operating effectively (Hooks et al., 1983). An individual may wish to adopt once being aware of the advantages of adoption but economic constraints (such as risk aversion, lack of capital or land) may prevent individuals from acting.

In the economic constraint model, farmers are assumed to maximize their utility, which is defined in terms of profit. They seek to optimize their factor input and production choice according to the assumptions of the neo-classical framework. Farmers will only introduce a new product if its utility, which is defined in terms of profit, is higher than the 'old' product. The choice of technology is influenced by profit prospects and theory assumes that households obtain different levels of profit from different technologies (Doll and Orazem, 1984).

Attempts were made to assert the 'superiority' of the economic constraint model over the innovation-diffusion paradigm. However, due to empirical evidence and the partial success of development projects, more recent economic adoption research integrates aspects derived from the economic constraint model (e.g. access to credit, off-farm income, market access), and sociological considerations (e.g. social network, attitudes, beliefs, perceptions) together with institutional (project participation, marketing channels) and physical aspects (plot-level characteristics such as soil quality) (Mbagalawa and Folmer, 2000).

Batz (1999) categorizes the factors influencing the profitability and the perception of the innovative technology as i) conditions under which the farmer operates, ii) characteristics of the farm, and iii) characteristics of the farmer himself. Farming conditions thereby include the production environment, infrastructure, and functioning markets.

These conditions of adoption may be captured by demographic variables (age, sex, gender), variables that indicate resource endowment (labour, land, capital), plot characteristics and institutional variables (education, technical assistance, access to market). Furthermore, attitudes towards risk and uncertainty are found to be important personal characteristics determining the rational production decisions related to technology choice and resource.

3.3 Review of Literature on the Adoption of Agricultural Technologies on Micro-level

There is a vast empirical literature of technology adoption on micro-level in developing countries²⁴. In the beginning, the adoption literature especially focused on technologies of the Green Revolution (fertilizer and pesticide use, improved varieties (especially maize and rice)) (e.g. Doss and Morris, 2001; Kosarek et al., 2002; Ransom et al., 2005), machinery, or irrigation technologies. Over the years, as environmental problems have increased, an expanding body of work have shifted the focus on the adoption of sustainable agricultural technologies and the adoption of new management practices²⁵. Particularly, low-input techniques used by smallholder farmers and natural resource conservation management gained increasing attention. Literature includes studies on new farming management practices (Abdulai and Binder, 2006; Abdulai et al., 2007), particularly integrated soil fertility and natural resources management, as well as soil and water conservation methods (Lapar and Pandey, 1999; Gebremedhin and Swinton, 2003; Pender et al., 2004; Hagos and Holden, 2006; Moser and Barrett, 2006)²⁶. Another issue is the cultivation of crops and livestock that are new to the farmers (Conley and Udry, 2001; Teklewold et al., 2006; Johnson et al., 2007).

²⁴ Due to the plethora of work, not all the studies can be introduced in this thesis. Several literature reviews provide overviews of research in the area of technology adoption. Feder and Umali (1993) give a detailed review of agricultural adoption literature with a special focus on developing countries. In 1985, Feder et al. reviewed the literature on technology adoption in a widely cited article. Besley and Case (1996) give an overview of methodological approaches. Another review of theoretical literature on technology adoption is given by Sunding and Zilberman (2001). Doss (2006) gives an overview of recent strands of adoption literature. Knowler and Bradshaw (2007) provide an overview of variables that are found to explain specifically the adoption of soil conservation measures.

²⁵ According to the definition of the FAO, sustainable agriculture has five attributes: resource conserving (e.g. land, water, plant, genetic resources), environmental non-degrading, technically appropriate, economically and socially acceptable (Lee, 2005).

²⁶ Soil and water conservation methods consist of several methods such as stone terraces, stone bunds, crop rotation, conservation tillage, contour farming (contour hedgerows, contour ploughing), or composting.

There are various issues of adoption research. A number of studies focus on the decisions of farmers with regard to the intensity of adoption (e.g. Dong and Saha, 1998; Kazianga and Masters, 2002; Grebmedhin and Swinton, 2003; Hagos and Holden, 2006; Namara et al., 2006). **BAIDU-FORSON (1999)** e.g. employs a Tobit analysis to identify factors that drive the level and the intensity of adoption of land-enhancing technologies such as half-crescent shaped earthen mounds (enriched with nutrient concentrations at planting holes) and improved 'tassa' in the Sahel zone of Niger. Results indicate that a higher percentage of degraded farmland, extension education, lower risk aversion and the availability of short-term profits are important for increasing the adoption and the intensity level. Some studies estimate the intensity of adoption by using a double-hurdle model due to the restrictions of the Tobit model (Dong and Saha, 1998)²⁷. One of these is the study of **NAMARA ET AL. (2003)**. They assess the adoption decision and the intensity of adoption of the system of rice intensification (SRI) in Sri Lanka. The main components of SRI are an improved seed sowing method, soil fertility management, weed control, and water irrigation management. Estimates reveal that the main variables influencing the adoption are the location of the farm, the type of farming system (rain-fed or irrigated), poverty status of the farmer, participation in training program, education status and the size and structure of the farm family. Adoption intensity however is mainly determined by cattle ownership, education status and the size and structure of the farm family. **GEBREMEDHIN AND SWINTON (2003)** investigate the factors for the adoption and intensity of stone terraces and stone bunds in Ethiopia estimating a double hurdle model. Data reveal that explaining factors differ sharply between long-term investment measures of stone terraces and short-term investments in soil bunds. Transactions costs of conservation investment such as travel costs to distant, highly fragmented, and small plots result in a higher probability of plots to be developed with soil bunds than with stone terraces. Furthermore, the availability of family labour encourages the adoption of stone terraces. Long-term land tenure security contributes in increased likelihood to invest in durable stone terraces, while short-term land tenure security are more likely to invest in less durable soil bunds. While most studies apply a Tobit model, a growing number of studies adopted the Heckman selection correction model, accounting for selection bias. **HAGOS AND HOLDEN (2006)** apply both the Heckman's selection correction model (Heckman, 1979), as well as Deaton's selection model (Deaton, 1997) to examine the

²⁷ The Tobit model of adoption restricts variables determining whether and how much to adopt to be identical (Dong and Saha, 1998). Furthermore, the Tobit model interprets the zero value for the dependent variable as a negative value for the underlying latent variable (representing the utility of adoption). Dong and Saha (1998) underline the inappropriateness of such an interpretation in the context of adoption.

determinants of adoption and adoption intensity of soil bunds and stone terraces in Ethiopia. As results did not indicate selection bias for both technologies, the adoption and intensity decisions are estimated separately by using a standard probit and Tobit model on plot-level. Plot-level characteristics, farm size, the perception of returns on conservation investment, risk aversion, education, and community-led conservation investments are found to contribute to higher intensity of conservation structures.

Another issue is the analysis of the continued use or disadoption of technologies as an important aspect of the dynamics of the adoption process (e.g. Amsalu and de Graaf, 2006; Moser and Barrett, 2006; Marenya and Barrett, 2007; Rahim et al., 2008). **NEILL AND LEE (2001)** e.g. estimate a bivariate probit of adoption and disadoption of a maize-*mucuna* cropping system as 'slash-mulch' system in Honduras. The practice was abandoned at the rate of 10% per year by previous adopters because of the emergence of another weed species that increased labour requirements and reduced maize yields.

While concerns have been raised by Feder et al. (1985) and Doss (2006) on the need to study the dynamic patterns of adoption, most empirical studies have relied on cross-sectional data to examine the adoption decision process. One of the few studies that use panel data to address the dynamic issue of adoption is the analysis of **MOSER AND BARRETT (2006)**. Using a quasi-panel data set, they explore the adoption of a rice intensification system (SRI) that is high-yielding but involves low external inputs by smallholder farmers in Madagascar. The extent of adoption is estimated by employing Powell's (1986) method for symmetrically censored least squares (SCLS) estimation to control for household fixed effects and heteroskedastic errors. Adoption and disadoption decision are estimated by using separate dynamic probit models. Results confirm the hypothesis that farmer's education, liquidity and labour availability increase the willingness of the farmer to adopt new, labour-intensive techniques. Furthermore, learning effects seem to play a significant role not only in the initial adoption decision but also in the extent and continuation of adoption. Unobserved farmer fixed effects tend to have a huge effect on adoption and continued use. Trying to distinguish between learning-by-doing effects and social conformity effects (towards a community norm), results also indicate that conformity effects may indeed be significant in explaining adoption. **AMSALU AND DE GRAAFF (2006)** examine the determinants of the adoption and disadoption of stone terraces as soil and water conservation method in Ethiopia. They specify a sequential two-stage decision-making model with sample selection. While age, farm size, perception on technology profitability and steep slope are found to have a positive and significant influence on adoption decision, livestock size, and high soil fertility exert a negative and significant effect. The results of the bivariate probit suggest that different factors

influence adoption decision and continuous use. Furthermore, estimated coefficients differ in sign and significance. Actual technology profitability, steep slope, and low fertility are significant in explaining continued use of stone terraces. Family and farm size, as well as participation in off-farm work have a negative and significant effect on continued use. Findings suggest that conservation effort is undertaken and continued on plots where the benefit is expected to be higher. The study of **MARENDA AND BARRETT (2007)** is another of the very few that used a panel data set. They investigate the adoption and disadoption of integrated management of natural resources (INRM) and soil fertility techniques (ISFM) in Kenya. They include four practices: stover/trash lines, agroforestry for soil nutrient replenishment using woody species, manure application, and chemical fertilizer use. Estimating a multivariate probit on plot-level, results suggest that the initial and sustained practice of ISFM/INRM methods appears to be strongly related to a range of indicators of household wealth – in terms of labour, land, livestock, and non-farm income and education. Furthermore, there seem to be important positive spillover benefits from universal education, both directly through increasing individual farmers' propensity to undertake ISFM/INRM practices and indirectly through the causal relation between educational attainment and non-farm cash incomes.

Most empirical studies focus on one specific technology. However, agricultural technologies are often introduced as packages consisting of several distinct technology components. While these components may complement each other, they may often be adopted independently. Thus, farmers may adopt complete packages of new technologies or subsets of these packages. A number of contributions consider simultaneous or sequential adoption patterns in case of interrelated technologies and technology packages either theoretically (e.g. Feder, 1982; Leathers and Smale, 1991) or empirically (e.g. Nkonya et. al., 2004). **BYERLEE AND PULCANO (1986)** find that farmers in Mexico adopt improved varieties, fertilizer, and herbicides in a step-wise manner rather than as a package by fitting logistic diffusion curves of the cumulative adoption levels. **RAUNIYAR AND GOODE (1992)** find empirical evidence for maize-growing farmers in Swaziland adopting technologies in clusters. Results of a factor analysis show that seven technologies are adopted in three independent packages that are a) modern variety maize seed, basal fertilizer, and tractor ploughing, b) top-dress fertilizer and chemicals, and c) planting date and density. **KALIBA AND RABELE (2001)** analyze the impact of long-term soil-conservation and short-term conservation measures on wheat yield in Lesotho using a data set of only 50 smallholder farmers²⁸.

²⁸ Long-term measures involve terraces, slit traps, waterways and sandbags, while short-term measure consist of crop-rotation, inter-planting, fallowing, contour ploughing and vegetation cover.

Estimates of two separate Tobit models suggest that long-term soil conservation investment significantly increase the adoption of short-term conservation measures. While the adoption of short-term conservation is significantly related with higher education, lower number of adults in the household and less monthly household income, farmers with lower education, higher monthly income and a higher number of adults in the household are more likely to adopt long-term conservation investment. These results suggest that short and long-term conservation technologies are substitutes to each other rather than complimentary. **ERSADO ET AL. (2004)** examine the adoption decision of high-yielding varieties, and bands and terraces as soil conservation measures in Ethiopia by modelling a multinomial logit model. Their findings confirm that adoption is characterized by sequential adoption pattern and that stepwise dissemination of technologies should be emphasized. **NKONYA ET AL. (2004)** find for Uganda that many land investments and annual soil fertility management practices are complementary, leading to greater benefits when such measures are used in combination. Land investments tend to favour labour-intensive land management practices, such as the application of manure, compost, mulch, and household residues.

A large body of empirical literature has analysed the impact of specific key factors on adoption behaviour (Feder et al., 1985). The study of **ERSADO ET AL. (2004)** is one of the very few studies that particularly consider the role of health in adoption decision. Results show that sickness significantly reduces the probability of adoption of both productivity-enhancing and resource-conserving technologies and makes simultaneous adoption of the technological package infeasible. Additionally, high opportunity costs of diverting labour to healthcare activities are significant in explaining lower adoption rate of both technology types.

By influencing the farmer's planning horizon and time preferences, land tenure security is an often-cited factor influencing land-related investments (e.g. Besley, 1995; Hayes et al. 1997; Shiferaw and Holden, 1998; Demeke, 2003; Gebremedhin and Swinton, 2003; Honlonkou, 2004). **LAPAR AND PANDEY (1999)** estimate the adoption probability of contour hedgerows for the Philippines. The empirical results show that adoption depends on several farm and farmer characteristics and that the relative importance of these factors differs across sites. Land ownership shows mixed effects for the two study areas. They conclude that land ownership may not be a good proxy for tenure security as the possession of a legal title to land is not necessary for ensuring the security of land tenure, while other social factors may provide land security even if the land is not owned. However, study results may suffer from small sample size, as the probit models for the two regions are based on 60 and 70 observations. **MORRIS ET AL. (1999)** find lower incidence of fertilizer use on rented and

sharecropped fields in Ghana. However, they note that an alternative explanation for this result may be that the lower incidence of fertilizer use on rented and sharecropped fields is attributable to greater fertility of these fields, rather than to tenancy status. However, a number of studies suggest that tenure security in form of land titling alone or land insecurity from land redistribution exerts only a weak or unclear link to conservation investment or improvement in productivity (e.g. Lapar and Pandey, 1999; Bekele and Drake, 2003; Yesuf, 2004). **KAZIANGA AND MASTERS (2002)** use field-level data from Burkina Faso to identify the determinants of farmers' investment in soil and water conservation techniques (field bunds and microcatchments). They employ a Tobit regression, using MLE and semi-parametric CLAD, as well as the Cragg (1971) model regression, to estimate the intensity of adoption. The results across the different specifications indicate that controlling for factor abundance and other influences, particularly cropland property rights and livestock intensification (indicating pasture scarcity and pasture rights) tend to increase adoption probability of both techniques. **SAKURAI (2002)** analyzes the adoption of modern rice varieties and water control technology (such as bund and irrigation canal construction) in lowland rice cultivation in Côte d'Ivoire on village and household level. Results on village level suggest that the expansion of lowland rice cultivation has been driven by population pressure while its sustainability depends on the adoption of water control technologies. Furthermore, the adoption of water control technologies is positively related with the accessibility to the market, number of immigrants and educational level in the village. Estimates on farmer-level reveal that the adoption of irrigation canals is influenced by land tenure security approximated by the status of tenants and landowners. Sakurai concludes that if a cultivator does not think that he/she can enhance tenure security by investing, he/she may not be willing to invest. However, analysis on farmer-level is based on a total sample of only 61 farmers. The analysis of **HAGOS AND HOLDEN (2006)** does not support a significant influence of the degree of security or differences in the tenure arrangement on investment behaviour of stone terraces and soil bunds in Ethiopia.

There is empirical evidence that population growth is important in explaining the adoption decision of new agricultural technologies. In the literature, the effect of population pressure on natural resources has taken two divergent views. A negative impact of population growth is assumed on natural resource conditions and welfare from the Malthusian perspective. The neo-Malthusian view is supported by several studies (e.g. Grepperud, 1996; Pender et al., 2001). In contrast, the view of Boserup is more optimistic. According to Boserup (1965), population growth causes intensification in agriculture and thus results in the adoption of improved farming practices. From this point of view it is assumed that population increase

results in a higher value of land. By increasing the demand for food and land, the incentive even for poor farmers increases to invest in land conservation measures. According to the results of **BYRINGIRO AND REARDON (1996)**, smaller farms are not more eroded than larger farms, but have twice the investment in soil conservation structures in Rwanda. For Burkina Faso, **SAKURAI (2002)** finds on village-level that intensification through the adoption of bunds and irrigation canals is not simply induced by increased village population, but rather by increased lowland users and the 'effective population pressure', indicated by the ratio of male to female village population. **PENDER ET AL. (2004)** support the Boserup hypothesis of population-induced agricultural intensification, while they do not support the hypothesis of less erosion. They investigate the adoption of various land management practices (use of slash and burn, inorganic fertiliser, manure or compost, incorporation of crop residues, crop rotation, mulching, household residues, pesticides, or integrated pest management) in Uganda. However, they find little evidence that the access to markets, roads and credit, land tenure or title determines agricultural intensification. **YESUF (2004)** finds that land fragmentation through increasing population does not lead to agricultural intensification in Ethiopia. The study of **HAGOS AND HOLDEN (2006)** suggests an inverse relationship between farm size and conservation intensity (of soil bunds and terraces) which is in line with the perspective of Boserup.

Literature has focussed on two dimensions of learning: learning about the parameters of the new technology and learning about its profitability. As natural resource management techniques are knowledge-intensive, there is large number of studies that find that education, skills, and information and learning have a positive effect on the adoption decision (e.g. Foster and Rosenzweig; 1996; Cameron, 1999; Weir and Knight, 2000; Conley and Udry, 2003; Knight et al., 2003; Asfaw and Admassie, 2004)²⁹. **ASFAW AND ADMASSIE (2004)** conclude that the role of education is particularly critical in encouraging farmers to adopt innovations in traditional areas. However, the role of education in increasing the probability of adopting chemical fertiliser in Ethiopia is substituted or eroded by other factors, such as mass media, traders, etc., in modern environments³⁰. Furthermore, results indicate that the educational level of household members has even stronger impact on fertiliser adoption than the educational level of the head of the household. Results of **ERSADO ET AL. (2004)**

²⁹ A survey of recent work on technology adoption and information acquisition is given by Huffman (2001).

³⁰ Modern environment is defined in terms of road accessibility, distance to main capital, district town, next high school, hospital and next market, number of elementary schools, clinics, shops, and radios.

indicate that the educational level of the household head is positively related to the adoption of productivity-enhancing technology, particularly in sequential adoption behaviour.

As economists emphasize, learning about a technology can also be obtained by the technical assistance of extension agents and programs. **BEKELE AND DRAKE (2003)** examine the factors that influence the adoption of soil and water conservation structures (soil and/or stone bunds) to reduce water run-off and soil loss in Ethiopia. The results of the multinomial logit model on plot-level indicate that adoption is positively determined by access to information and support programmes for initial investment. Additionally, plot-level characteristics (slope and area), and land holding per economically active person of the family are found to be significant in explaining adoption behaviour. However, the duration of plot use, indicating the perception of tenure security, and credits for food and fertilizer do not appear to be significant determinants. Results of **JAGGER AND PENDER (2003)** suggest that the presence and the household involvement in programs and organizations, as well as the focus of programs and organization tend to influence the use of land management practices (such as inorganic fertilizer use, pesticides, crop residues, mulching and animal manure) in Uganda. They apply a two-stage probit model and consider the endogeneity of the presence of programs and the household's involvement in programs. They conclude that direct involvement of households in programs and organizations that promote such technologies may be critical to ensure technology diffusion throughout communities. Furthermore, analysis indicate that the spill-over effects of programs and organizations may be greater for technologies with short-term benefits and technologies that require some degree of coordination to be effective. **HONLONKOU (2004)** estimates a three-step decision model on information acquisition, adoption, and adoption intensity of a *mucuna*-fallow system in Benin. He also accounts for selection bias in estimating the intensity of adoption. He shows that the information acquisition decision is influenced by actions of official extension services. Results of a positive impact of prior utilization of *mucuna*-technology also suggest that farmers are 'learning by doing' and tend to persist in using the technology. Similarly, **HAGOS AND HOLDEN (2006)** confirm the significance of public-led conservation programs in increasing private investments in land conservation. **ABDULAI ET AL. (2008)** explicitly account for the endogeneity of information acquisition and estimate the information acquisition and the adoption of crossbreeding cattle in Tanzania under uncertainty with a bivariate probit model. Estimates show that information acquisition and the adoption of crossbred cows in Tanzania are made jointly. Accounting for selection bias, the intensity of adoption is examined. Results show that human capital, access to formal credit, and scale of operation increase the information acquisition and adoption probability, as well as the intensity of adoption.

Furthermore, risk is found to exert a significant effect on adoption and intensity through the perceived profitability of the new technology.

Empirical studies did not only focus on formal sources of information, but also have stressed on information channelling and learning through the farmer's social network. A growing number of studies examine the role of social learning and social capital in the adoption process (e.g. Conley and Udry, 2000; Isham, 2000; Mazzucato and Niemeijer, 2000; Conley and Udry, 2003; Bandiera and Rasul, 2006; Monge et al., 2008; Nyangena, 2008). Social capital is however not only important with regard to learning effects but also with regard to obtaining other resources. **BOAHENE ET AL. (1999)** find that education and the amount of information accumulated from extension agents are important in determining the adoption decision of hybrid cocoa in Ghana. Results suggest that economic constraints may be overcome by social support. Some of the resources obtained from the farmers' social networks (cooperative labour and network information) are also important in influencing the adoption. Thereby, network effects are higher for smaller-scale farmers than for larger-scale farmers. Social status appears to have only an indirect effect on adoption, by influencing access to credit. In addition, the number of previous successful adopters in the farmer's network and the number of contacts with extension agents have a significant positive impact on the adoption decision. Furthermore, analysis suggests that information acquired for acquaintances is substituted for information obtained from extension agents while in communication sociology it is assumed that information obtained from acquaintances and formal sources are complementary (Rogers, 1995). **ISHAM (2000)** analyzes the adoption probability of improved fertilizer in Tanzania. He finds that tribally based social affiliations act as a form of social capital in the adoption decision. Data reveal that the adoption is related with the presence of tribally based social affiliations, the cumulative proportion of adopters, land endowment, and the village distance from a local market. When adoption patterns are omitted from the model, it is shown that the probability of adoption remains increasing in land endowments and ethnic affiliations, and is also positively associated with consultative norms, the adoption of improved seeds, the availability of credit and extension services, and the average number of years that households have resided in the village. **CONLEY AND UDRY (2005)** test whether farmers adjust their inputs to align with those of their information neighbours who were surprisingly successful in previous periods to investigate the role of social learning for the adoption of pineapple in Ghana. They find evidence that social learning and networks are important in the diffusion of knowledge regarding pineapple cultivation. Data reveal that farmers adopt practices of surprisingly successful neighbours, conditional on potentially confounding factors (such as common growing conditions, credit

arrangements, clan membership, and religion). While Conley and Udry (2005) examine the importance of social learning after a new technology has been adopted, **BANDIERA AND RASUL (2006)** address the question of whether social learning leads initial adoption decisions to be correlated within the social network. They find an inverse-U shaped relationship between the probability of adoption and the number of adopters in the farmer's network for the adoption of sunflower cultivation in Northern Mozambique. Results suggest that the marginal effect of having one more adopter among friends and family is positive when there are few adopters in the network, and negative when there are many. Thereby, adoption decisions are found to be more correlated within family and friends than within religion-based networks, and uncorrelated among individuals of different religions. Furthermore, farmers that are more informed about the new crop are less sensitive to the adoption choices of others.

Another strand of literature has focused on the issues of time preferences and risk aversion. It was found that risk is a major factor in determining adoption rate (e.g. Hiebert, 1974, Feder, 1980; Feder, 1982; Tsur et al., 1990; Pitt and Sumodiningrat, 1991; Knight et al., 2003; Marra et al., 2003; Ghadim et al., 2005; Hagos and Holden, 2006, Abdulai et al, 2008)³¹. Soil conservation emerges as a viable insurance strategy against low-probability catastrophic losses for some households in the study of **SHIVELY (2001)**. By using a stochastic dynamic model, the study concludes that the assumption of risk-neutrality may be misleading in low-income settings where risk of food insecurity is high. Because of raising the short-run risk of consumption shortfall into regions of insufficiency soil conservation is especially costly on small farms and the probability of adoption can be assumed to rise with farm size. However, empirical data indicate an even higher rate of adoption on small farms than predicted by the theoretical model. This pattern has often been observed empirically among low-income farmers in India (e.g. Rosenzweig and Wolpin, 1993), Africa (e.g. Ndiaye and Sofranko, 1994) and Asia (e.g. Pattanayak and Mercer, 1998). As **KNIGHT ET AL. (2003)** note, most of the studies focussing on the risk attitude have concentrated on exogenous risk, e.g. due to unpredictable rainfall. Another type of risk is endogenous and arises from the farmer's choice of technology. It is involved in the adoption process of new technologies under conditions of uncertainty about outputs and returns (Knight et al., 2003). Knight et al. (2003) examine whether farmers' risk attitude towards endogenous risk and education are correlated and analyse the role of these factors in the adoption process for Ethiopia. Results indeed suggest that educated farmers are less risk-averse than those

³¹ For a literature review on the role of risk, information, and learning in the context of adoption, see Marra et al. (2003).

without education are. Both, schooling and risk attitudes were found to be important for innovation. According to **YESUF (2004)**, high subjective time discounting rates appear to discourage land investment decisions with short-term costs and long-term benefits due to high consumption smoothing problems (resulting from limited cash liquidity). Yesuf (2004) investigates the role of market and institutional imperfections in the context of fertilizer and soil conservation structures as jointly made decisions in Ethiopia. Controlling for plot-level differences, the results of a two-stage bivariate model indicate that the adoption of soil conservation structures has a negative and significant effect on the use of fertilizer under factor market imperfections. However, the reverse causality is found to be insignificant. Thus, soil conservation structures seem to be a substitute, while they are complements in production. Limited access to formal credit market is found to be significant in explaining the non-use of fertilizer but does not appear to be significant in determining the use of soil conservation methods. Furthermore, households with relatively high subjective time discount rates and a higher degree of risk aversion are less likely to adopt soil conservation techniques and fertilizer. Analysis suggests that relieving market imperfections increases the adoption rate of farm technologies. **HAGOS AND HOLDEN (2006)** estimate adoption and intensity decision of soil bunds and stone terraces in Ethiopia by a standard probit and Tobit model, as results of the Heckman's selection correction model and the Deaton's selection model did not indicate selection bias. They find that households' time preferences do not significantly explain investment pattern and household endowment (asset poverty) only tends to have a weak effect on the adoption behaviour. However, aversion appears to be an important factor in the intensity decisions. Furthermore, plot-level characteristics and household perceptions of returns on conservation investment appear to be critical in determining adoption and intensity decision.

There is another body of literature concerning the role of the perception of innovative technology (profitability and other traits), as well as the perception of the need for the new technology (e.g. perception of the soil erosion problem). **ADESINA AND ZINNAH (1993)** examine the technology characteristics and farmers' perceptions of mangrove swamp rice varieties. Besides farm and farmer specific factors, they find that the perception of technology-specific traits of these varieties (such as taste, yield, ease of cooking, tillering capacity, and the ease of threshing) have been the major factors conditioning adoption behaviour. The study of **NEGATU AND PARIKH (1999)** concludes that the perception of modern wheat varieties has a highly significant effect on the adoption of these varieties in Ethiopia. They estimate a simultaneous equations model combining the probit and ordered probit approaches to model the two-way relationship between perception and adoption.

However, the study is based on only 96 observations. **SOMDA ET AL. (2002)** find that the perception of the yield effect of compost compared to that of other fertilizers is one of the most important determinants of adoption of compost in Burkina Faso. Similarly, **HAGOS AND HOLDEN (2006)** find that household perceptions of returns on conservation investment appear to be critical in determining adoption and intensity decision of soil bunds and stone terraces in Ethiopia.

Not only the perception of the technologies' traits may influence adoption, but also the farmers' perception of production constraints, such as the threat of soil degradation. One of the studies focusing on this issue is **MBAGA-SEMGALAWE AND FOLMER (2000)**. They explore the adoption probability and intensity of improved conservation measures (such as bench terraces, infiltration ditches, and macro-contour lines) in Tanzania. Data suggest that the perception of erosion as production problem is mainly determined by sex, marital status, and the level of exposure to soil and water conservation (SWC) activities. The adoption decision is estimated by a logit model. It appears to be positively determined by the knowledge and recognition of soil erosion, the ranking of the soil erosion problem, and the participation in SWC programmes and labour-sharing groups. The effort devoted to soil conservation among adopters is analyzed using a Poisson regression accounting for sample selection bias. Results show that the level of investment in conservation measures is positively related to the endowment with family labour, the support from SWC programmes, while off-farm income and the household's ranking of the soil erosion problem exert a significant and negative influence on adoption intensity. **DEMEKE (2003)** shows that the perception of benefits from conservation structures have a positive and significant effect on the adoption probability and continued use of conservation practices in Ethiopia. The perception of soil degradation as a production threat is positively related with the adoption of conservation structures, but statistically insignificant. However, the logistic regression is based on a small sample consisting of only 78 farm households. **SIDIBE (2005)** analyses the determinants for the adoption of two soil and water conservation techniques ('zai' and stone strips) in northern Burkina Faso³². Results are based on 230 farmers and indicate that the most significant variables for the adoption of both conservation techniques are training in conservation practices and small ruminants holding. Variables such as the perception of soil degradation and education are determinants only for the adoption of 'zai' technique. In case of stone strips however, the membership in a farmer's association and area cultivated are

³² "Zai" is a traditional technique to restore degraded soils by digging and sowing into holes in which manure or compost has already been deposited. To create stone strips, stones are arranged perpendicular to the slope of the land in order to slow down water flow, encourage water infiltration, and increase the sedimentation of the materials reconstituting soil (Sidibe, 2005).

positively related to adoption, while the perception of soil degradation do not seem to be related with adoption.

Market imperfections have been found to be significant in determining the adoption pattern. **PENDER AND KERR (1998)** explore the determinants of farmers' investments in indigenous soil and water conservation measures (such as terracing, levelling, gully checks, field boundary bunds, grass strips, drainage, and others) in the semi-arid tropics of India. Based on a theoretical model the determinants of such investments are analyzed in the context of possibly imperfect factor markets. Data confirm that land markets have important impacts on investment incentives. There is also evidence that credit and labour market imperfections tend to affect conservation investments. **BULTE AND VAN SOEST (1999)** conclude that higher output prices contribute to the adoption of soil conservation measures if agricultural producers face a set of perfect markets for their inputs and outputs. In case of imperfect labour markets, the level of commodity prices has a theoretically ambiguous impact on soil conservation investments. In case that the absolute value of elasticity exceeds unity, producers should respond to higher prices by reducing their labour input invested in soil regeneration to restore equilibrium. Higher market access implies that the marginal return to labour invested in crop production and land management is higher, but the opportunity costs of labour may also be higher. Moreover, the positive effect of market and road access on input use may have further impacts on the use of labour-intensive practices. These impacts depend on whether capital and labour-intensive practices are complements or substitutes.

Most of the literature made in the field of agricultural technology adoption and the adoption of natural resource management practices do not relate natural resource management decisions to the livelihood strategies of households (Nkonya et al., 2004). **PENDER ET AL. (2001)** include the livelihood strategy in the analysis of the determinants of the adoption of various soil fertility management and soil conservation practices such as fallow, manure, compost, fertilizer, stone terraces, soil bunds, gully check, tree planting, and live fence for Ethiopian highlands using community-level data. By employing a maximum likelihood censored regression model and a censored least absolute deviations (CLAD) estimator, results indicate that different livelihood strategies favour different types of land management strategies. Physical conservation structures appear e.g. to be less common in areas of perennial crop production. With regard to off-farm activities, they find a positive effect on soil bunds. **NKONYA ET AL. (2004)** conclude by employing a multinomial logit model that different income strategies were associated with different land management practices in Uganda. Households with legume production as primary income source were more likely to use manure and compost. Perennial crop production promotes the application of manure and

compost, mulch and household residues, and reduces the use of slash-and-burn, fertilizer, and crop rotation.

3.4 Review of Economic Impact Studies on Agricultural Technologies

The use of new agricultural technologies has been propagated due their productivity-increasing potential in agronomic experiments. However, there is empirical evidence of yield gaps between possible and actual yields, and that productivity gains achievable from improved agricultural technologies have not been fully exploited by farmers in developing countries due to a number of reasons (such as poor extension, institutional and cultural constraints) (Xu and Jeffrey, 1998; Kalirajan and Shand, 2001; Evenson and Gollin, 2003; Alene and Manyong, 2006). Thus, to assess the real economic impact on farm outcomes, econometric studies are required that analyse the impact of technologies under farmers' conditions. This section gives an overview of selected studies that aim to investigate the economic impact of agricultural technology adoption (particularly of soil and water conservation methods) in developing countries.

A number of studies undertook simulation models to analyze the economic impact of improved agricultural technologies under farmers' conditions. **LÓPEZ-PEREIRA ET AL. (1994)** analyze the potential farm-level income effects of a technology package consisting of stonewalls and ditches combined with living tree barriers to prevent erosion and a package of improved sorghum seed, seed treatment and nitrogen fertilization for Honduras. Results of a whole-farm Discrete Stochastic Programming (DSP) approach show that erosion control is moderately profitable for small-scale hillside farmers. However, the profitability of the farm can be remarkably increased with improved sorghum varieties and moderate doses of chemical fertilizer. **MAATMAN ET AL. (1998)** show that rock bunds may increase food security in Burkina Faso by applying a three-stage stochastic programming model. With regard to improved varieties, **KARANJA ET AL. (2003)** use simulations models to evaluate the impact of regionally differentiated new maize technology on aggregate incomes and income distribution in Kenya. They find that maize technologies developed for high potential regions are likely to have more pronounced aggregate impacts on maize production than technologies that have been developed for marginal regions. Furthermore, results reveal that the technology diffusion in high potential regions is likely to have substantially greater effects on aggregate farm profits and real incomes than in marginal potential areas. **JOHNSON ET AL. (2007)** explore the effect of new cassava varieties on poverty applying a linear programming approach. Using a 'heterogeneous agent' approach they simulate the

behaviour across the entire surveyed population and avoid the aggregation bias associated with representative-farm models. They find a strongly poverty-alleviating effect and a substantial potential to spread from Nigeria to neighbouring countries, where their impact is likely to provide significant benefits to the most resource-poor farmers. Analyzing the impact of NERICA (New Rice for Africa), results of **KIJIMA ET AL. (2008)** reveal that adoption has the potential to increase per capita income by US\$20 on average (12% of actual per capita income). Furthermore, NERICA adoption may decrease poverty incidence (measured by the headcount ratio) by 5 percentage points.

Among the econometric studies on the impact of technology adoption, many have treated technology choice as exogenous variable without considering the endogeneity of technology choice. **BYRINGIRO AND REARDON (1996)** find that farms with greater investment in soil conservation have much better land productivity than other farms in Rwanda. Farms that gain most from soil conservation investments are those with a high share of annual food crops, high erosion, and low fertilization rates. Results are obtained by estimating an unrestricted translog production function, and the average and marginal value products of land and labour. However, the type of conservation is not specified in the analysis. **SHIVELY (1998A)** shows that the impact of contour hedgerows on maize productivity in the Philippines is positive in the long-run by estimating an agricultural production function employing OLS. However, results find that in the short run, newly established hedgerows do not only reduce area available for cultivation on a plot, but also reduce the performance of corn in the remaining alleys. The time required for hedgerows to compensate for the area they occupy is found to be approximately eight years. **KALIBA AND RABELE (2001)** estimate the Battese's modified Cobb-Douglas production function by employing a non-linear seemingly unrelated regression framework. Results indicate that a one unit increase of soil conservation efforts have a much greater effect on wheat yields than a unit increase in the use of inorganic fertilizer. Non-use of fertilizer will result in significant lower yields, while the use of hybrid varieties reveals a positive but not significant effect on wheat yields. However, this study is based on a small sample size of 50 households. **ADÉGBIDI ET AL. (2004)** investigate the productivity of indigenous soil and water conservation (SWC) technologies (stone bunds, tie-ridging, and ridging, water catchments, animal manure, green manure, and mulching, fallowing and crop rotation) in Benin. They estimate a Cobb-Douglas production function using OLS and control for SWC technologies by including technology choice dummies. They find that once controlled for observable and unobservable household characteristics by applying a household fixed effects model, indigenous SWC could obtain large productivity effects. Productivity appears to be most effective on plots with flat or light slopes, but less

effective on steep slopes. Furthermore, they find a positive interaction effect between plot size and SWC on productivity, as well as between fertilizer and SWC on productivity.

Studies have become more sophisticated by considering the endogeneity of technology choice. In 1998, **ZELLER ET AL.** investigated the adoption of hybrid maize and tobacco as new crops and the impact of adoption on the crop income in Malawi. Data show that increasing the cropping share of tobacco have a relatively large, while increasing the cropping share of hybrid maize has a very small positive effect. Using a Tobit model including the predicted probabilities of using modern varieties and irrigation canals, **SAKURAI (2002)** suggests that neither irrigation canals nor modern varieties have a significant effect on the use of chemical fertilizer. However, Sakurai notes that this result is not consistent with the common findings of studies done in Asian countries. He concludes that this result may be due to little variation in production environment. The rice yield function is estimated by applying OLS where the predicted probability of the use of irrigation canals is included. It shows that the adoption of irrigation canals enhances rice production. The adoption of modern varieties appears to have no significant effect on the rice yields. This may be because most cultivators have already adopted modern varieties. However, the estimate is based on a small sample consisting of 64 farmers. **BARRETT ET AL. (2004)** analyze productivity gains associated with a new system of rice intensification (SRI) in Madagascar by controlling for farmer and plot heterogeneity. The findings support the notion that the application of SRI indeed generates substantial productivity gains (estimated average output gains of more than 84%). However, half of the observed yield increases result from farmer characteristics rather than SRI itself. The increased estimated yield risk associated with SRI would make the technology unattractive to many farmers within the standard range of relative risk aversion. **PENDER ET AL. (2004)** find that the value of crop production is not significantly related to the use of various land management practices (such as slash and burn, inorganic fertiliser, manure or compost, incorporation of crop residues, crop rotation, mulching, household residues, pesticides, or integrated pest management) in Uganda. They apply OLS and IV to account for endogeneity and a reduced-form regression. Instead, they find that the value of crop production is related to the agro-climatic zone, primary income source of the household, age of the household head, land holding, livestock, participation in agricultural extension and training programs, and how the plot was acquired. **PLACE ET AL. (2004)** find that improved fallows almost always double on-farm maize yields in Kenya, while results do not indicate a significant effect of improved fallow on improved household level food security or poverty indicators. They estimate a two-stage regression, where the use of improved fallow is predicted in the first step. **ALENE AND MANYONG**

(2006) estimate a translog stochastic frontier production function for adopters of improved cowpea in Northern Nigeria. To account for the possible endogeneity of technology adoption, they include the predicted values of the adoption variables in estimating the stochastic frontier and inefficiency model. They show that differing adoption rates of the technology package (seed, insecticide, fertilizer, and recommended cereal-cowpea cropping pattern) explain much of the yield variation among adopters of improved cowpea varieties in Nigeria, with farmers adopting only parts of the package are less efficient. Crop management information is an often-missing technology component, and appears to account for much of the yield variation. **BRAVO-URETA ET AL. (2006)** analyze farm income in El Salvador and Honduras by estimating a three-equation system in which farm income is determined simultaneously by the adoption decision of soil and water conservation methods and by the level of diversification on the farm. The analysis is accomplished by using a two-stage least squares to account for potential simultaneity bias. Results indicate that the adoption of forestry systems and of soil and water conservation practices and structures contribute significantly to the increased agricultural earnings.

Considering the endogeneity of technology choice by estimating a single-equation in which the technology has only intercept effects, while the same set of variables is assumed to have the same effects of adopters and non-adopters, is very restrictive and not empirically tested. However, a small but growing number of studies explicitly accounts for the issue of selection bias in estimating the impact of new agricultural technologies. The problem of self-selection arises as farmers select themselves into treatment. Thus, groups of adopters and non-adopters may differ systematically. Inferences about the technology effect on outcomes may be biased if self-selection is not accounted for. Estimating the adoption effect on the outcome of adopters and non-adopters by applying endogenous switching regression allows the determinants of the outcome of interest to differ between both groups. **SHIVELY (1998B)** aims at determining the impact of soil and water conservation measures on agricultural productivity and yield variability. The study is based on a two-stage regression accounting for endogenous switching and conditional heteroskedasticity. Results indicate that hedgerows are associated with higher yields and lower yield variability in the Philippines. However, the magnitude and statistical strength of this relationship depends on the estimation model. Information on latent variables of the adopters reduces the statistical strength of soil conservation parameters in the yield equation. Estimates by using OLS were found to overstate yield impact compared with their heteroskedastic model that accounts for latent adopter characteristics by employing a first-stage probit model. **SAVADOGO ET AL. (1998)** examine the levels of land and labour productivity for adopters and non-adopters of animal

traction adoption in Burkina Faso by controlling for selectivity bias. Data indicate that animal traction greatly improves land and labour productivity. Results also suggest that controlling for selectivity bias is justified empirically. **ABDULAI AND BINDER (2006)** examine the adoption decision of the slash-and-burn practice and the impact of technology adoption on the application of commercial fertilizer and pesticides, as well as yields and net returns. They apply an endogenous switching-regression model to consider sample selection. They find that education, access to credit, land rights, and visits by extension agents reduce the probability of farmers to practice slash-and-burn in Nicaragua. However, environmental variables such as soil quality and plot slope do not exert an effect on adoption decision but affects yields of adopters and non-adopters. Results also confirm that bias occurs if not accounting for selection bias. **NYANGENA (2006)** investigates the impact of soil conservation on (conditional) yields and factor returns in Kenya using plot-level longitudinal data accounting for self-selection and simultaneity. Descriptive analysis suggests that plots without soil and water conservation generally have higher yields per hectare. This is expected to result from negative selection as a probit model suggests that plots with soil and water conservation are significantly steeper, more eroded than plots without soil and water conservation and have less soil depth. A two-stage random effects switching regression is used to compare three soil and water conservation techniques (benches, bunds and ridges) on plot-level. Results indicate that soil and water conservation increase returns from degraded plots and partly from other inputs. Furthermore, results reveal that bunds contribute to higher productivity of fertilizers. With regard to crop income, **KIJIMA ET AL. (2008)** find that selection bias does not occur by estimating a Heckman model and thus estimate the plot-level income from New Rice for Africa (NERICA) and alternative crops in Uganda by a household fixed model applying OLS. They find empirical evidence that income from NERICA plots is significantly higher than the income from other crops, and that households with NERICA-growing experience derive much higher income from NERICA plots. However, NERICA yields appear to be highly responsive to soil fertility.

One of the very few studies that account for selection bias by using the non-parametric method of matching in the context of technology adoption in agriculture is undertaken by **MENDOLA (2007)**. This study analyzes the impact of adoption of high yielding rice varieties on poverty and income for Bangladesh. The results of the propensity score matching approach indicate a positive and robust effect of adoption on farm household wellbeing and that the adoption effect on income increases with land size owned by the farmer. Another study is undertaken by **KASSIE ET AL. (2008)** who analyse the impact of stone bunds on crop production value per hectare in Ethiopia. Using cross-sectional plot-level data they

account for endogeneity and selection bias by applying parametric regression (modified random effects model proposed by Mundlak (1978) and pooled OLS), stochastic dominance analysis, as well as propensity score matching. To ensure that estimates are obtained from comparable observations, the parametric regression and the stochastic dominance analysis are based on a nearest-neighbour propensity score matching. Results of these methods consistently indicate that stone bunds have a positive and statistically significant effect on productivity in low rainfall areas. However, results indicate that plots with stone bunds are more productive than plots without such technologies in semi-arid areas, but not in higher rainfall areas, implying that the performance of stone bunds varies by agro-ecological type. Thus, the moisture-conserving benefits of stone bunds seem to be more beneficial in drier areas.

The stochastic dominance analysis is an analytical technique to rank two alternatives based on cumulative distributions. It can be used to compare yield changes and changes in the variability to investigate not only the impact of technology adoption on yields, but also on yield variability in the context of risk. An analysis applying the stochastic dominance approach is done by **SHIVELY (1999)** who examines risks and returns of soil conservation on hillside farms in the Philippines. Stochastic efficiency analysis is combined with a heteroskedastic regression model to assess the impacts of contour hedgerows on low-income corn farms. Regression analysis indicates that contour hedgerows can improve yields up to 15% compared with conventional practices over time. The analysis also provides weak support for a hypothesis that hedgerows are variance reducing. However, the reduction in yield variability achieved by hedgerows seems to be modest. Furthermore, yield variability may increase by as much as 5% as hedgerow intensity rises. Tests for stochastic dominance however show that hedgerows do not constitute an unambiguously dominant production strategy compared to the conventional tillage system. Hedgerows are found to dominate the conventional cropping strategy only for decision-makers with relative risk aversion coefficients in the range of 3–5.5. **BEKELE (2005)** analyses the impact of soil and water conservation on yield and income, and the variability in yields and income by estimating a stochastic dominance analysis. Results suggest that investment in soil and water conservation results in higher yields and higher net returns. The normalized second order SD analysis results do not support the hypothesis that conservation strategy is unambiguously better than a noconservation strategy in reducing variability in yield and net return to farmers. However, it is shown that conservation has second order dominance under low yield and income levels that often correspond to unfavourable rainfall conditions.

3.5 Concluding Remarks and Contribution of the Analysis

Reviewing the impact evaluation literature of technology adoption in agriculture shows that less effort has been made to assess the economic impact of agricultural technologies on farm outcomes compared to the vast literature that aims to determine the factors affecting adoption behaviour in developing countries. With regard to soil and water conservation methods, empirical literature tends to confirm that adoption exerts a positive impact on productivity, however few results suggest a negative relationship (e.g. Place and Hazell, 1993; Shively, 1998a).

To identify the true technology effect, unconfounded with other farmer and farm characteristics, impact evaluation of technology adoption has to account for selection bias. However, only few studies have focused on the economic impact of soil and water conservation methods accounting for selection bias. Selection bias may occur due to the fact that technology adoption may not be random but farmers select themselves into adoption. Impact estimates that do not consider self-selection bias may result in biased estimates and wrong policy implications.

The few studies undertaken with regard to soil and water conservation investment mostly focused on long-term investment structures. Additionally, most impact evaluation studies do not consider technology effects resulting from differing adoption rates of a technology package. However, Alene and Manyong (2006) e.g. provide evidence that differing adoption rates of the technology package explain much of the variation of the technology impact. In case of technology packages, the impact of a single technology may not be clear, as the observed result may appear due to the combined effect and the impact of joint adoption may be higher than of single components (López-Pereira et al., 1994).

This analysis contributes to the literature by analyzing the technology impact of a short-term water conservation method that has to be rebuilt every cropping season and dibbling method as seed-sowing and fertilizer application method that are disseminated as technology package by explicitly accounting for selection bias using parametric and non-parametric estimation approaches. While many empirical studies are limited to an analysis of productivity, this study will also investigate the technology effect on fertilizer demand, and net returns, which are outcomes of major interest to farmers and policy makers.

Accounting for the endogeneity of technology choice and selection bias in the impact analysis requires identifying the determinants driving the adoption behaviour of soil bunds and dibbling method. Reviewing the empirical adoption literature makes clear that

determinants explaining adoption of agricultural technologies vary significantly according to location and technology characteristics. Furthermore, the adoption decisions of related technologies may influence each other (Kazianga and Masters, 2002). In addition, Feder and Umali (1993) underline that the explanatory determinants vary on the diffusion-path of the new technology and that major determinants in the early phases of diffusion process may be different to those that drive adoption when diffusion have reached the final stage of the diffusion process (Feder and Umali, 1993). Empirical results also reveal that different factors are significant in explaining adoption of short-term and long-term conservation measures (e.g. Hayes et al., 1997; Kaliba and Rabele, 1999; Grebremedhin and Swinton, 2003). While several studies in the adoption literature refer to long-term conservation investments, bund technology in the study region can be considered as short-term conservation technique that involves yearly decisions, as the bunds have usually to be rebuilt every cropping season. Moreover, many empirical studies investigating the determinants of soil and water conservation methods suffer from low sample size and are thus limited in accounting for the variety of effects (derived from the economic constraint model, innovation-diffusion paradigm and the perceived-attributes paradigm) found in the literature.

These limitations underline that results of technology adoption literature may not be generalized and stress the importance of a technology and site-specific analysis to identify the determinants driving the adoption decision of bund construction and dibbling method in the study region. The present analysis therefore investigates the joint adoption decision of bund technology and dibbling method as technology package in a first step.

Chapter 4

Theoretical Model

Chapter 4 presents the theoretical framework linking the technology adoption process to farm outcomes such as input demand, and output supply decision-making.

It is assumed that households make farm production decisions independently of their consumption and time-allocation decisions. This assumption has been commonly made in the empirical literature (see e.g. Abdulai and Huffman, 2000, for efficiency of rice farmers in Northern Ghana). There are some reasons to assume the separability of production, consumption, and time-allocation: All rice farmers in the sample produced rice mainly for sale (as rice is the main commercial crop), but also for home consumption. Furthermore, farm households in the sample participated actively in the local labour market.

To link the adoption decision process to the input demand and output supply decision making, assume that the farmer is risk neutral and maximizes expected net returns, instead of expected utility³³.

$$\max_v E[pq(v, D, Z) - r'v] \quad (4-1)$$

$$\max_v E[pf(v, D, Z) - r'v] \quad (4-2)$$

where E is the expectation operator conditional on the information currently available to farmers; p is output price; q is the expected output level; v is a (2×1) vector of variable inputs (labour, fertilizer); D is the technology choice (traditional or improved practices such as bund technology or dibbling method), Z is a vector of fixed factors such as socio-economic household characteristics and endowments influencing production of the output; r is a column vector of input prices; and f is the production function.

³³ As noted by Abdulai and Binder (2006), under market imperfections small farm resource allocation will usually not follow conventional profit maximization. As demonstrated by Singh et al. (1986), a theoretically complete approach to small farm production would require simultaneous treatment of production and consumption choices of the farmer household. The assumption of risk-neutrality is commonly made; see e.g. Abdulai and Binder (2006).

It is assumed that the farmer maximizes (expected) profit subject to competitive input and output markets, thus being price-takers in both output and variable input markets. Furthermore, a single-output technology is assumed that is quasi-concave in the vector of variable inputs, and the vector of fixed factors³⁴. Under these assumptions, profit-maximizing behaviour under restriction of a production function can be described by a profit function that is the so-called dual of the production function.

A set of dual transformation relations connects the concave production function and the convex profit functions³⁵. Every concave production function has a dual that is a convex profit function, and vice versa (Lau and Yotopoulos, 1972). Specifically, the profit function is a logical extension of the production function under mild 'regularity conditions' (Sadoulet and de Janvry, 1995). These regularity conditions require that the function must be non-negative, monotonically increasing in output, convex and homogeneous of degree zero in all prices. Duality assures, that, starting from a profit function, the resulting system of supply and variable factor demand functions is obtainable from profit maximization of a farmer with a production function concave in the variable inputs subject to given fixed inputs and under competitive markets (Lau and Yotopoulos, 1972). Thus, without loss of generality, one can consider only profit functions in the empirical analysis of the behaviour of profit-maximizing, price-taking farmers (Lau and Yotopoulos, 1972). From the empirical viewpoint, it is preferable to work with the concept of the profit function than the production function. This is because it is a function only of predetermined variables and thus econometrically more appropriate for estimation (Sidhu and Baanante, 1979).

The profit function expresses what profit will be (assuming the farmer is profit maximizing) given a set of output and variable input prices, and a set of given technology and household characteristics. The maximized profit is expressed as a function of the output price, variable input prices and fixed factors, instead of the quantities of inputs and output, as follows:

$$\pi(p, r, D, Z) = pq(p, r, D, Z) - r'v(p, r, D, Z) \quad (4-3)$$

Assuming two variable inputs (labour and fertilizer), the profit function can be expressed as follows:

$$\pi(p, r, D, Z) = pf(v_l(p, r, D, Z), v_f(p, r, D, Z)) - r_l v_l(p, r, D, Z) - r_f v_f(p, r, D, Z) \quad (4-4)$$

³⁴ These assumptions imply e.g. decreasing returns to scale in the variable inputs (Lau and Yotopoulos, 1972).

³⁵ This duality is widely documented in the literature (e.g. Lau, 1971; McFadden, 1971).

The properties of the profit function are as follows (see Chambers, 1998, for more details): The profit function is non-decreasing in p and non-increasing in r ; homogenous of degree one in $\omega = [p, r]$; convex in $\omega = [p, r]$, continuous in $\omega = [p, r]$, at least when $\omega \geq 0$. A restricted profit function (with fixed factors) will also be concave and continuous in v , which is the vector of fixed factors.

According to the Hotelling's Lemma, demand functions for variable input factors can be obtained by differentiating the profit function with respect to factor prices while the output supply function can be obtained by differentiating it with respect of the output price (Hotelling, 1932). This yields the corresponding input demand and output supply equations (netput functions).

The derivation of the profit function with respect to p can be given as:

$$\begin{aligned} \frac{\partial \pi(p, r, D, Z)}{\partial p} &= p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_l} \frac{\partial v_l(p, r, D, Z)}{\partial p} + \\ & p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_f} \frac{\partial v_f(p, r, D, Z)}{\partial p} + \\ & f(v_l(p, r, D, Z), v_f(p, r, D, Z)) - r_l \frac{\partial v_l(p, r, D, Z)}{\partial p} - r_f \frac{\partial v_f(p, r, D, Z)}{\partial p} \end{aligned} \quad (4-5)$$

Rearranging equation (4-5), by collecting the terms $\frac{\partial v_l(p, r, D, Z)}{\partial p}$, and $\frac{\partial v_f(p, r, D, Z)}{\partial p}$

results in:

$$\begin{aligned} \frac{\partial \pi(p, r, D, Z)}{\partial p} &= \frac{\partial v_l(p, r, D, Z)}{\partial p} \left(p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_l} - r_l \right) + \\ & \frac{\partial v_f(p, r, D, Z)}{\partial p} \left(p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_f} - r_f \right) + \\ & + f(v_l(p, r, D, Z), v_f(p, r, D, Z)) \end{aligned} \quad (4-6)$$

As $\left(p \frac{\partial f(v_l, v_f)}{\partial v_i} - r_i \right) = 0$ for $i = l, f$, equation (4-6) simplifies to the following expression:

$$\frac{\partial \pi(p, r, D, Z)}{\partial p} = f(v_l(p, r, D, Z), v_f(p, r, D, Z)) \quad (4-7)$$

This yields the following optimal output supply equation:

$$\frac{\partial \pi(p, r, D, Z)}{\partial p} = q^*(p, r, D, Z) \quad (4-8)$$

To obtain optimal input demand, deriving the profit function with respect to r_f results in the following expression:

$$\begin{aligned} \frac{\partial \pi(p, r, D, Z)}{\partial r_f} &= p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_l} \frac{\partial v_l(p, r, D, Z)}{\partial r_f} + \\ & p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_f} \frac{\partial v_f(p, r, D, Z)}{\partial r_f} + \\ & - r_l \frac{\partial v_l(p, r, D, Z)}{\partial r_f} - r_f \frac{\partial v_f(p, r, D, Z)}{\partial r_f} - v_f(p, r, D, Z) \end{aligned} \quad (4-9)$$

Rearranging equation (4-9) results in:

$$\begin{aligned} \frac{\partial \pi(p, r, D, Z)}{\partial r_f} &= \\ & \frac{\partial v_l}{\partial r_f} \left(p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_l} - r_l \right) + \\ & \frac{\partial v_f}{\partial r_f} \left(p \frac{\partial f(v_l(p, r, D, Z), v_f(p, r, D, Z))}{\partial v_f} - r_f \right) + \\ & - v_f(p, r, D, Z) \end{aligned} \quad (4-10)$$

As $p \frac{\partial f(v_l, v_f)}{\partial v_i} - r_i = 0$ for $i = l, f$, this results in the following optimal input equation for fertilizer:

$$\frac{\partial \pi(p, r, D, Z)}{\partial r_f} = -v_f^*(p, r, D, Z) \quad (4-11)$$

In the reduced form, the explicit functions of the variable input demand and output supply, as well as net returns, can be given as:

$$V = V(R, D, P, Z) \quad (4-12)$$

$$Q = Q(R, D, P, Z) \quad (4-13)$$

$$\pi = \pi(R, D, P, Z) \quad (4-14)$$

Equations (4-12), (4-13), and (4-14) indicate that input demand, output supply, as well as net returns are influenced by the technology choice, household characteristics, as well as output and input prices.

To model these relationships for the empirical analysis, the relationship can be represented by $Y_k = X_k' \beta_k + \eta_k$, where Y_k is the decision variable (such as input demand and output supply). X_k represents a vector of farm input prices, plot-level characteristics, household endowments and characteristics (such as farm size, education and other socioeconomic and resource characteristics), and η_k is the error term with $\eta_k \sim N(0, \sigma)$ (Rahm and Huffman, 1984).

Chapter 5

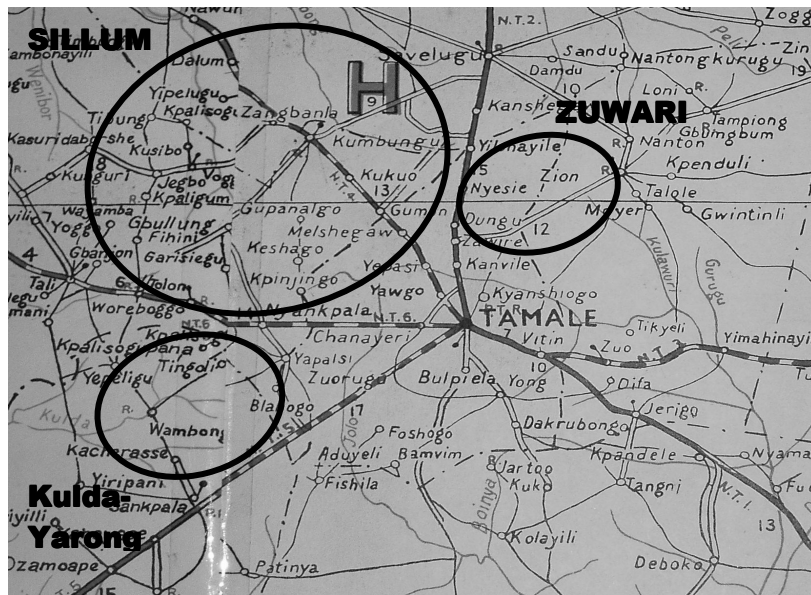
Adoption Survey

Chapter 5 starts with background information about household structure and farming practices in the study region and gives some definitions that are needed for the analysis. Then, a discussion of data collection and sampling procedures employed follows. The chapter also contains descriptive statistics of the survey data generated.

5.1 Background and Working Definitions

The data of the survey was collected in 24 communities that are located in three river valleys within a 50 km radius around the regional capital Tamale. The location of the three river valleys (Kulda-Yarong valley, Sillum valley, and Zuwari valley) is presented in figure 5-1.

Figure 5-1: Location of river valleys covered by the survey



The study region is traditionally inhabited by Dagomba people (Sillum and Zuwari valley) and Gonja people (Kulda-Yarong valley). Farmers in the study region are subsistence farmers and their primary objective is producing all the food staples needed by the household.

Especially, self-sufficiency in maize (the main food staple) is very important (Abu, 1992). Although some rice is used for home consumption, rice is of major importance in most communities as a cash crop because of its storability and its profitability even in years with normal rainfall (MoFA, 1997; Kranjac-Berislavjevic et al., 2003). Cropping season of lowland rice begins in April with land preparation and planting in May/June and ends with harvesting in November/December (see cropping calendar in appendix 3).

The basic unit of social organization is the compound household, living in a single, walled compound or house. Its nucleus is an elementary or polygynous family, to which may be attached the descendants of the head's grandfather (Abu, 1992)³⁶. Thus, the compound household may consist of several farm families. The household head provides food staples for the entire household from the produce of the household farms which are under his decision. Dependent men are the backbone of the labour force for the household farms³⁷. Farm produce from household farms (provided by household heads) is mainly for consumption. In addition to meeting their absolute obligations on the household farms, the dependent men cultivate their own farms (under their own decision) which produce is considered theirs, and they are thus free to dispose of it. Dependent men tend to concentrate on cash crops and cultivate them on their individual farms (Abu, 1992). In the study region, there are different kinds of communal labour, while hired labour is generally uncommon in the study area (MoFA, 1997). Working groups consist of about 5-6 farmers and work rotationally on the farms of their members against the customary provision of meal (MoFA, 1997).

Traditionally, there is no land title and land belongs to the indigenous tribal community. Using rights are permanent and granted by the tribal chief. Farm families control the land they cultivate which is transferable through patrilinear inheritance (MoFA, 1997). Male farmers have permanent custody of lands, while female farmers generally have annual temporary custody of land for the cultivation of any cash crop of their choice³⁸. For the purpose of

³⁶ Polygyny is the most common form of polygamy, where a male individual may be married with more than one wife at the same time.

³⁷ Dependent men (or junior men) are grown up enough to farm but are not yet household heads. The levels of activity and decision taking of the household head and dependent men vary with the household head's age. The authority passes gradually to the most senior of the dependent men, who will ultimately inherit the headship of the household. Household heads have the authority to make all decisions about farm activities and management of household farms (but likely with consulting the young men). However, dependent men cultivate own farms under own decision, except decisions that would involve heavy commitment of resources of the compound household will be taken by the household head (Abu, 1992). Adoption of bund technology and dibbling, use of fertilizer and credits are under the decision of the rice farmer.

³⁸ Female farmers being widowed and staying in the husband's house may have permanent custody of farmland.

farming, an inhabitant is entitled to occupy and cultivate any vacant land. Strangers are required by custom to seek the local chief's permission before they can cultivate own farms. Additionally, they have to give part of their farm produce to the Chief after harvest (Mahama, 2004).

Based on the farming system and the household structure in the study region, the following definitions are introduced for this particular study.

Household:

In this particular study, the household size is defined as the sum of family and non-family members living in the compound and "eating from the same pot".

Decision-maker:

This study focuses on the rice farmer himself as the decision maker of rice production. This is due to the fact that the rice farmers are the ultimate decision makers with respect to rice production and the adoption decision of self-made bunds and dibbling.

Adopter:

An adopter is defined as somebody who used the technique at least in some part of the rice area cultivated with lowland rice in 2005.

Bund technology:

Bund technology does refer to the adoption of any kind of bunds made by the farmers, including intermediary and contour bunds.

5.2 Data Collection

Data collection was conducted from October 2005 to April 2006. To get basic background knowledge of production system, technology adoption and socio-economic system, techniques of Rapid Rural Appraisal (RRA) (such as focus group discussion, pair wise ranking of crops cultivated, and off-farm activities) were used³⁹. A preliminary survey was conducted to identify communities with both adopters and non-adopters of bunds and

³⁹ RRA refers to a range of investigation techniques that emerged in the 1970s as a more efficient and cost-effective way of learning by outsiders, particularly about agricultural systems, than was possible by large-scale social surveys or brief rural visits by urban professionals. Using local knowledge, research is ideally carried out by a multi-disciplinary team. For differences of RRA and Participatory Rural Appraisal (PRA) see Krummacher (2004).

dibbling. To control for the community level effect in the adoption decision analysis, only communities with both adopters and non-adopters were selected. Micro-level data were then obtained by a formal data collection. Questionnaires were administered on farmer, household, and community level from January to April 2006 (see appendix 4 to 6).

5.2.1 Sampling Procedure

A multistage sampling procedure with purposive selection of villages and random selection on household-level was employed. Using information from the Intensive Survey conducted by the FSRPOP in 2004 and a preliminary survey (interviewing key persons and group discussions), communities could be identified with both adopting and non-adopting farmers. Finally, 24 communities (out of 58 LRDP communities) were chosen for the survey, covering all river valleys.

Lowland rice farmers were selected randomly and proportionately within the strata of adopters and non-adopters of bund technology and LRDP participants and non-participants⁴⁰. Table 5-1 presents the resulting sample structure.

Table 5-1: Sample structure

	Number of observations	Adoption rate	
		Bund technology (%)	Dibbling method (%)
Sillum valley	262	47.31	75.19
Zuwari valley	39	53.85	64.10
Kulda-Yarong valley	41	53.66	24.39
	<i>342</i>	<i>48.54</i>	<i>67.84</i>

Source: Survey data

5.2.2 Survey Instruments and Implementation

The initial version of the questionnaire of the formal survey was prepared based on background information generated through RRA techniques. Enumerators speaking the local language (Dagbani) and English, and with experiences in agricultural and/or rural development were hired and trained before they undertook the survey. After training the

⁴⁰ Only rice farmers who were mono-cropping lowland rice were selected to allow for uncounfounded causal inference of technology adoption on outcomes.

enumerators, pre-testing of the questionnaire was done by involving the enumerators. The questionnaire was a structured type and was administered in the local language.

Due to the household structure in the study region, the individual-level questionnaire includes a rice farmer questionnaire as well as a compound section. While the rice farmer questionnaire focuses on individual rice production data, plot characteristics and socio-economic data of the farm family including sections for adopters and non-adopters only, the compound section focuses on socio-economic data of the compound household. The village questionnaire was conducted by interviewing key persons of the community (chief, village elderly, or religious leader) or by the enumerators' own observations.

All questionnaires were controlled and discussed with the enumerators. In case of missing information or inconsistent answers, the enumerators had to rerun the relevant questions. The enumerators had to spend much time to exactly specify the meaning of definitions and questions used in the present study. This was essentially because some definitions used in the present study had different meanings when used by LRDP, FSRPOP and previous surveys that were implemented to evaluate the success of LRDP and FSRPOP.

5.3 Descriptive Analysis

This section presents the sample structure, adoption pattern, farm and farmer characteristics, farming practices, perception, and differences between adopters and non-adopters.

5.3.1 Sample Structure and Adoption Pattern

The cross-section sample consists of 342 farmers from 285 compound households operating 439 plots⁴¹. Table 5-2 clearly shows the presence of four technology adoption regimes with regard to bund construction and dibbling method. These regimes are i) adopters of both techniques, ii) non-adopters of both technologies, iii) adopters of bund technology while non-adopting dibbling method, and iv) adopters of dibbling technology while non-adopting bund construction.

⁴¹ Two farmers were excluded from the econometric analysis, as they were not allowed by the landholder to construct bunds and are thus not the decision-maker of the adoption decision.

Table 5-2: Adoption pattern in the sample

		Dibbling seed		(%)	Total
		Adopters	Non-adopters		
Bund construction	Adopters	142	24	48.54	166
	Non-adopters	90	86	51.46	176
(%)		67.84	32.16		
Total		232	110		342

Source: Survey data

At the time of the survey, 49% of sample farmers used bund technology, while the adoption rate of dibbling seed was about 68% in 2005. Adoption rate of dibbling as seed sowing method seems to be higher than that of dibbling as fertilizer application method (28.82% of farmers). Only 28.61% of the farmers in the sample dibbled both seed and first round fertilizer. Among LRDP project participants, the adoption rates are higher as 61% have constructed bunds and 80% have used dibbling as seed sowing method, compared to only 37% bund users and 57% users of dibbling method among non-participants. A further look to the adopters of bund construction shows that 83.73% of them have fully adopted bund construction. Only 27 farmers were partial adopters of bund technology. However, among farmers cultivating more than one rice plot, only 41.49% were complete adopters of bund technology while 28.72% were partial adopters. The average share of adoption is 43.56% among partial adopters of bund construction. Among adopters of dibbling, nearly all farmers were full adopters (92.24%). Among farmers cultivating more than one rice plot, only 22.50% were partial adopters of dibbling as seed sowing method. The average share of rice area that is dibbled among partial adopters is 43.08%. These figures reveal that partial adoption seems to be more common for bund technology than for dibbling method. At plot-level, 205 out of 439 plots (46.70%) were bundled in 2005. Seed was dibbled at 295 out of 439 plots (67.20%) in 2005. Dibbling is mostly spread among plots that have both LRDP induced bunds, as well as bunds constructed by the farmers themselves. 89% of these plots are dibbled whereas 81% of the plots with only self-constructed bunds were dibbled, and only 79% of plots initiated by LRDP bunds are dibbled. However, only 43% of plots without any kind of bund are dibbled. Among plots that are covered with LRDP bunds, 60% are also equipped with self-constructed bunds, while only 40% of plots outside the LRDP bundled area are covered with bunds constructed by the farmers.

Table 5-3 presents the adoption pattern of several techniques among lowland rice farmers in the study region. 57.68% of the farmers in the sample have levelled their rice plots. A high percentage of farmers (74.27%) used fertilizer in rice cultivation, while the percentage of

farmers who applied fertilizer to other crops is lower at 68.42%. However, 63.09% of the farmers in the sample faced constraints resulting from weather conditions (e.g., drought and flood) in applying the usual amount of fertilizer. An even higher percentage of farmers weeded their rice farms two times or more on average (79.94%). This equals to 70.16% of the plots in the sample that are weeded twice in the cropping season, while 16.63% of the plots were weeded only once, 9.79% of the plots were weeded three times, 1.14% of the plots were weeded four times, and 2.28% of the plots were not weeded at all. The t -statistic of mean difference indicates that weeding activities are significantly higher (at the 1% level) on plots where dibbling method was used. Plots that are dibbled were manually weeded on average 2.02 times in the 2005 cropping season, while plots that are not dibbled were manually weeded only 1.63 times in the 2005 cropping season. However, no significant difference in the frequencies of weeding was found between plots that were covered with self-made bunds and plots without. Only 26.34% of the farmers in the sample adopted the whole intensification package consisting of intensified weeding (average weeding more than two times) and dibbling seed and fertilizer.

In the sample, 47.37% of the farmers participated in the LRDP and 23.68% of the farmers indicated that they were supported by the FSRPOP project. Among farmers supported by FSRPOP, 79.01% have already been participating in the LRDP. As shown by Table 5-3 a higher percentage of adopters than of non-adopters participated in the LRDP and FSRPOP (significant at 1% level). Moreover, the participation rate in any other project before the LRDP is significantly higher among adopters in the whole sample (at the 5% level).

Table 5-3: Adoption pattern and technology use of adopters and non-adopters

Characteristics	Bund technology		Dibbling seed	
	Sample mean	Diff.	Sample mean	Diff.
	Non-adopters	Adopters	Non-adopters	Adopters
Use of bunds (%)			21.82 61.21	39.39***
Use of dibbling (%)	51.14 85.54	34.41***		
Improved rice variety (%)	85.63 95.78	10.15***	76.15 97.40	21.26***
Levelling of rice plot (%)	46.11 70.39	24.29***	39.81 66.20	26.40***
Number of manual weeding	1.88 1.98	0.08	1.63 2.05	0.42***
Farmer participated in FSRPOP (%)	13.64 34.34	20.70***	10.91 29.74	18.83***
Participated in LRDP (%)	35.80 59.64	23.84***	30.00 55.60	25.60***
Participated in any project before LRPD (%)	16.28 25.47	9.19**	11.32 25.11	13.79**
<i>Number of farmers</i>	<i>N=176</i>		<i>N=110</i>	
	<i>N=166</i>		<i>N=232</i>	

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

5.3.2 Household Characteristics

Average households size was 19 persons, with an average of 5.52 adult women, 5.01 adult men, and 7.55 children (below 14 years). On average, the farmers in the sample were 37 years old and 42.40% of farmers in the sample were household heads. Very few rice farmers in the study region were female. According to the LRDP, in 2001, only 6.7% of LRDP project farmers were female, most of them owning plots for the first time (Jenin and Awuni, 2001). Moreover, according to Doss (2002), rice can be considered as men's crop. Thus, the proportion of female farmers in the sample is very small (4.97%).

79.82% of the farmers in the sample had no formal school education (70% were illiterate and 9.70% only had some English or Dagbani literacy). The average number of years of formal schooling among those having formal school education was 9.28 years. According to the t -statistic of mean difference, no significant differences in the number of years of formal schooling could be observed between adopters and non-adopters of bund construction. In terms of literacy, adopters of bund construction do not seem to be more literate than non-adopters do (see table 5-4). However, in case of dibbling, a significant higher number of farmers who adopted dibbling were found to be literate compared to non-adopters. LRDP participants in the sample turn out to have less educational background than non-participants of LRDP have: only 25% of LRDP farmers were literate compared to 33% of the non-participants. Likewise, years of formal schooling were 1.26 years on average among LRDP participants compared to an average of 2.35 years among non-participants.

As it can be observed from table 5-4, the t -statistic of mean differences indicates that labour endowment is higher among adopters of bund technology while the number of family members who are frequently ill is significantly lower (at the 5% level). The share of off-farm income is significantly lower for adopters of bund construction than for non-adopters (at the 5% level). Statistically significant differences were also found between adopters and non-adopters regarding literacy and household headship, implying that literate farmers and household heads are more likely to dibble.

Table 5-4: Household characteristics of adopters and non-adopters

Characteristic	Bund technology		Dibbling seed	
	Sample mean	Diff.	Sample mean	Diff.
	Non-adopters Adopters		Non-adopters Adopters	
Age of the respondent (years)	37.78	-0.97	37.32	-0.01
	36.81		37.31	
Farmer being literate (%)	28.16	2.56	22.22	10.54**
	30.72		32.76	
Farmer being head of the household (%)	43.10	-0.93	37.61	7.41*
	42.17		45.02	
Farmer's compound has a higher social status than average (%)	25.43	-1.34	24.07	1.03
	24.10		25.11	
Labour endowment of compound household (labour equivalents) ⁴²	12.54	1.76**	12.92	0.70
	14.30		13.62	
Labour equivalents frequently ill	2.39	0.65**	2.25	-0.26
	1.74		1.99	
<i>Number of farmers</i>	<i>N=176</i>		<i>N=110</i>	
	<i>N=166</i>		<i>N=232</i>	

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

5.3.3 Production System and Farm Characteristics

Individual farm size averages 7.35 acres, with an average of 2.17 acre of farm land covered with lowland rice. Comparing adopters and non-adopters of dibbling, the average area cultivated with rice is significantly smaller for adopters of dibbling (see table 5-5). Farmers in the sample cultivated on average 4.25 plots in total. The average number of lowland rice plots cultivated is 1.28. The average size of lowland rice plot without LRDP bunds is 1.81 acre, while the average size of LRDP plot is smaller, with 1.42 acre. This is due to the restriction of one acre of LRDP area given to each farmer. 40.06% of the farmers in the sample cultivated plots within LRDP bunds. Among these 137 farmers cultivating LRDP area,

⁴² Labour equivalents are calculated with following factors: men (14-60 years) = 1; women (14-60 years) = 0.75; elderly / children (<14 years and >60 years) = 0.5.

70.80% cultivated only one acre of LRDP area whereas 90.51% cultivated two acre or less in 2005. The majority of the farmers (72.51%) cultivated only one lowland rice plot in 2005, 26.32% cultivated two lowland rice plots and 1.17% of the farmers cultivated three plots. Looking at land tenure status, most rice plots are owned by the farmers themselves (91.61%), while family ownership (6.06%) and communal ownership (2.33%) can also be observed. Furthermore, statistically significant differences were found between adopters and non-adopters with regard to off-farm income.

Table 5-5: Farm characteristics of adopters and non-adopters

Characteristic	Bund technology		Dibbling seed	
	Sample mean	Diff.	Sample mean	Diff.
	Non-adopters Adopters		Non-adopters Adopters	
Rice size cultivated in 2005 by responding farmer (acres)	2.09 2.26	0.18	2.45 2.03	-0.42**
Area cultivated by farmer with other crops in 2005 (acres)	5.15 5.21	0.07	5.39 5.08	-0.31
Total farm size cultivated by farmer in 2005 (acres)	7.24 7.47	0.24	7.84 7.12	-0.72
Number of total rice plots	1.17 1.40	0.24***	1.14 1.35	0.22***
Number of LRDP plots	0.27 0.55	0.28***	0.19 0.51	0.32***
Off-farm income of farm family (GHC)	503,795.5 449,405.1	-54,390.32	537,409.5 448,936.5	-88,473.03
Share of off-farm income (farm family) (%)	13.68 10.12	-3.56**	13.47 11.24	-2.23
Respondents with off-farm activity (%)	38.23 33.33	-4.90	50.00 29.26	-20.74***
Membership in any crop related farmer group (without FSRPOP) (%)	37.93 37.35	-0.58	35.78 38.53	2.75
Number of bikes owned	1.00 1.07	0.07	0.93 1.08	0.16***
Ownership of tractor (%)	1.15 5.42	4.27**	0.92 4.33	3.41**
Number of bullocks (pairs) owned	0.14 0.16	0.19	0.14 0.15	0.01
<i>Number of farmers</i>	<i>N=176</i> <i>N=166</i>		<i>N=110</i> <i>N=232</i>	

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

An overview of crops cultivated by rice farmers in the sample is given in table 5-6. Farmers are subsistence farmers cultivating primarily for their own needs. Groundnuts are another cash crop of importance, while cotton as cash crop is of minor importance in the sample. Table 5-6 indicates that maize (as the main food staple) is cultivated by 88.30% of the farmers in the sample.

Table 5-6: Frequency of other crops cultivated

Type of crop	Frequency (% farmers)
Maize	88.30
Groundnut	71.05
Yam	49.12
Guinea corn	14.62
Cassava	12.57
Cowpea	6.73
Beans	5.56
Millet	4.68
Soybean	4.68
Pigeon pea (<i>Cajanus cajan</i>)	1.75
Sorghum	0.58
Sweet potato	0.88
Bambara nuts (<i>Vigna subterranean</i>)	0.58
Pepper	33.33
Tomato	14.33
Okra	11.70
Tobacco	1.46
Mango	1.46
Cotton	1.17
Sheanut	2.63

Source: Survey data

Data reveal that nearly all farmers in the sample cultivated improved rice varieties (90.59%). It can be observed from table 5-3 that the proportion of farmers adopting improved varieties is higher among adopters of bund and dibbling technology. At plot-level, 89.99% of the plots were cultivated with improved varieties (see table 5-7). Most common varieties were GR18 (used on 47.62% of plots) and TOX varieties (with 25.92% of plots), followed by IR12 and Afefe (see table 5-7). Only 9.99% of the plots were cultivated with local varieties. In most

cases, own seed is used (82.71%). Seed was obtained by exchange with other farmers in 13.21% of the rice varieties. The remaining respondents generated seeds from their parents or from mix of different sources.

Table 5-7: Rice varieties cultivated (plot-level)

Variety	Number of plots	(% plots)
<i>Improved varieties</i>	378	89.99
GR 18 (Afefe)	225	53.57
TOX/TOX 3107	109	25.95
IR12 (Abirikuguo)	35	8.33
GR 19	6	1.43
GR 21 (Faro 15)	3	0.71
<i>Local varieties</i>	42	9.99
Mendi	20	4.76
Jakuku	9	2.14
Pole	3	0.71
Kukpula	3	0.71
Anyufula	1	0.24
Talam	1	0.24
not specified	5	1.19
<i>Number of plots</i>	<i>N=420</i>	<i>N=100</i>

Source: Survey data

Regarding land preparation, 95.01% of the sample farmers ploughed while only 65.21% of farmers harrowed their rice plots in 2005. Table 5-8 presents the equipments used for ploughing and harrowing. Most of the farmers used tractors to prepare their plots of land: 76.68% out of those farmers who harrowed, and 83.84% of those who ploughed in 2005.

Table 5-8: Equipment for land preparation

Equipment	Ploughing (% responses)	Harrowing (% responses)
Tractor	83.84	76.68
Bullock	8.54	10.76
Hoe	3.96	12.56
Tractor + Bullock	3.35	–
Hoe + tractor + bullock	0.30	–
<i>Responding farmers</i>	<i>N=328</i>	<i>N=223</i>

Source: Survey data

5.3.4 Plot-level Characteristics

Table 5-9 gives a summary of plot-level differences that appear to be statistically significant. The share of plots with very good water retention, loamy soil and LRDP bunds is significantly different between plots with and without self-made bunds. While 56.84% of the plots without self made bunds have very good water retention status, this was so only for 45.85% of the plots with self-made bunds. This indicates that construction of bunds may be less beneficial on plots that already had a very good water retention status compared to plots with a critical water retention status, where bund construction may be a pre-condition for rain-fed rice cultivation. 20.51% of the plots without self-made bunds have loamy soil as compared to only 14.63% of those with self-made bunds. The share of plots with LRDP bunds is much higher for adopters (40.98%) than for non-adopters (23.83%). Furthermore, the average size of plots with self-made bunds is significantly smaller among non-LRDP plots, while it tends to be higher among LRDP-bundled plots. This may be due to the fact that labour requirement to construct bunds is in general higher on larger plots. As levelling may be more necessary on large plots in addition to bund construction, the probability to construct bunds may be higher on smaller plots. However, among plots with LRDP contour bunds, the construction of intermediary bunds within the LRDP bunds may be more useful for larger plot sizes. This is because bund construction reduces the area that could be used for cultivation. Furthermore, the need for intermediary bunds may be higher on larger plots to better divert the water within the plot.

Table 5-9: Differences in plot-level characteristics

Plot characteristic	Self-made bunds		Dibbled	
	Sample mean	Diff.	Sample mean	Diff.
	No bunds Bunds		Not dibbled Dibbled	
Very good water retention (%)	56.84	-10.98**	50.34	2.04
	45.85		52.38	
Very good soil quality (%)	52.99	-4.21	44.83	9.25**
	48.78		54.08	
Loamy soil (%)	20.51	-5.88*	17.24	0.79
	14.63		18.03	
LRDP bunds (%)	23.83	17.15***	14.48	25.86***
	40.98		40.34	
Located in lowlands (%)	82.48	1.84	86.21	-4.30
	84.31		81.91	
Average plot size (without LRDP bund) (acres)	1.93	-0.29**	2.16	-0.59***
	1.64		1.57	
Average plot size (LRDP bund) (acres)	1.29	0.21*	1.90	-0.57***
	1.51		1.34	

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

Very good soil quality and the provision of LRDP bunds is found to be statistically more likely among dibbled plots than among plots where dibbling was not used. Furthermore, smaller plots seem to be dibbled more often.

5.3.5 Credit and Market Access and Information Sources

40.29% of the farmers in the sample received credit in the last ten years. A significant difference (at the 1% level) in the access to credit was found between adopters and non-adopters of both technologies. While only 28.41% of non-adopters of bund technology had access to credit, 53.01% of adopters had access to it. Looking at dibbling method, among non-adopters only 24.55% indicated to have access to credit, while credit was available for 47.84% of adopters. However, only 17.94% of the farmers in the sample received credits not related to LRDP or FSRPOP in these years. In the cropping season 2005, 19.41% of the farmers in the sample received credit. 78.79% of farmers who received credit in 2005,

obtained it from FSRPOP. Other sources of credits received in the last ten years are as follows:

Table 5-10: Credit source of non-project credits

Credit source	% responses
Relatives, neighbours, friends	23.40
Government institutions, NGO's	21.28
Bank	17.02
Traders	14.89
Local moneylenders	14.89
Saving groups, farmer groups	8.51
<i>Total responses</i>	<i>N=47</i>

Source: Survey data

The perception about the marketability of rice was measured on a five-point scale from 1 (=strongly disagree), 2 (=disagree), 3 (=partly agree), 4 (=agree) to 5 (=strongly agree). 29.71% of responding farmers agreed that the price paid for rice is too low, further 62.94% of the farmers even strongly agreed. Similarly, 21.76% of responding farmers agreed that the demand for rice is too low and 48.24% of the farmers strongly affirmed this perception. However, 30% of the responding farmers did not share this perception.

Farmers in the sample indicated various sources of their knowledge about bund technology and dibbling (see table 5-11). The most common source of knowledge is the LRDP and other LRDP farmers. Extension agents are indicated as second most important source by 38.43% of the respondents. Other fellow farmers are also found to be an important source of information. Nearly all respondents (91.67%) sought advice from agricultural extension agents (AEAs). Among the remaining farmers, 38.46% participated in the LRDP as project farmers and were thus members of farmers groups that were advised by AEAs.

Table 5-11: Ranking of sources of knowledge of bunds and dibbling

Source	First source (frequency)	Second source (frequency)	Third source (frequency)
LRPD	102	30	15
AEA	23	83	42
Other LRDP farmer	49	21	22
Fellow farmer	34	43	31
Farmer group	6	11	17
Family members	10	4	5
Friends	-	7	26
Radio	2	17	22
Botanga	1	-	-
Own knowledge	2	-	-
<i>Responding farmers</i>	<i>N=229</i>	<i>N=216</i>	<i>N=180</i>

Source: Survey data

Thus, while formal information sources such as the LRDP and agricultural extension agents working for the LRDP seem to be the main information source, also the social network of the farmer appears to be an important source of information,.

5.3.6 Input Demand, Output and Net returns

The average sample yield is 7.20 bags per acre. The average outcome levels and the *t*-statistics of mean differences in input demand, output supply and net returns between adopters and non-adopters are given in table 5-12 and table 5-13.

Table 5-12: Outcomes of adopters and non-adopters

Outcome	Adopters		Non-adopters		Diff.
	Sample mean	Standard deviation	Sample mean	Standard deviation	
Bund construction					
Average output (bag/acre) ⁴³	7.59	4.19	6.84	4.17	0.75**
Average net returns (GHC/acre) ⁴⁴	788,301.1	688,346.1	736,962.6	628,145.5	51,338.5
Average nitrogen demand (kg/acre)	12.88	9.72	10.12	9.01	2.76**
Dibbling seed					
Average output (bag/acre)	7.91	4.25	5.71	3.65	2.2***
Average net returns (GHC/acre)	849,815.3	690,099.8	591,437.8	549,685.6	258,377.5***
Average nitrogen demand (kg/acre)	12.99	9.49	8.25	8.02	4.74***

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

As shown by table 5-12, average output of adopters of bunds was 7.59 bags per acre in 2005. This is significantly higher than that of non-adopters with 6.84 bags per acre. However, controlling for the use of dibbling as planting method, no significant difference in the average output between adopters and non-adopters of bunds remains (see table 5-13). The average yield of adopters of dibbling is 7.91 bags per acre, while the average yield of non-adopters of dibbling is significantly lower with 5.71 bags per acre. The joint adoption of the two interrelated technologies also appears to impact on output. In particular, the analysis indicates that among farmers using bunds, adopting dibbling method increases yields by 2.41 bags per acre (see table 5-13). The corresponding output increase among non-users of bund technology is slightly lower with 2.10 bags per acre. The analysis of the mean differences implies that the higher rice productivity of adopters of bund construction may be mainly due to the adoption of the dibbling method.

⁴³ 1 bag of rice = 82 kg.

⁴⁴ GHC/US\$ (2005) = 9,130.8.

In the overall sample, average application rate of nitrogen was 11.46 kg per acre (= 28.32 kg/ha)⁴⁵. Adopters of bund construction seem to have a significantly higher nitrogen demand than non-adopters. However, controlling for the use of dibbling, the significant difference in the demand for nitrogen between users and non-users of bunds disappears. On the other hand, the *t*-statistic of mean difference indicates a significantly higher fertilizer demand for adopters of seed dibbling than for non-adopters. Data also reveal that among non-users of bunds, dibbling seed appears to increase average nitrogen demand by 4.51 kg per acre (significant at the 1% level), while among users of bunds, the adopters of seed dibbling turn out to have a higher demand for nitrogen by 3.64 kg per acre (significant at the 5% level).

Turning to net returns, no significant difference in net returns between adopters and non-adopters of bund technology was found. This difference even turns out to be negative, but insignificant when seed dibbling was controlled. This finding is in line with the observation that bunds seem to be more often constructed on plots that are marginal in terms of water retention and fertility (see table 5-9). On the other hand, the average net returns are statistically higher for adopters of dibbling technology than for non-adopters. Quite interesting is the fact, that dibbling increases net returns of both adopters and nonadopters of bund technology. Adopting dibbling method results in a significant increase of net returns by 322,703.6 GHC for users of bunds. Among non-users of bunds, the increase in net returns is lower with 248,817.8 GHC (significant at the 1% level). The results suggest that the adoption of dibbling method in addition to the use of bunds gives the highest increase in net returns.

⁴⁵ This is quite high compared to the national average application rate of 6 kg/ha (SSA: 21.6 kg/ha). However, the dose of fertilization recommended and supported by credits of is two bags of NPK 15-15-15 and one bag of Ammonia (FSRPOP, 2005). This corresponds to a nitrogen input rate of 25.5 kg/acre (= 62.48 kg/ha). According to the LRDP Final Report, fertilizer trial studies suggested that the optimum nitrogen rate based on economic returns would be even 90 kg/ha (MoFA, 2002).

Table 5-13: Difference in outcomes between adopters and non-adopters

Outcome	Bund construction	
	No seed-dibbling	Seed-dibbling
Average output (bags/acre)	-0.241	0.071
Average net returns (GHC/acre)	-92,379.96	-18,494.13
Average nitrogen demand (kg/acre)	1.953	1.081
	Seed-dibbling	
	No bunds	Bunds
Average output (bags/acre)	2.100***	2.412***
Average net returns (GHC/acre)	248,817.8***	322,703.6**
Average nitrogen demand (kg/acre)	4.508***	3.636**

Note: *, ** and *** indicate significance of the t -statistic of mean difference at the 10%, 5% and 1% level, respectively

Source: Survey data

However, while being illustrative, simple univariate comparisons of mean differences using the t -statistics of mean differences do not account for the effect of other characteristics of the farmer and the farm under conditions, whether factors than technology adoption cannot be controlled. Thus, the effect of technology adoption on input demand, output supply, and net returns may be confounded with the influence of other characteristics. To investigate the pure impact of technologies on these outcomes, multivariate approaches are required.

5.3.7 Perception of Technology and Constraints in Lowland Rice Production

Table 5-14 reveals that the percentage of farmers who perceived bunds as effective is significantly higher among adopters of bunds than among non-adopters. Similarly, the percentage of farmers who perceive dibbling method as highly yield-increasing is significantly higher among adopters of dibbling method than among non-adopters. However, no significant difference was found between the percentages of adopting and non-adopting farmers that mentioned labour to be the most important constraint in their rice production.

Table 5-14: Perception of adopters and non-adopters

Characteristic	Bund technology		Seed-dibbling		
	Sample mean	Diff.	Sample mean	Diff.	
	Non-adopters	Adopters	Non-adopters	Adopters	
Perception of bunds as effective (%)	45.03	58.75		13.72***	
Perception of dibbling as highly yield-increasing (%)			41.28	70.22	28.94***
Perception of labour as most constraining input in lowland rice production (%)			32.73	30.60	-2.12
<i>Number of farmers</i>	<i>N=176</i>	<i>N=166</i>	<i>N=110</i>	<i>N=232</i>	

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively
Source: Survey data

Looking at the differences in the perception of the technologies by adopters and non-adopters, the perception was rated on a five-point scale anchored as 1=strongly disagree, 2=disagree, 3=partly agree, 4=agree and 5=strongly agree. The average score for each statement is given in table 5-15 for adopters and non-adopters.

Table 5-15: Perception of bunds and dibbling among adopters and non-adopters

Statement	Average score		Diff.
	Non-adopters	Adopters	
<i>Bund construction</i>			
'Water shortage is the most important factor in my lowland rice production'	4.568	4.446	0.122**
'Bunds increase rice yield significantly'	4.464	4.434	0.030
'Bunds significantly increase rice income'	4.317	4.313	0.005
<i>Dibbling seed</i>			
'Dibbling increase rice yields significantly'	4.382	4.661	0.278***

Note: *, ** and *** indicate significance of the *t*-statistic of mean difference at the 10%, 5% and 1% level, respectively
Source: Survey data

The perception that water shortage is the most important constraint in lowland rice production is ranked quite high among all farmers and is significantly higher for adopters of

bund technology at the 5% level. However, the perception of bunds as yield-increasing does not statistically differ between adopters and non-adopters of bund construction. Similarly, the perception of bunds to be income-increasing is not significantly different for adopters and non-adopters and is even less strong for both groups than the perception that bunds are yield-increasing. With regard to dibbling method, however, adopters of seed dibbling are more convinced that dibbling is yield-increasing. Comparing the two technologies, the perception of the technologies of being yield-increasing appears to be stronger for dibbling method than for bund technology.

5.3.8 Reasons for Use and Non-use of Bund Construction and Dibbling Method

The reasons for the farmers to construct bunds or to use dibbling were obtained through direct elicitation. Based on the findings of focus group discussions, adopters were asked in the farmer-level questionnaire to rank the reasons to adopt bund technology and dibbling method. Tables 5-16 and 5-17 show a summary of reasons for adoption with the first reason as the most important. The reasons mentioned by the farmers to construct bunds clearly indicate that the most important reason is to improve water retention (93.27% of responses). Conservation of fertilizer is given as second important reason (56.88% of responses). As third important reason most farmers indicated the conservation of soil fertility (57.08% of responses).

Table 5-16: Ranking of reasons to use intermediary bunds according importance (% of responses)

Reason	First reason	Second reason	Third reason	Forth reason	Fifth reason
Water retention	93.27	4.13	1.83	0	0
Conservation of fertilizer	5.38	56.88	24.66	5.11	7.92
Conservation of soil fertility	0.45	23.39	57.08	13.14	2.97
Marking the field	0.45	6.42	10.05	48.91	33.66
Bund can be used as foot path	0.45	9.17	6.39	32.85	55.45
<i>Total responses</i>	<i>N=223</i>	<i>N=218</i>	<i>N=219</i>	<i>N=137</i>	<i>N=101</i>

Source: Survey data

Direct revelation of reasons confirms that dibbling method is considered by most farmers mainly as a seed sowing method. The importance of dibbling in enhancing fertilizer uptake

seems to be unrecognized among the responding farmers (see table 5-17). This corresponds to the finding that only 28.61% of the farmers dibble both seed and first round fertilizer application. Easy weeding was indicated to be the most important reason to use seed dibbling as seed sowing method (43.14%). It was mentioned as first or second most important reason by 68.24%, while 84.32% of responses indicated yield increases as the first or second most important reason for dibbling seed.

Table 5-17: Ranking of reasons for dibbling seed (% of responses)

Reason	First reason	Second reason	Third reason	Forth reason
Easy weeding	43.14	25.10	29.25	3.47
Yield increase	42.75	41.57	13.04	3.47
Save seed	14.12	25.49	37.55	22.28
Easy and improved fertilizer application	0	7.84	20.55	70.79
<i>Total responses</i>	<i>N=255</i>	<i>N=255</i>	<i>N=253</i>	<i>N=202</i>

Source: Survey data

Non-users of bund and dibbling technology were asked for their reasons not to use these techniques. Tables 5-18 and 5-19 show the frequency of reasons given for not using bund technology and dibbling as seed sowing method. A number of reasons were identified for not using intermediary bunds and contour bunds (see table 5-18). 25.84% and 24.62% of respondents indicated no need to construct intermediary or contour bunds, respectively. However, only 12.92% and 11.28% of the respondents indicated that water was abundant and that they therefore did not need to construct intermediary and contour bunds, respectively. Some farmers perceived no necessity for bund construction as they had levelled or harrowed their plots. However, levelling and harrowing are land preparation activities that are complementary to bund construction.

Most important constraints indicated by the farmers for not constructing bunds are related to labour and capital constraints, weather, plot characteristics, and lack of knowledge (see table 5-18). Only one farmer perceived bunds as not useful and mentioned that bunds are not effective.

Table 5-18: Percentage distribution of reasons given for not using bund technology

Reason	Intermediary bunds (% responses)	Contour bunds (% responses)
<i>Labour constraints</i>	29.78	21.54
Too time consuming	28.65	20.51
Health problems	1.12	1.03
<i>No need because...</i>	25.84	24.62
...water was abundant	12.92	11.28
...harrowing is done	4.50	4.62
...field is levelled	3.37	1.54
... land is flat	1.12	2.05
...plot have LRDP contour bunds	0.56	1.54
...no reason	3.37	3.59
<i>Financial constraints</i>	18.54	27.18
Too costly	6.18	14.87
Lack of capital	12.36	12.31
<i>Constraints due to lack of knowledge</i>	10.67	11.28
No knowledge	7.87	10.26
Was not project farmer	1.12	0.51
Had no idea	1.69	0.51
<i>Weather/plot specific constraints</i>	4.49	4.10
Flooding at time of bund construction	1.69	1.03
Too much water in the plot	0.56	0.51
Bunds are easily washed away	1.12	1.54
Rain disturbance	0.56	0.51
Too much running water		0.51
Soil type not adequate	0.56	
<i>Lack of farm inputs</i>	3.93	5.13
No support given	2.81	2.05
Not enough lowlands	1.12	1.03
Lack of implements		1.03
Lack of farm inputs / resources		1.03

Reason	Intermediary bunds (% responses)	Contour bunds (% responses)
<i>Other reasons</i>	5.62	5.63
Too difficult	3.37	3.08
Difficult to maintain	0.56	0.51
Not interested	0.56	0.51
Not yet prepared	0.56	0.51
Land tenure problems		0.51
No cultivation in LRDP area	0.56	0.51
Bunds not effective: divert water from the farm		0.51
<i>Farmer was not allowed</i>	1.12	1.03
Land owner did not allow	0.56	0.51
Fellow farmers did not want it in the valley	0.56	0.51
<i>Total responses</i>	N=178	N=195

Source: Survey data

With regard to dibbling method, labour constraints were most frequently mentioned as reasons for not using it (58%) (see table 5-19). Financial constraints were indicated as second important (16%). Only 9% of the respondents emphasised issues related to the weather such as flooding or fear of flooding. Flooding discourages dibbling as seed sowing method as it makes it impossible to sow the seed directly in the earth. Furthermore, the fear of delays in planting due to the time-intensiveness of the technique may discourage farmers from dibbling seed.

Table 5-19: Percentage distribution of reasons given for not dibble seed

Reason	% responses
Labour constraints	57.47
Too time consuming	57.47
Financial constraints	16.09
Lack of capital	12.64
Too costly	3.45
Weather conditions/plot characteristics	10.35
Flooding	5.75
Too much water in the plot	2.30
Fear of flooding	1.15
Soil type inadequate	1.15
Other reasons	16.10
More easy to broadcast / too difficult	9.20
Was no project farmer	2.30
No need	2.30
Land tenure problems	1.15
Delayed land preparation / farming	1.15
Total responses	N=87

Source: Survey data

Comparing the reasons for not using bunds and dibbling, the general perception of the technique to be difficult to use in the lowland rice cultivation is less important in case of bund construction. While 9.20% of responding farmers mentioned that dibbling is too difficult, only 3.93% and 3.59% indicated that the construction and maintenance of intermediary and contour bunds, respectively, is too difficult. However, the reasons behind this perception remain unclear. Another 11% of responding non-users of intermediary or contour bunds indicated that they had no idea or lack of knowledge about bunds. In contrast, no farmer indicated lack of knowledge as a reason for not using dibbling as seed sowing method.

Financial constraints seem to be slightly more important for the adoption decision of intermediary and contour bunds than for dibbling method. 18.54% and 27.18% of the respondents indicated lack of capital and costs of bund construction, respectively, as reasons for not using. Lack of capital was mentioned only by 16.09% of the respondents as a reason for not using dibbling. Labour constraints seem to be more important for the adoption decision of dibbling. While 57.47% of the respondents mentioned dibbling as too time-consuming, only 28.65% indicated that the construction of intermediary bunds is to time-

consuming. Weather specific constraints were mentioned by 9.20% of responding farmers referring to dibbling method and by only 4.49% and 4.10% of the non-using respondents for intermediary and contour bunds, respectively. While only 2.30% of respondents indicated no need of dibbling method, 12.92% of respondents indicated to have no need of intermediary bunds due to water abundance.

5.3.9 Bund Construction Equipment and Maintenance Measures

Most commonly, bund construction is undertaken manually with hoe (see table 5-20).

Table 5-20: Main construction equipment (% of responses)

Equipment	Intermediary bunds	Contour bunds
Hoe	86.13	80.77
Tractor	12.72	19.23
Bullock	1.16	0
<i>Total responses</i>	<i>N=173</i>	<i>N=130</i>

Source: Survey data

As indicated in table 5-21, most of the respondents have taken some measures to maintain their intermediary or contour bunds. Among the 167 respondents, the most common activities are reshaping and raising bunds, which was undertaken by 92.22% of the farmers, while partial reconstruction was undertaken by 78.88%. Cutting or spraying weeds was mentioned by 74.44% of the farmers. Out of the 134 farmers who have maintained contour bund, the most common activity is spraying or cutting weeds (61.54%) as well as reshaping or raising (58.46%) the bund levels.

Table 5-21: Maintenance measures (% of responses)

Maintenance	Intermediary bunds	Contour bunds
Reshaping/raising	92.22	58.46
Partial reconstruction	78.88	3.08
Spraying/cutting weeds	74.44	61.54
Uproot weeding	40.00	24.62
Complete reconstruction	28.88	5.38
Using sand bags	10.00	10.77
Planting cover crops	1.11	1.54
<i>Responding farmers</i>	<i>N=167</i>	<i>N=134</i>

Source: Survey data

5.3.10 Concluding Remarks

Mean comparisons between adopters and non-adopters of bund construction and dibbling method indicate that outcomes such as net returns, output supply and nitrogen demand are quite different between the two groups. Furthermore, the comparisons suggest that both groups are different in terms of farm and farmer characteristics as well as plot characteristics such as the perception of technologies, the number of plots, the size of rice cultivation area, tractor ownership, off-farm income, labour endowment, literacy, household headship, project participation, and use of interrelated technologies (such as improved varieties, weeding frequency, and levelling). This may support the notion that adopter groups may be systematically different due to self-selection into adoption. Selection bias may arise if unobservable factors influence both adoption decision as well as outcomes. Hence, to investigate the determinants of the adoption decision and to detect the unconfounded effect of technology adoption on farm outcomes such as net returns, output supply, and input demand, multivariate analysis is required that accounts for self-selection of farmers into adoption status.

Chapter 6

Econometric Model

As noted earlier, multivariate analysis of the adoption decision and impact assessment is required to investigate the influence of farmer characteristics on adoption decision and the unconfounded impact of technology adoption on potential outcomes such as net returns, output supply, and input demand. This chapter outlines the econometric models that are used in the analysis to explore not only the correlations but also the causation of technology adoption on outcomes. To analyse the technology impact, methods are required that control for selection bias. This thesis uses the endogenous switching regression as parametric approach and the non-parametric matching method. Endogenous switching regression involves an endogenous technology choice model in the first stage. Matching method requires identifying the relevant covariates that may influence outcomes as well as adoption decision. Thus, to understand adoption behaviour in-depth, the adoption decision of bund construction and dibbling method is analyzed in a first step.

The structure of the chapter is as follows: The first section of the chapter presents the limited dependent variable model used to estimate the adoption probability of the farmer. The second section introduces the econometric models to assess the impact of technology adoption. The problem of selection bias, which is the main concern of impact evaluation, is discussed in section 6.2.1. After outlining the main differences between two methods used for impact evaluation, the parametric framework of the endogenous switching-regression model is presented in section 6.2.2, while the propensity score matching method is introduced in section 6.2.3.

6.1 Adoption Decision

The expected utility of wealth from adoption can be represented by $U_A^*(\pi)$ and the expected utility of wealth from non-adoption can be represented by $U_N^*(\pi)$, where profits (π) represent wealth. Adoption occurs if the expected utility from adoption is higher than the

expected utility from non-adoption ($U_A^*(\pi) > U_N^*(\pi)$). The farmer's expected utility of adoption can be related to a set of explanatory variables (Z) as follows:

$$U_j^*(\pi) = \gamma_j' Z_j + \varepsilon_j \quad (j = \text{bund technology, dibbling method}) \quad (6-1)$$

with γ being a vector of parameters that have to be estimated. The error term ε_j with mean zero and variance σ_ε^2 captures measurement errors and factors unobserved to the researcher but known to the farmer (e.g. unobserved variation in preferences). Variables in Z_j include determinants of the adoption decision such as plot characteristics, resource characteristics of the farm, as well as socio-economic characteristics of the farmer and the farm family (e.g. education, age or status). Policy variables and characteristics of the village may also be included in the vector Z_j .

However, the utility derived from adoption ($U_j^*(\pi)$) is not observable. What can be observed is the choice of adoption or non-adoption. The adoption status can be represented by the variable $D_j(\pi)$ that equals one if the technology is adopted when the utility from adoption is higher than from non-adoption ($U_j^* = U_A^*(\pi) - U_N^*(\pi) > 0$) and $D_j(\pi) = 0$ otherwise, when utility derived from adoption is lower than that from non-adoption ($U_j^* = U_A^*(\pi) - U_N^*(\pi) \leq 0$).

The probability of adoption may then be expressed as:

$$\Pr(D_j = 1) = \Pr(U_A^*(\pi) > U_N^*(\pi)) = \Pr(\varepsilon_j > -\gamma_j' Z_j) = 1 - F(-\gamma_j' Z_j)$$

where F is the cumulative distribution function for ε_j . The assumptions made on the functional form of F result in different models.

The technology adoption decision can be modelled by a standard limited dependent variable method (Maddala, 1991). Generally, the separate estimation of the adoption equations for bund construction and dibbling method is possible. The assumption behind this estimation strategy with two separate equations is that there is no correlation between the error terms of the adoption equations of bund technology and dibbling method ($Cov(\varepsilon_1, \varepsilon_2) = 0$).

However, if simultaneity in decision is detected and/or unobserved heterogeneity affects the two adoption decisions (resulting in $Cov(\varepsilon_1, \varepsilon_2) = \rho \neq 0$), estimating the adoption decisions separately in single probit equations may cause bias, inconsistency and inefficiency in the parameter estimates (Maddala, 1991; Greene, 2003). In this case, the total effect of adopting several conservation practices simultaneously does not necessarily equal the sum of the effects of adopting each practice separately (Wu and Babcock, 1998). The system of adoption equations should then be estimated using a bivariate probit procedure. The specification of a joint binary-choice model would allow to test whether the correlation

coefficient (ρ) between the error terms of the two equations is zero. In this case, the disturbances of the two selection equations have a bivariate normal distribution with mean vector zero and covariance matrix $\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

To estimate the joint probability of adoption of two interrelated technologies, a seemingly unrelated bivariate probit model is estimated using the STATATM statistical package 9.2 (StataCorp, 2005). The bivariate probit estimation procedure includes the joint estimation of two probit equations with correlated disturbances that relate technology choices to farmer characteristics and random error terms ε_j . The general specification for the maximum-likelihood estimation of the two-equation model for bund technology and dibbling method is as follows (Greene, 2003):

$$\begin{aligned} U_1^* &= \gamma_1 Z_1 + \varepsilon_1 \\ U_2^* &= \gamma_2 Z_2 + \varepsilon_2 \end{aligned} \tag{6-2}$$

However, the utility derived from adoption U_j^* , which is related to a set of explanatory variables Z_j , is not observable. What can be observed is the choice of adoption or non-

adoption that can be represented by $D_j = \begin{cases} 1 & \text{if } U_A^*(\pi) > U_N^*(\pi) \\ 0 & \text{if otherwise} \end{cases}$ with $j = 1, 2$.

The error terms ε_1 and ε_2 are assumed to be identically distributed according to a standard normal distribution with a correlation ρ .

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \approx N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

The bivariate normal cumulative distribution function (cdf) can be noted as $\Phi_2(z_1, z_2, \rho)$ and can be expressed as follows (Greene, 2003):

$$\Pr ob(Z_1 < z_1, Z_2 < z_2) = \int_{-\infty}^{z_2} \int_{-\infty}^{z_1} \phi_2(\delta_1, \delta_2, \rho) d\delta_1 d\delta_2, \text{ where } \delta_{ij} = z'_{ij} \beta_j$$

$$\text{The density is } \phi_2(z_1, z_2, \rho) = \frac{e^{-(1/2)(z_1^2 + z_2^2 - 2\rho z_1 z_2)/(1-\rho^2)}}{2\pi(1-\rho^2)^{1/2}}.$$

The probabilities that enter the likelihood function are:

$$\Pr ob(D_1 = D_{i1}, D_2 = D_{i2} | z_1, z_2) = \Phi_2(w_{i1}, w_{i2}, \rho_{i*}), \quad \text{where } w_{ij} = q_{ij} z_{ij}, \quad q_{i1} = 2D_{i1} - 1, \\ q_{i2} = 2D_{i2} - 1; \text{ and } \rho_{i*} = q_{i1} q_{i2} \rho.$$

Then, the log-likelihood function is $\log L = \sum_{i=1}^n \ln \Phi_2(w_{i1}, w_{i2}, \rho_{i^*})$.

The marginal effects resulting from the bivariate probit are then computed as follows (Greene, 2003):

$$\frac{\partial E[D_1 | D_2 = 1, z]}{\partial z} = \frac{\partial [\text{prob}(D_1 = 1 | D_2 = 1, z)]}{\partial z} = \frac{\partial \left[\frac{\Phi_2(z' \gamma_1, z' \gamma_2, \rho)}{\Phi(z' \gamma_2)} \right]}{\partial z}$$

where z is defined as a vector $z = z_1 \cup z_2$ and $z' \gamma_1 = z_1' \beta_1$. Thus, γ_1 contains all non-zero elements of β_1 and possibly some zeros in the positions of variables in z that appear only in the other equation; γ_2 is defined likewise.

6.2 Impact Assessment of Technology Adoption on Farm Outcomes

In the absence of experimental data sets, where the counterfactual information would normally solve the problem of causal inference, statistical approaches have to be applied to identify the direct causal effect of adoption on farm outcomes (such as net returns, output supply and input demand). Aiming to isolate the direct technology effect from other effects, such as household or farm effects, impact assessment needs to account for selection bias in cross-sectional data sets.

The univariate t -statistics of mean differences, presented in table 5-14 in chapter 5, suggest that adopters and non-adopters of dibbling and bund technology differ in their household and farm characteristics. This finding supports the notion that self-selection of farmers into adoption status occurs and that the adoption decision may be related with the expected net benefits of adoption. Thus, unbiased adoption impact estimates have to control for potential selection bias, which is the fundamental evaluation problem of observational (or non-experimental) data. Estimates that ignore the problem of self-selection will be biased and will result in misleading policy implications.

This section first elucidates the basic problem of selection bias and causal inference in cross-sectional and non-experimental data sets. After that, the endogenous switching-regression model and the propensity score matching estimation approach are introduced in more detail.

6.2.1 The Problem of Selection Bias and Non-experimental Solutions

For expositional purposes, the following relationship should represent the relationship between the outcome variable Y_k (such as input demand, yield and net returns, extent of adoption) while X_k represents a vector of determining variables such as household endowments and other characteristics (socio-economic and resource characteristics, as well as farm input and output prices and plot-level characteristics):

$$Y_k = X_k' \beta_k + \eta_k \quad (6-3)$$

where η_k is the error term with $\eta_k \sim N(0, \sigma)$ (Rahm and Huffman, 1984).

As indicated earlier, the utility derived from adoption (U_j^*) is a latent variable, which is not observable. Only the choice of adoption or non-adoption can be observed, which can be represented by the variable dichotomous D_j as follows:

Treatment equation: $U_j^* = \gamma_j' Z_j + \varepsilon_j$ with $j =$ bund technology, dibbling method

$$\begin{aligned} \text{where } D_j &= 1 \text{ if } U_j^* > 0 \\ D_j &= 0 \text{ if } U_j^* \leq 0 \end{aligned} \quad (6-4)$$

where Z_j are the independent variables used to explain the adoption decision of bund technology and dibbling method, γ is a vector of parameters to be estimated, and the error term is $\varepsilon_j \sim N(0, \sigma)$.

Selectivity bias arises if factors of the adoption decision are also relevant to the process determining the outcome. If self-selection arises, either, it may be that the relationship between the two processes can be accounted for by observable characteristics. Then, selection bias can be avoided by including these relevant variables in outcome equation. But commonly, unobservable factors may influence both the selection and the outcome equation, resulting in correlation of the error terms of outcome equation (η) and the technology choice equation (ε) with $corr(\varepsilon, \eta)$. When $corr(\varepsilon, \eta) \neq 0$, controlling for differences in observable characteristics will not alleviate the selectivity bias⁴⁶. Then, standard regression techniques applied to the regression equation yield biased results.

⁴⁶ However, including observable characteristics may minimise the bias associated with unobservable characteristics to a certain extent. In case that the observable is highly correlated with the unobservable, it may capture some of the effect of the unobservable (Bryson et al., 2002).

In the research of cross-sectional impact evaluation analysis, a number of alternative approaches accounts for the problem of selection bias. Among non-experimental estimation strategies, parametric and non-parametric solutions can be found. The main parametric regression estimation approach that deals with selection bias is the selection correction model, developed by Heckman (1979)⁴⁷. This method is more robust than the instrumental variable (IV) estimator (Blundell and Dias, 2000)⁴⁸. The non-parametric matching method is based on pairing treatment and comparison units that are similar in terms of their observable characteristics (Dehejia and Wahba, 2002). When outcomes are independent of treatment assignment, conditional on observable pre-treatment covariates, matching methods can yield unbiased estimates of the treatment effect as the differences in outcomes between the matched treated and untreated individuals that are similar in terms of their observable characteristics can be attributed to the treatment. None of these estimators however considers general equilibrium effects (Bryson et al., 2002)⁴⁹.

Three main features distinguish the matching method from the selection correction model⁵⁰. First, matching method explicitly acknowledges the common support problem. The matching approach can only estimate treatment effects within the region of common support. In parametric approaches, the model results can be used to extrapolate to unsupported regions. In case of poor overlap in support between treated and non-treated groups, the robustness of traditional methods relying on functional forms to extrapolate outside the common support is questionable (Bryson et al., 2002). Second, non-parametric methods remove some of the restrictive assumptions of the parametric solution techniques. In contrast, Heckman's selection correction model comes at the costs of imposing strong distributional assumptions such that the unobserved determinants of the outcome and technology adoption are jointly normally distributed, with zero means and constant

⁴⁷ This approach was fully integrated into the evaluation literature in Heckman and Robb (1985). For an overview of selection models, see, e.g., Winship and Mare (1992), Vella (1998), Wooldridge (2002).

⁴⁸ The instrumental variables estimator (IV) imposes a linear functional form and requires that the set of valid instruments must be relevant and exogenous and the assumption that the instrumental variable is independent of outcomes, given observable controls. These requirements lead to the common problems of weak instruments and non-compliance (i.e. imperfect control of the treatment assignment) (Mendola, 2007). Another drawback of the IV estimation approach is that coefficients of control variables are restricted to be the same for adopters and non-adopters (Heckman and Navarro-Lozano, 2004).

⁴⁹ The 'Stable Unit Treatment Value Assumption' (SUTVA) is required for matching and all other partial equilibrium estimation strategies such as the Heckman selection model. According to this assumption, the impact of treatment on a person does not depend on whom else, or on how many others, are participating in the programme or are adopting but depends only on the individual (Bryson et al., 2002).

⁵⁰ See Heckman et al. (1997) on the use and critics of matching procedure in econometric selection models.

variances. Furthermore, the exclusion restriction required for the Heckman procedure is an untestable assumption and often difficult to make, as it is quite difficult to find variables that affect the probability of adoption but not the outcomes other than through their effect on adoption (Bryson et al., 2002). Furthermore, matching estimation removes the assumption of 'constant technology effect' that is required for parametric solutions. This assumption means that the technology effect is always the same, irrespective of the values taken by the variables Z (Mendola, 2007). Moreover, matching does not require assumptions of the functional form for the outcome equation that are usually not justified either by economic theory or by the data (Dehejia and Wahba, 1998). Furthermore, the matching approach particularly allows not only for the possibility of direct outcome effects of technology adoption but also allows for interactions of technology with other variables (substitution effects between factors) (Mendola, 2007). The third difference between these approaches is that the Heckman selection correction models tries to control for unobservables, while the matching approach takes only account of selection on observables assuming that selection can be explained purely in terms of observable characteristics (as is also assumed in the standard OLS estimation) (Bryson et al., 2002). Thus, matching is only feasible, where there is a firm understanding and information, either from theory or from empirical evidence, about the determinants of treatment selection and outcomes. Furthermore, matching procedure requires a rich data set in terms of variables determining selection and outcome, as well as sample size, to make this assumption plausible (Bryson et al., 2002).

This analysis employs the matching method, as well as the Heckman selection correction estimator in the framework of the endogenous switching-regression approach to analyse the adoption impact, as well as the determinants of adoption outcomes. This choice is due to the advantages outlined above. In contrast to the matching estimation procedure, the endogenous switching-regression model allows further insights in the process determining farm outcomes, as the influence of technology adoption and other explanatory variables on the outcomes can be estimated. Different to the IV approach, the endogenous switching-regression approach allows identifying differing determinants for the groups of adopters and non-adopters as the coefficients of the explanatory variables are allowed to differ between these groups.

6.2.2 The Endogenous Switching-regression Model

To estimate the effect of determinants on adoption outcomes such as net returns, farm output, and fertilizer demand, the parametric framework of endogenous switching-regression is used. Given that the choice of technology is endogenous, OLS estimates of the parameters will suffer from sample selection bias. Lee (1982) developed the endogenous switching-regression model as a generalization of Heckman's selection correction approach. This approach treats selectivity as missing-variable problem. In the switching-regression approach, the farmers are partitioned according to their classification as adopters and non-adopters, and separate equations are specified for these groups. Modelling two equations (rather than one equation with a dummy of adoption status) allows coefficients to differ between adopter regimes. Then, adoption is allowed not only to have an intercept effect on the outcome, but also to exert slope effects that may be different between the two groups.

Separate equations are estimated for the demand of fertilizer, net returns, and output supply as follows:

$$\text{Regime 0 (Non-adopters): } Y_{k,N} = X' \beta_{k,N} + \eta_{k,N} \quad \text{if } -Z'_j \gamma \geq \varepsilon_j \Leftrightarrow D_j = 0 \quad (6-5)$$

$$\text{Regime 1 (Adopters): } Y_{k,A} = X' \beta_{k,A} + \eta_{k,A} \quad \text{if } -Z'_j \gamma < \varepsilon_j \Leftrightarrow D_j = 1$$

In this system, X' are the exogenous determinants of the decision variable (such as net returns, input demand and output supply), while Z' are the determinants explaining the technology adoption. The vectors β and γ are the associated parameters that have to be estimated.

The three error terms $\varepsilon, \eta_A, \eta_N$ are assumed to be correlated and to have a jointly normal distribution, with mean vector zero and the following variance-covariance matrix:

$$\text{Cov}(\eta_A, \eta_N, \varepsilon) = \Sigma = \begin{bmatrix} \sigma_A^2 & \sigma_{AN} & \sigma_{AT} \\ & \sigma_N^2 & \sigma_{NT} \\ & & \sigma_T^2 \end{bmatrix} \quad (6-6)$$

where $\text{var}(\eta_A) = \sigma_A^2$, $\text{var}(\eta_N) = \sigma_N^2$, $\text{var}(\varepsilon) = \sigma_T^2$, $\text{cov}(\eta_A, \eta_N) = \sigma_{AN}$, $\text{cov}(\eta_A, \varepsilon) = \sigma_{AT}$, $\text{cov}(\eta_N, \varepsilon) = \sigma_{NT}$. For this reason, the error terms in equation (6-5), conditional on the sample selection criterion, have nonzero expected values and OLS estimates of coefficients β_A and β_N suffer from sample selection bias (Lee, 1982; Maddala, 1991).

The rationale behind the Heckman selection estimator is to control directly for the part of the error term in the outcome equation that is correlated with the selection dummy variable. According to Johnson and Kotz (1970), the expected values of the truncated error terms ($\eta_A|D=1$) and ($\eta_N|D=0$) are then given as:

$$E(\eta_N|D=0) = E(\eta_N|\varepsilon \leq -Z'\gamma) = \sigma_{NT} \frac{-\phi(Z'\gamma/\sigma)}{1-\Phi(Z'\gamma/\sigma)} \equiv \sigma_{NT} \lambda_N \quad (6-7)$$

$$E(\eta_A|D=1) = E(\eta_A|\varepsilon > -Z'\gamma) = \sigma_{AT} \frac{\phi(Z'\gamma/\sigma)}{\Phi(Z'\gamma/\sigma)} \equiv \sigma_{AT} \lambda_A \quad (6-8)$$

where ϕ and Φ are the probability density and cumulative distribution function of the standard normal distribution, respectively. The ratio of ϕ and Φ evaluated at $Z'\gamma$ is referred to as the inverse Mills ratio λ_A, λ_N (selectivity terms).

The estimation procedure proceeds in two stages, where the adoption decision is modelled by a standard limited dependent variable approach⁵¹. The first stage involves a probit regression to determine the probability of adoption, estimating the parameter γ . These estimates are then used to calculate the selectivity terms (λ_A, λ_N) according to equation (6-7) and (6-8). The selectivity terms can then be considered as missing variables in equation (6-5).

Incorporating the selectivity terms in the specification given in equation (6-5) results in:

$$\begin{aligned} \text{Regime 0 (Non-adopters): } & Y_{k,N} = X' \beta_{k,N} + \sigma_{NT} \lambda_N + \mu_{k,N} & \text{if } -Z'_j \gamma \geq \varepsilon_j \Leftrightarrow D = 0 \\ \text{Regime 1 (Adopters): } & Y_{k,A} = X' \beta_{k,A} + \sigma_{AT} \lambda_A + \mu_{k,A} & \text{if } -Z'_j \gamma < \varepsilon_j \Leftrightarrow D = 1 \end{aligned} \quad (6-9)$$

These equations are then estimated by OLS. The coefficients of the variables λ_A, λ_N provide estimates of the covariance terms σ_{AT} and σ_{NT} , respectively. If the covariance terms are nonzero, OLS estimates of equation (6-5) (without including the selectivity terms) are biased because of selectivity bias. The new residuals μ_A and μ_N have conditional means of zero but are heteroskedastic (Maddala, 1991). The method of Lee and Trost (1978) to obtain efficient parameter estimates is advantageous, since their weighting procedure always yields positive values for $\hat{\sigma}_A^2$ and $\hat{\sigma}_N^2$. Furthermore, the standard errors have to be

⁵¹ The notion of applying the two-stage method to estimate the switching simultaneous-equations models is discussed by Lee et al. (1980). For a discussion of efficiency problems of the two-stage estimation procedure see Tunali (1986). See Winship and Mare (1992) for a discussion of robustness and sensitivity of the Heckman estimator.

corrected as the selectivity terms in equation (6-9) were estimated in the first stage equation. This is done by using the standard error correction presented in Lee et al. (1980). Due to the recursive structure of the model, identification of the model requires that there be at least one variable in the adoption equation that does not appear in the outcome equation (Blundell and Dias, 2000)⁵².

6.2.3 The Matching Estimation Approach

6.2.3.1 The Counterfactual Framework

In practice, it is not possible to study the treatment effect on individual level due to missing data. Therefore, the evaluation problem has to be reformulated on population level as average treatment effect. The primary interest in non-experimental settings in impact evaluation studies is the average treatment effect (ATE), defined as $\tau_{ATE} = E(Y_1 | D=1) - E(Y_0 | D=0)$, where Y_1 denotes the value of the outcome under adoption, while Y_0 denotes the value of the same variable under non-adoption. This is the effect of treatment for a randomly assigned individual in the population (Heckman et al., 1997). The standard framework in impact evaluation analysis to formalize the problem of causal inference is the counterfactual or potential outcome framework, which can be rooted to Neyman (1923) and Fisher (1935) and has been explicated by Roy (1951) and Rubin (1974). The counterfactual framework assumes an observed mean outcome under the condition of treatment $E[Y_1 | D=1]$ for the treated individuals and an unobserved mean outcome under non-treatment $E[Y_0 | D=1]$. Conversely, individuals of the control group have an observed mean outcome $E[Y_0 | D=0]$, and an assumed unobserved mean outcome of $E[Y_1 | D=0]$.

As there is general heterogeneity in the impact across individuals, an important question of impact analysis is to decide on which individuals the impact evaluation should focus. The parameter used in this study is the 'Average Treatment Effect for the Treated' (ATT). This is the most common evaluation parameter in the empirical literature⁵³. It focuses on the effect on those for whom the programme is actually intended and is thus the most policy relevant parameter.

⁵² Although it is formally identified even if $X = Z$, multicollinearity may be a problem (Willis and Rosen, 1979).

⁵³ Other evaluation parameters are the 'Average Treatment Effect on the Untreated', and the 'Local Average Treatment Effect' that gives the mean impact of the treatment on those whose treatment status changes due to a change in policy (Imbens and Angrist, 1994).

The ATT is defined as follows:

$$\tau_{ATT} = E(\tau | D = 1) = E(Y_1 - Y_0 | D = 1) = E(Y_1 | D = 1) - E(Y_0 | D = 1) \quad (6-10)$$

The counterfactual mean for those being treated, $E[Y_0 | D = 1]$, can not be observed. Thus, the main challenge of impact analysis is to choose a proper substitution for $E[Y_0 | D = 1]$ to estimate the ATT. In non-random data sets, where the distribution of covariates may not be identical in the two groups, it is not a good approximation to use the mean outcome of untreated individuals $E[Y_0 | D = 0]$ instead of $E[Y_0 | D = 1]$ as self-selection bias may occur. Using $E[Y_0 | D = 0]$ as substitute for $E[Y_0 | D = 1]$ results in bias of the estimated average treatment effect for the treated as follows:

$$E[Y_1 | D = 1] - E[Y_0 | D = 0] = ATT + \{E[Y_0 | D = 1] - E[Y_0 | D = 0]\} \quad (6-11)$$

The term $\{E[Y_0 | D = 1] - E[Y_0 | D = 0]\}$ is due to selection bias. The true parameter ATT is only identified if selection bias is zero ($\{E[Y_0 | D = 1] - E[Y_0 | D = 0]\} = 0$). This kind of bias is the main concern in non-experimental studies. Where assignment to treatment is random (such as in experimental data) and where there is no selection bias, this is ensured and the average treatment effect (ATT) can be identified (Caliendo and Kopeinig, 2008).

Matching methods have been developed to account for selection bias due to observable differences between treatment and control groups (Dehejia and Wahba, 2002). To reach this, matching methods construct a statistical comparison group by matching every individual observation on adopters with individual observation from the group of non-adopters with similar characteristics. The matching approach tries to balance the distribution of relevant observable variables Z , as in non-random data sets the covariates do not have an identical distribution in the two groups. Thus, matching is an attempt to correct the violation of the assumption of conditional independence (CIA) to estimate causal effects from observational data.

Matching on Z is based on the assumption that the selection bias is zero, as conditioning on (observable) characteristics Z eliminates the bias (Heckman et al., 1997). The fundamental assumption of the matching approach is the assumption of conditional independence (CIA) as follows⁵⁴:

⁵⁴ The CIA is also referred to as 'selection on observables' (Heckman and Robb, 1985), 'ignorable treatment assignment' (Rosenbaum and Rubin, 1983b), 'exogeneity' (Imbens, 2004). CIA and overlap condition together are also called 'strong ignorability'.

$$Y_1, Y_0 \perp\!\!\!\perp D \mid Z \quad (6-12)$$

where $\perp\!\!\!\perp$ denotes statistical independence. Conditional on a set of observable covariates Z that are not affected by the treatment, potential outcomes (Y_1, Y_0) are independent of treatment assignment. If the estimation does not contain all variables influencing simultaneously both participation and outcome, CIA is violated since the treatment effect will be accounted for in part by information that is not available to the evaluator (Bryson et al., 2002). If the CIA holds, the matching process is analogous to creating an experimental data set in that, once controlled for observed characteristics Z , the technology adoption is random and uncorrelated with the outcome (Mendola, 2007). Consequently, the distribution of the counterfactual outcomes for the treated is the same as the observed outcomes for the non-treated (Bryson et al., 2002). Thus, under the CIA a valid estimation of $E(Y_0 \mid D = 1)$ is warranted by approximating it through $E(Y_0 \mid D = 0)$. While this assumption is also an issue of critique of the matching method, the CIA is more plausible than in case of OLS estimation, as the technology effect among groups of farmers having similar behaviour (in terms of their observables Z) is evaluated⁵⁵. Matching methods assume that technology choice is random (uncorrelated with Z) within groups of households that have the same behaviour towards adoption (Mendola, 2007).

Matching on the propensity score (PSM) can be seen as improved version of simple matching on covariates. This new approach was brought up by Rosenbaum and Rubin (1983) as an extension of Cochran (1968). It reduces the multidimensionality of Z , such that households with similar probabilities of adopting the new technology given the relevant controls Z are compared to derive the technology effect. PSM matches observations on a single index, the 'propensity score' ($p(Z)$), to identify similar households or farmers. Thus, similar households (with the same probability for selecting the new technology, controlled for Z) are compared, instead of comparing the outcome of the group of adopter with the outcome of a group of non-adopters (Mendola, 2007). Rosenbaum and Rubin (1983) show for the single treatment case that it is not necessary to condition on Z (which is limited in case of a high dimensional vector Z). Instead, it is sufficient to use so-called balancing scores to achieve consistent estimates of the treatment effect. A balancing score is a function such that the conditional distribution of Z given $b(Z)$ is the same in both groups, i.e. conditional to $b(Z)$, Z and D are independent. The propensity score is one possible balancing score, and serves only as device to balance the observed distribution of

⁵⁵ The assumption of the (standard) OLS about independence of the error term from the independent variable is nothing else than the assumption of unconfoundedness (Imbens, 2004).

covariates across the treated and the untreated groups (Rosenbaum and Rubin, 1983). The propensity score can also be used as a partial balancing score with $b(Z) = [P(Z), \tilde{z}]$ where \tilde{z} is a sub-vector of Z (Lechner, 2002).

The propensity score is defined as the conditional probability to adopt the new technology given the control of Z (Rosenbaum and Rubin, 1983):

$$p(Z) \equiv P(D = 1 | Z) = E(D | Z) \quad (6-13)$$

where $D = \{0,1\}$ is the indicator of exposure to treatment and Z is the multidimensional vector of pre-treatment characteristics. Any standard probability model can be used to estimate the propensity score (Becker and Ichino, 2002). However, there is no consensus on which variables should be included in the estimation of the propensity score. Heckman et al. (1997) show that it makes a substantial difference to the performance of the estimator which variables are included in Z to estimate the propensity score.

Given the propensity score, the balancing property of propensity score is as follows (Lee, 2008)⁵⁶:

$$D \perp\!\!\!\perp Z | p(Z) \quad (6-14)$$

Observations with the same propensity score must have the same distribution of observables Z independently of treatment or participation status (=conditional distribution of Z given $p(Z)$ is the same for treated and control units). If the potential outcomes are independent of treatment conditional on covariates Z , they are also independent of treatment conditional on $p(Z)$. This means that for a given propensity score, exposure to treatment should be on average observationally identical. Hence, if the unconfoundedness assumption holds, all biases due to observable components can be removed by conditioning on the propensity score (Imbens, 2004).

Another assumption is required for conducting the propensity score matching method, which can be specified as follows:

$$0 < P(D = 1 | Z) < 1 \quad (6-15)$$

By imposing this assumption, the propensity score is bounded away from 0 and 1, excluding the tails of the distribution of $p(Z)$. Thus, equation (6-15) embodies some kind of

⁵⁶ The balancing property of propensity score has to be distinguished from the CIA as one does not imply the other (Lee, 2008).

randomness that guarantees that all individuals with the same characteristics Z actually can be observed in both states of treatment. This condition ensures that all treated observations have a counterpart in the non-treated group (Heckman et al., 1997). However, Heckman et al. (1997) point out that matching is only justified when performed over the region of common support of Z ⁵⁷. This is because only in the overlapping subset within the sample of the treated and non-treated individuals comparable observations can be matched⁵⁸. A violation of the common support condition is a major source of bias due to comparing incomparable individuals (Heckman et al., 1997). Individuals that fall outside of the region of common support have to be disregarded and the treatment effect cannot be estimated (Bryson et al., 2002). Problems may arise if the number of lost observations due to the implementation of the common support condition is too large. Then, the estimated effect on the remaining individuals might not be seen as representative (Caliendo and Kopeinig, 2008). If treatment effects differ non-randomly with those unsupported characteristics, the treatment effect relevant to the supported sub-population will not provide a consistent estimate for the unsupported sub-population. The estimated treatment effect can then be regarded as the treatment impact for the treated observations whose propensity scores lie within the region of overlapping support (Smith and Todd, 2005).

Under the CIA and the common support condition, ATE and ATT can be defined for all values of Z (Rosenbaum and Rubin, 1983)⁵⁹. The ATT, given a population of units denoted by i , can then be estimated as follows if the propensity score $p(Z_i)$ is known (Becker and Ichino, 2002):

$$\tau_{ATT} = E\{Y_{1i} - Y_{0i} \mid D_i = 1\} = E\{E\{Y_{1i} - Y_{0i} \mid D_i = 1, p(Z_i)\}\} = E\{E\{Y_{1i} \mid D_i = 1, p(Z_i)\} - E\{Y_{0i} \mid D_i = 0, p(Z_i)\} \mid D_i = 1\} \quad (6-16)$$

where the outer expectation is over the distribution of $(p(Z_i) \mid D_i = 1)$ and Y_{1i} and Y_{0i} are the potential outcomes in the two counterfactual situations of adoption and non-adoption.

⁵⁷ The support of Z is the set of all possible values the vector of explanatory variables Z may take. The common support of Z is then the space of Z that is simultaneously observed among treated and non-treated observations for the specific data set (Blundell and Dias, 2000).

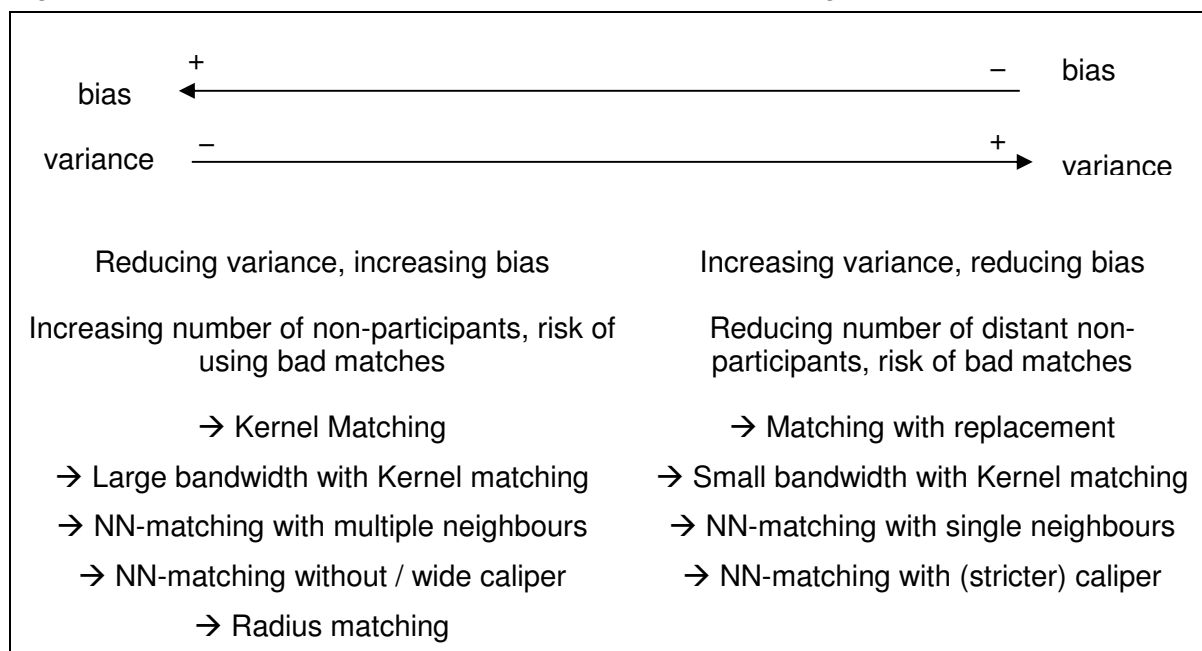
⁵⁸ There are various ways of defining common support: Minima and Maxima comparison method deletes all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group (Dehejia and Wahba, 2002). Trimming method was first suggested by Heckman et al. (1997) and Heckman et al. (1998). Here, the region of common support is defined as those values of $p(Z)$ that have a positive density within the $D=0$ and $D=1$ observations (Smith and Todd, 2005).

⁵⁹ For the estimation of ATT, the assumptions of unconfoundedness and overlap can be weakened (Heckman et al., 1997; Heckman et al., 1998). However due to functional-form assumptions it is not possible to identify average effects on transformations of the original outcome (such as logarithms) without the stronger assumptions (Imbens, 2004).

6.2.3.2 Matching Algorithms

After estimating the propensity scores (to capture the similarities), in the next step these similarities are used to match each adopter with the closest non-adopter in terms of the propensity score. Several techniques have been suggested in the literature to identify similar observations in the non-treatment group as ‘closest’ neighbour⁶⁰. Asymptotically, all PSM estimators should yield the same results, because with growing sample size they all become closer to comparing only exact matches. However, especially in small samples the choice of the matching algorithm turned out to be important (Heckman et al., 1997). Five matching approaches have been commonly used to match treatment and control groups. While nearest neighbour matching, kernel based matching, stratified matching and radius matching are matching methods that are only based on the propensity score, Mahalanobis metric matching is a multivariate covariate matching method that allows for including the propensity score as well as other covariates. The choice of the matching method usually involves a trade-off between average matching quality (bias) and variance (see figure 6-1).

Figure 6-1: Trade-off in terms of bias and variance in matching methods



Source: Caliendo and Kopeinig (2008)

The performance of the different matching estimators varies case-by-case and depends largely on the data structure (Caliendo and Kopeinig, 2008). This thesis employs

⁶⁰ Smith and Todd (2005) and Caliendo and Kopeinig (2008) present comprehensive overviews on various matching algorithms.

Mahalanobis metric matching including the propensity score and further variables to account for multiple treatments. To check the robustness of the results, the analysis additionally employs kernel based matching and k -nearest-neighbour matching, that are most common in empirical literature. After presenting the general form of the matching estimator, the matching algorithms used in this analysis are presented in more detail.

In general, the matching estimator takes the following form:

$$\hat{\alpha}_M = \sum_{i \in I_1 \cap S_p} \left[Y_{1i} - \sum_{j \in I_0} W_{i,j} Y_{0j} \right] w_i, \quad (6-17)$$

where $W_{i,j}$ is the weight that is placed on the control observation j for the treated individual i and w_i accounts for the reweighting that reconstructs the outcome distribution for the treated sample. I_1 denotes the set of treated, I_0 the set of non-treated and S_p the region of common support.

The **nearest neighbour matching (NNM)** is the most straightforward approach, traditionally as pair wise matching. The individual of the comparison group is matched with a treated individual that is closest in terms of the propensity score (Caliendo and Kopeinig, 2008). NNM sets:

$$C(P_i) = \min_j \|P_i - P_j\|, \quad j \in I_0 \quad (6-18)$$

where $C(P_i)$ is the set of control units matched to the treated unit i with an estimated value of the propensity score of P_i . Non-treated with the value of P_j that is closest to P_i is selected as match (Todd, 2006).

Then, the NNM estimator can be written as follows (Becker and Ichino, 2002):

$$\hat{\alpha}_{NN} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left[Y_{1i} - \hat{E}(Y_{0i} | D_i = 1, P_i) \right], \quad (6-19)$$

with

$$\hat{E}(Y_{0i} | D_i = 1, P_i) = \sum_{j \in I_0} W(i, j) Y_{0j} \quad (6-20)$$

where I_1 denotes the set of treated, I_0 the set of non-treated and S_p the region of common support; n_1 is then the number of persons in the set $I_1 \cap S_p$.

NNM minimises the bias but may involve an efficiency loss, since a large number of close neighbours is disregarded. A variant of nearest neighbour matching, the k -nearest neighbour matching, suggests to use $k > 1$ nearest neighbours as matching partners for the treated. Using more information to construct the counterfactual for each participant will reduce variance but will increase bias as poorer matches are used on average (Smith and Todd, 2005).

Caliper matching (CM) (Cochran and Rubin, 1973) sets a tolerance level on the maximum propensity score distance for the matching partner to avoid bad matches. An individual from the comparison group that lies within the caliper ('propensity range') and is closest in terms of propensity score is chosen as a matching partner for a treated individual. Thus, it is one form of imposing a common support condition, as treated individuals for whom no matches can be found within the caliper are excluded from the analysis (Caliendo and Kopeinig, 2008). However, as fewer matches are performed, the variance of the estimates increases⁶¹. In case of CM, a match for a treated individual i is selected only if a matching partner lies within a tolerance level on the maximum distance $\|P_i - P_j\|$ (Cochran and Rubin, 1973). The neighbourhood is defined as

$$C(P_i) = \{P_j \mid \|P_i - P_j\| < \varepsilon\}, \quad j \in I_0 \quad (6-21)$$

where ε is a pre-specified tolerance range of the propensity score.

Radius matching is a variant of caliper matching suggested by Dehejia and Wahba (2002). Here, not only the nearest neighbour within the caliper is used but also all of the comparison members within the caliper are used as matching partners. This approach shares the attractive feature of oversampling but avoids the risk of bad matches.

All of these approaches use only few observations from the comparison group to construct the counterfactual outcome of a treated individual. **Kernel based Matching (KBM)** enables a one-to-many matching, using the weighted average of the outcome variable for (nearly) all individuals in the control group to construct the counterfactual outcome, giving more importance to those observations that provide a better match. This weighted average is then compared with the outcome of the treated observation. The difference between the two terms yields an estimate of the treatment effect for the treated case. A sample average over all treated cases is then the estimate of the sample average treatment effect for the treated

⁶¹ However, variance comparisons between matching estimators with and without calipers are not obvious (Caliendo and Kopeinig, 2008).

group. The choice of the kernel function for KBM seems to be relatively unimportant in practice (DiNardo and Tobias, 2001). KBM reduces the variance by using more non-participants and thus more information for each participant. On the other hand, it may increase the bias, as observations might be used that are bad matches. Hence, the proper imposition of the common support condition is of major importance for applying KBM (Hujer et al., 2004).

The kernel based matching estimator can be described as follows (Heckman et al., 1997):

$$\hat{\alpha}_{KM} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left\{ Y_{1i} - \sum_{j \in I_0 \cap S_p} W(i, j) Y_{0j} \right\}, \quad (6-22)$$

where n_1 is the number of treated cases and Y_{1i} is the outcome for treated case i . The term $\sum_{j \in I_0 \cap S_p} W(i, j) Y_{0j}$ measures weighted average of the outcome for all non-treated cases who match to participant i on propensity score differentially. $\sum_{j \in I_0 \cap S_p} W(i, j) Y_{0j}$ is a consistent estimator of $E(Y_0 | D = 1, P_i)$ under standard conditions on the bandwidth and kernel (Smith and Todd, 2005). In the above equation $W(i, j)$ is the weight or distance on propensity score between i and j and is defined as follows:

$$W(i, j) = \frac{G\left(\frac{P_j - P_i}{a_n}\right)}{\sum_{k \in I_0} G\left(\frac{P_k - P_i}{a_n}\right)},$$

where $G(\cdot)$ is a kernel function, a_n is a bandwidth parameter and P_i , P_j , and P_k are the estimated propensity scores. The neighbourhood $C(P_i)$ depends on the specific kernel function chosen for the analysis.

The most common multivariate covariate matching is based on the minimum **Mahalanobis distance** and was invented prior to the PSM (Cochran and Rubin, 1973; Rubin, 1976a, 1980). Mahalanobis metric matching is a one-to-one matching method where the non-treated subject j that has the minimum distance $d(i, j)$ to the treated is chosen as match for the treated individual. The Mahalanobis distance is calculated as follows (Rubin, 1980):

$$d(i, j) = (u - v)^T C^{-1} (u - v) \quad (6-23)$$

where u and v are values of the matching variables for treated subject i and non-treated subject j , and C is the sample covariance matrix of the matching variables from the full set of non-treated subjects. As noted earlier, the estimated propensity score can be added as additional covariate. Using MMM with the propensity score as additional covariate is particularly useful in the present analysis with multiple treatments. In this case it may be quite important to obtain very good matches with respect to specific variables that may be highly correlated with the outcome variables as well as with selection (such as technology use or region) (Lechner, 2002; Caliendo and Kopeinig, 2008). Another strategy to put greater emphasis on these specific variables is to implement matching separately for the different subgroups or to estimate multiple treatment effects (Heckman et al., 1998). This approach is especially recommendable if one expects the effects to be heterogeneous between certain groups. However, due to the sample size this analysis controls for multiple treatments by using the Mahalanobis metric matching. Another advantage of the Mahalanobis metric matching combined with the propensity score is that PSM is particularly good at minimizing the discrepancy along the propensity score, while MMM is particularly good at minimizing the distance between individual coordinates of Z (orthogonal to the propensity score) (Rosenbaum and Rubin, 1985). Furthermore, empirical evidence indicates that MMM performs better than other matching algorithms (such as NNM, radius, KBM, stratified matching), particularly with calipers (Baser, 2006). However, as this matching method is based on a number of covariates, it is more difficult to find close neighbours.

All matching algorithms can be conducted with or without replacement of non-treated observations. Matching with replacement allows an untreated observation to be used more than once. Matching with replacement is especially useful where the propensity score distribution is very different in the treatment group and the control group (e.g. many treated individuals with high propensity score but only few control individuals with high propensity score). Allowing replacement reduces the probability that high-score participants will be matched with low-score non-participants, and thus increases the average quality of matching and decreases the bias. However, as it reduces the number of non-participants used to construct the counterfactual this matching approach increases the variance (Smith and Todd, 2005).

Due to the reasons outlined above, the present study employs Mahalanobis metric matching. In addition, treatment effects are estimated with two commonly used matching approaches to check the robustness of results across matching algorithms. These approaches are kernel based matching and oversampling k -nearest-neighbour matching. Due to the large number of relevant covariates, the propensity is used as balancing score to

reduce the high dimensionality of covariates in order to be able to find matching partners. Furthermore, all matching estimates are conducted with replacement due to the relatively small sample size. This allows non-treated individuals to be matched more than once. Calipers are set in case of nearest neighbour matching and Mahalanobis metric matching to avoid bad matches, while kernel based matching does not allow for calipers. The calipers are set at a level that maximises the balancing quality.

6.2.3.3 Assessing the Matching Quality

It is important to note that the main purpose of matching is to balance the observed distribution of covariates across the treated and the untreated group (Bryson et al., 2002). The primary purpose of the propensity score is thus to serve as a balancing score. Consequently, matching can be considered as successful when after matching farmer's behaviour within each group is 'really similar' (Mendola, 2007). To measure the success of matching, this study employs balancing tests to check to which extent differences in the covariates in the two groups have been eliminated in the matched sample (Lee, 2008)⁶². If differences in the covariates in the two groups remain in the matched sample, matching on the propensity score was not (completely) successful. Then, either the propensity score model should be re-estimated using a different approach (i.e. fine-tuning the specification of the propensity scores by including non-linear or higher-order terms or interaction terms) because the current estimated score might not be an adequate balancing score or a different matching approach should be used (because for a given data set, covariate differences are removed to a different extent by the different approaches) or both (Caliendo and Kopeinig, 2008; Lee, 2008)⁶³. However, in the worst case no adjustment can lead to balance on the matched samples, where it might be necessary to conclude that propensity score matching methods cannot solve the selection problem due to a fundamental lack of comparability between both groups (Blundell et al., 2005).

Multiple versions of balancing tests exist in the literature⁶⁴. This thesis uses the method of standardized differences that is commonly used in empirical literature to control for the reduction in covariate imbalance. The standardized difference (or standardized bias) between treatment and control sample was suggested by Rosenbaum and Rubin (1985) as

⁶² This is as checking for balance in the matched sample is crucial, as the matched sample may be different to the full sample (Lee, 2008). Ensuring balance for the full sample does not imply balance for the matched sample.

⁶³ Lee (2008) notes that it may be difficult to disentangle these effects.

⁶⁴ The two-sample t -test is an alternative balancing test (Rosenbaum and Rubin, 1985).

a suitable way to quantify the bias between the groups of adopters and non-adopters before and after matching. For each covariate Z it is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups. For each variable, the mean standardized difference can be computed as follows (Lee, 2008):

$$B_{before}(Z) = 100 \frac{\bar{Z}_T - \bar{Z}_C}{\sqrt{\frac{V_T(Z) + V_C(Z)}{2}}} \quad \text{and} \quad B_{after}(Z) = 100 \frac{\bar{Z}_{TM} - \bar{Z}_{CM}}{\sqrt{\frac{V_T(Z) + V_C(Z)}{2}}}$$

where \bar{Z}_T and \bar{Z}_C are the sample means for the full treatment and comparison groups. \bar{Z}_{TM} and \bar{Z}_{CM} are the sample means for the matched treatment and comparison groups, while $V_T(Z)$ and $V_C(Z)$ are the corresponding sample variances. For binary data, the standardized bias is computed as:

$$B_{before}(Z) = 100 \frac{\bar{Z}_T - \bar{Z}_C}{\sqrt{\frac{p_T(1-p_T) + p_C(1-p_C)}{2}}}$$

where p_C is the proportion of the covariate in the control group, and p_T is the proportion of the covariate in the program group. Total bias of all variables can then be yielded by the unweighted average across all variables. Rosenbaum and Rubin (1985) suggest that a standardized difference of greater than 20% should be considered as 'large'.

The total bias reduction achieved by matching procedure can be computed as follows (Solivas et al., 2007):

$$BR = 100 \left(1 - \frac{B_{after}}{B_{before}} \right)$$

In addition to the standardized bias, the pseudo- R^2 from the propensity score estimation and the re-estimation of the propensity score after matching on the matched samples is calculated as suggested by Sianesi (2004). The pseudo- R^2 indicates how well the regressors explain the adoption probability. After matching there should be no systematic differences remaining in the distribution of covariates between both groups and therefore the pseudo- R^2 should be fairly low. The corresponding p -values of the likelihood-ratio test of the joint significance of all regressors in the probit model should be rejected after matching (Sianesi, 2004). Before matching, the significance of the regressors should never be rejected.

6.2.3.4 Sensitivity Analysis

Matching only balances the distribution of observed characteristics. If unobserved variables simultaneously affect assignment into treatment and the outcome variable, hidden bias may arise to which matching estimators are not robust (Rosenbaum, 2002). This study addresses this problem of hidden bias using the bounding approach proposed by Rosenbaum (2002). This approach does not test the unconfoundedness assumption itself, because this would mean to test that there are no (unobserved) variables that influence the selection into treatment. Instead, the Rosenbaum bounds provide evidence how strongly an unobserved factor must influence the selection process to alter the inference of the matching analysis. As Aakvik (2001) emphasizes, this should not be confused with the observed selection process as there is no need for the unobserved selection to follow the same pattern as the observed selection process.

To show the basic idea of the Rosenbaum approach, it is presented in the following. Consider the participation probability for an individual i with observed characteristics z_i in a programme to be:

$$\pi_i = \Pr(D_i = 1 | z_i) = F(\beta z_i + \gamma u_i) \quad (6-24)$$

where u_i is the unobserved variable and γ is the effect of u_i on the adoption decision. If the study is free of hidden bias, γ will be zero and the participation probability will solely be determined by z_i . If there is hidden bias, two individuals with the same observed covariates z have differing chances of adoption. Under the assumption of a matched pair of individuals i and j , and with F as the logistics distribution, the odds that the individuals receives treatment is then given by $\pi_i / (1 - \pi_i)$ and $\pi_j / (1 - \pi_j)$.

The odds ratio can then be expressed as:

$$\frac{\frac{\pi_i}{1 - \pi_i}}{\frac{\pi_j}{1 - \pi_j}} = \frac{\pi_i (1 - \pi_j)}{\pi_j (1 - \pi_i)} = \frac{\exp(\beta z_j - \gamma u_j)}{\exp(\beta z_i - \gamma u_i)} = \exp[\gamma (u_i - u_j)] \quad (6-25)$$

The z -vector cancels in case that both units have the same observed covariates z_i (as implied by the matching procedure). Then, the individuals differ in their odds of adoption decision by a factor that involves the parameter γ and the difference in their unobserved covariates u . The sensitivity analysis evaluates how causal inference about the adoption is altered by varying values of γ and $(u_i - u_j)$.

For reasons of simplicity, it can be assumed that the unobserved covariate is a dummy variable with $u_i \in \{0,1\}$ (Rosenbaum, 2002). Rosenbaum (2002) shows that equation (6-25) implies the bounds on the ratio of the odds that either of the two matched individuals will adopt as follows:

$$\frac{1}{\Gamma} \leq \frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)} \leq \Gamma \quad (6-26)$$

Both matched individuals have the same probability of adoption only if $\Gamma = 1$. Then, the study would be free of bias. If, e.g., $\Gamma = 2$, then individuals who appear to be similar (in terms of observables covariates z) could differ in their odds of adoption by as much as a factor of 2. Thus, $\Gamma = 2$ implies that if two individuals are matched exactly on observed covariates, one individual might be twice as likely as the other individual to adopt because they differ in terms of a covariate that is not observed (Rosenbaum, 2005). In this sense, Γ is a measure of the degree of departure from a study that is free of hidden bias (Rosenbaum, 2002). For each value of Γ , hypothetical significance levels, representing the bounds on the significance level of the adoption effect in case of unobserved self-selection into adoption status, and confidence intervals can be derived (Caliendo and Kopeinig, 2008). These can then be compared to assess at which level of $\Gamma = e^\gamma$ the inference about the adoption effect will change (DiPrete and Gangl, 2004). The upper and lower bound estimates of significance levels at given levels of hidden bias are calculated by the Wilcoxon's signed-rank test. As already noted, if $e^\gamma = 1$, the bounds are equal to the 'base' scenario of no hidden bias. With increasing e^γ , the bounds on the significance level move apart reflecting uncertainty about the test-statistics in the presence of unobserved selection bias (Hujer et al., 2004). The unknown null distribution of the Wilcoxon's signed-rank test-statistic (that is only fixed under the null hypothesis of no treatment effect) is bounded by two known distributions (Rosenbaum, 2002). Under positive (unobserved) selection (in the sense, that those most likely to adopt, given that they have the same z -vector, also have a higher outcomes), the estimated adoption effect overestimates the true adoption effect. This leads to an upward bias in the estimated adoption effect. Hence, the reported test statistic is too high and should be adjusted downwards (Becker and Caliendo, 2007). Under negative (unobserved) selection (those that are most likely to adopt, given that they have the same z -vector, have also lower outcomes), the estimated treatment effect underestimates the true treatment effect and the test-statistic should be adjusted upwards (Aakvik, 2001).

Sign-score statistics, such as the Wilcoxon's signed-rank statistic take the following form (Rosenbaum, 2002):

$$T = t(Z, r) = \sum_{s=1}^S d_s \sum_{i=1}^2 c_{si} Z_{si}$$

where Z is the treatment assignment, that equals one if a individual is treated and zero otherwise, while r is the outcome for each case in the S pairs, and c_{si} is binary ($c_{si} = 1$ or $c_{si} = 0$). Both $d_s \geq 0$ and c_{si} are functions of r , and thus are fixed under null hypothesis of no adoption effect. In a randomized experiment, $t(Z, r)$ is compared to its randomization distribution under the null hypothesis. However, the null distribution of the test-statistic $T = t(Z, r)$ is unknown under non-random non-experimental conditions, but is bounded by two known distributions for each fixed γ .

Under the assumption of a confounding variable, for each possible (γ, u) , the test-statistic $t(Z, r)$ is the sum of S independent variables, where the s th variable equals d_s with a

probability $p_s = \frac{c_{s1} \exp(\gamma_{s1}) + c_{s2} \exp(\gamma_{s2})}{\exp(\gamma_{s1}) + \exp(\gamma_{s2})}$ and equals zero with the probability $1 - p_s$.

With $\Gamma = \exp(\gamma)$, Rosenbaum (2002) defines p_s^+ and p_s^- as follows:

$$p_s^+ = \begin{cases} 0 & \text{if } c_{s1} = c_{s2} = 0 \\ 1 & \text{if } c_{s1} = c_{s2} = 1 \\ \frac{\Gamma}{1+\Gamma} & \text{if } c_{s1} \neq c_{s2} \end{cases} \text{ and } p_s^- = \begin{cases} 0 & \text{if } c_{s1} = c_{s2} = 0 \\ 1 & \text{if } c_{s1} = c_{s2} = 1 \\ \frac{\Gamma}{1+\Gamma} & \text{if } c_{s1} \neq c_{s2} \end{cases}$$

where $p_s^- \leq p_s \leq p_s^+$ for $s=1, \dots, S$. For any specific γ , the unknown null distribution of the test statistic $T = t(Z, r)$ is bounded by the distributions of T^+ and T^- . T^+ is defined as the sum of S independent random variables, where the s th variable equals d_s with probability p_s^+ and takes the value 0 with probability $1 - p_s^+$. Similarly, T^- is defined with p_s^- instead of p_s^+ (Rosenbaum, 2002). The expectation and variance of T^+ are as follows:

$$E(T^+) = \sum_{s=1}^S d_s p_s^+ \text{ and } \text{var}(T^+) = \sum_{s=1}^S d_s^2 p_s^+ (1 - p_s^+).$$

The expectation and variance of T^- are defined with the same formulas but with p_s^- instead of p_s^+ .

The bounds of the significance level of the null hypothesis of no effect of the treatment can then be computed for any specific Γ as $(T - E(T^+)) / \sqrt{\text{Var}(T^+)}$ and $(T - E(T^-)) / \sqrt{\text{Var}(T^-)}$, where T is the Wilcoxon's signed-rank statistic (DiPrete and Gangle, 2004).

Chapter 7

Econometric Results

This chapter is divided in three main sections. The first section (7.1) presents the econometric results of the joint adoption decision model of bund construction and dibbling method on farmer-level. Section 7.2 then reports the results of the parametric impact assessment of the technologies carried out by using the endogenous switching-regression model. After that, section 7.3 shows the results of the non-parametric impact analysis employing the propensity score matching estimation. In each of these sections, first, the variables included in the analysis are presented, followed by the results of the estimates. Each section then concludes with a discussion of the results.

7.1 Determinants of the Adoption Decision of Bunds and Dibbling

7.1.1 Variables Included in the Model

Farmers who adopted dibbling or bund construction at least at some part of their rice cultivation area are regarded as adopters of the new technique. The adoption status of bund construction is represented by the variable 'USE_B' that equals to one if the rice farmer constructed any kind of bunds in 2005. The variable 'USE_D' takes the value one if the rice farmer dibbled seed in 2005.

The selection of explanatory variables included in the model is guided by the findings of empirical and theoretical adoption literature. However, previous empirical literature does not give an exact guideline of selecting relevant variables. Explanatory variables are selected based on the concepts of innovation-diffusion, resource constraints, and perceived attributes theories. Thus, factors such as household characteristics, farm characteristics, resource constraints, and variables representing technology perception were included. An overview of the expected impact of the explanatory variables on the adoption decision of dibbling and bund technology is given in table 7-1. Table 7-2 presents the definitions and sample characteristics of the variables used in the analysis.

Table 7-1: Expected impact of determinants on adoption probability of dibbling and bund technology

Variable	Expected net effect		Effects
	Bunds	Dibbling	
Age	+ / -	+ / -	→ decreasing planning horizon (-) → farming experience (+) → status / access to information (+) → labour help (-)
Family labour	+	+	→ labour potential (+) → need for yield-increasing technologies (+)
Illness	-	-	→ labour endowment (-)
Land/labour ratio	+ / -	+ / -	→ decreasing population pressure (-) → food security, wealth of household (+)
Education	+	+	→ 'allocative ability' (+)
Farm size	+ / -	+ / -	→ wealth (+) → need for land conservation / intensification (-) → experimentation of new technologies (+) → labour burden (-) → increasing opportunity costs for rice cultivation (-)
Other crop size	-	-	→ opportunity costs of rice production (-) → lower market orientation / importance of rice cultivation (-)
Credit	+	+	→ cash for capital-intensive inputs and labour (+)
Off-farm income	+ / -	+ / -	→ access to cash (+) → opportunity costs of labour-intensive techniques (-)
Household headship	+ / -	+ / -	→ alleviation of labour constraint of rice production (+) → information / network (+) → orientation towards food staples (-)
Assets (bullock / tractor)	+ / -	+ / -	→ wealth (+) → enhancing construction of bunds (+) → delayed land preparation (-) → increasing off-farm activity possibilities (-)
Farmer group member	+	+	→ good perception of technology (+) → decreased uncertainty about technology (+) → peer-group pressure (+) → access to exchange labour
Project participation	+	+	→ innovativeness (+) → motivation (+) → information about technologies (+) → better networks (+)
Status	+	+	→ access to communal labour (+) → access to information (+)

Variable	Expected net effect		Effects
	Bunds	Dibbling	
Good results reported	+	+	→ perceived high benefit of technology (+) → social learning (+)
Perception of adoption benefits	+	+	→ perceived benefit of technology (+)
Soil fertility	+ / -	+ / -	→ benefit of technology (+ / -)
Good water retention		-	→ flooding of plot (-)

Table 7-2: Variable names, definitions, and selected descriptive statistics for the sample

Variable name	Variable definition	Sample mean	Standard deviation
<i>Dependent variables</i>			
OUT_AC	Output of lowland rice production (bags per acre) ⁶⁵	7.20	4.19
N_AC	Application of nitrogen in lowland rice cultivation (kg per acre)	11.46	9.30
NRET_0	Net returns per acre in lowland rice cultivation (=NRET_AC divided by 100,000) (GHC per acre) ⁶⁶	7.38	6.51
USE_B	1 if farmer uses bunds, 0 otherwise	0.49	0.50
USE_D	1 if farmer dibbles seed, 0 otherwise	0.68	0.47
USE_D_SF	1 if farmer dibbles seed and fertilizer, 0 otherwise	0.29	0.45
USE_INTEN	1 if farmer dibbles seed and fertilizer and does improved weeding, 0 otherwise	0.61	0.49
<i>Independent Variables</i>			
AGE_R	Age of respondent (years)	37.31	10.82
HEAD	1 if farmer is head of the household, 0 otherwise	0.42	0.49
GEQ_HH	Number of labour equivalents living in the compound household	13.40	9.46
GEQ_ILL	Number of labour equivalents regularly helping in lowland rice production, suffering from frequent illness	2.07	2.80
DEP_HH	Dependency ratio for compound household: (children < 14 years + elderly > 60) / total number of persons in compound household	0.45	0.14
AV_FSZ	Family land per labour equivalent of household (acres)	1.28	1.01
FSZ	Total area cultivated by the respondent (under own decision) (acres)	7.35	5.29
R_SZ	Total area cultivated by respondent with lowland rice (acres)	2.17	1.37

⁶⁵ 1 bag of rice = 82 kg.⁶⁶ GHC/US\$ (2005) = 9,130.8.

Variable name	Variable definition	Sample mean	Standard deviation
CROP_SZ	Area cultivated by rice farmer under other crops (acres)	5.18	4.53
TRACTOR	1 if farmer owns tractor, 0 otherwise	0.03	0.18
MOTOR	1 if farmer has access to motorized vehicle, 0 otherwise ⁶⁷	0.95	0.22
BIKE	Number of bicycles owned by the farmer	1.03	0.53
BULL	Number of bullocks owned by the farmer (pair)	0.15	0.40
CREDIT	1 if farmer had access to any credit in last ten years, 0 otherwise	0.40	0.49
Credit_05	1 if farmer received any credit in 2005, 0 otherwise	0.19	0.39
FOOD_HH	Number of months with food security from household's produce	8.58	2.54
OFF_R	1 if rice farmer has any off-farm income, 0 otherwise	0.36	0.48
OFF_SH	Share off-farm income of total income of farm family (%)	11.95	17.83
STATUS_HH	1 if farmer's compound has an higher status than average, 0 otherwise	0.25	0.43
INFS_R	1 if farmer is literate, 0=farmer is not literate in English / has Koranic education	0.29	0.46
EDUC_R	Educational level of farmer: 0=no education, 1=literacy, 2=formal school education	0.49	0.80
FSRPOP	1 if farmer participated in FSRPOP, 0 otherwise	0.24	0.43
LRDP	1 if farmer participated in LRDP as project farmer, 0 otherwise	0.47	0.50
PROJ	1 if farmer participated in any other project before LRDP, 0 otherwise	0.21	0.41
CGROUP	1 if farmer was member in crop related group, 0 otherwise	0.56	0.50
CGROUP2	1 if farmer was member in crop related group (excluding FSRPOP), 0 otherwise	0.38	0.49
CGROUP3	1 if farmer was member in crop related group (excluding working groups and FSRPOP), 0 otherwise	0.07	0.26

⁶⁷ Own, household, borrowed or hired tractor, car, and motorbike.

Variable name	Variable definition	Sample mean	Standard deviation
DROUGHT	1 if there was drought in early growing stage of rice plant in 2005, 0 otherwise	0.47	0.50
CON_FERT	1 if farmer indicated weather constraint for not applying preferred amount of fertilizer, 0 otherwise	0.63	0.48
PRICE_AV	Average price of nitrogen (GHC per kg)	19,596.77	4,209.70
DIST_AV	Mean distance from compound to plot (bicycle min)	16.12	14.36
TRAC_PL	1 if farmer ploughs with tractor, 0 otherwise	0.84	0.37
USE_IMP	1 if farmer cultivated improved rice varieties, 0 otherwise	0.91	0.29
KY	1 if farmer is located in Kulda-Yarong valley, 0 otherwise	0.12	0.33
ZUWARI	1 if farmer is located in Zuwari valley, 0 otherwise	0.11	0.32
CON_L	1 if labour is ranked first or second as most constraining for lowland rice production	0.31	0.46
REPRES	Percentage of good results reported to the farmer: 1=0-25%, 2=25-50%, 3=50-75%, 4=75-100%	2.61	1.01
B_EFF	1 if farmer perceives bunds as highly effective as water conservation method, 0 otherwise	0.52	0.50
DIB_Y	1 if farmer perceives dibbling as highly yield-increasing, 0 otherwise	0.61	0.49
WEED_R	Rank of weeding as labour constraint in lowland rice production	1.55	0.76
DIB_CON	Farmers was impeded in 2005 to dibble	0.02	0.15
BUND_CON	Farmer was impeded in 2005 to construct bunds	0.06	0.25
SH_LRDP	Share of area cultivated with LRDP bunds	0.28	0.39
SH_VRET	Share of area cultivated with very good water retention	0.52	0.48
SH_LOAM	Share of area cultivated with loamy soil	0.17	0.36
SH_BUND	Share of area cultivated with bunds	0.56	0.47
SH_DIB	Ratio of rice area that seed dibbling is used to total rice area	0.65	0.47
SH_VSOIL	Share of area cultivated very good soil	0.51	0.48

Source: Survey data

The impact of the rice farmer's age ('AGE_R') on adoption probability is a-priori ambiguous. Age-squared ('AGE2_R') is included to account for non-linear life cycle effects. Younger farmers tend to have a longer planning horizon and are thus more likely to adopt new technologies. On the other hand, older farmers may not be able to adopt labour-intensive technologies such as bund construction that require heavy physical efforts. Older farmers may also have less need for extra income from intensified cash crop production. However, older farmers tend to be less constrained by financial resources and to have more time to observe the farming outcome from other farmers. Thus, they may be more likely to adopt new farming practices. Farmer's age may also be a proxy of farming experience. Farmers with more years of farming experience probably have better knowledge about the cause-and-effect chain of soil depletion and water conservation. This may be a precondition for the willingness to adopt. Similarly, the impact of household headship of the farmer is ambiguous. On the one hand, household heads are less likely to adopt bund construction and dibbling method. As household heads are responsible for feeding the compound family, they are expected to be more interested in the production of food crops (such as maize) than in the cultivation of rice as a cash crop. Furthermore, they are assumed less market-oriented in their rice production. On the other hand, dependent men have the obligation to work on the household head's farm which produce is meant for family feeding. Thus, household heads are less constrained in labour and are thus more likely to adopt (labour-intensive) technologies.

Education of the rice farmer (who is the decision-maker about the adoption bunds or dibbling) is hypothesized to have a positive effect on adoption.

According to the human-capital theory to allocative efficiency, 'allocative ability' is a skill that "is acquired at a cost and yields a valuable stream of services of future periods" (Huffman, 1977, p. 60). It is assumed to be acquired by schooling, seeking information, and experience from reallocation of resources. Allocative skills enable farmers to critically evaluate characteristics, benefits, and costs of technology innovations (Abdulai and Huffman, 2005). Under this hypothesis, highly educated and better-informed farmers make better assessment of farm-level performance of technologies and hence will make more efficient adoption decisions (Schultz, 1975; Huffman, 2001).

It is commonly assumed in the adoption literature that the probability of adoption increases with farm size. Due to scale effects, the average fixed costs (e.g. associated with learning costs, training for hired or exchange labour) may be lower for large-scale farmers and this may make adoption more profitable. Larger farmers may also have more access to information and more land to diversify and to experiment with sequential adoption on some

plots. Furthermore, farm size and wealth may be positively related, increasing adoption probability. In addition, potential loss of land resulting from bund construction may discourage adoption on small farms and plots. According to the hypothesis of Boserup (1965), population growth resulting in decreasing farm-size stimulates adoption of intensification technologies. Contrarily, the Neo-Malthusian argument says that land redistribution and land fragmentation from increasing population pressure does not lead to more intensification of farming but instead leads to cultivation of marginal lands and further land degradation. Thus, the impact of plot size on technology adoption decisions is an empirical issue. The family land holding per household member is included in the econometric analysis to capture the effect of population-density-driven intensification. It is expected that households with lower land/labour ratio may have incentives to invest in land-saving (but labour-intensive) intensification techniques.

Labour endowment may contribute to a higher adoption rate of bund technology and dibbling method by reducing labour constraints of labour-intensive technologies. Family labour is the main source of labour for households. However, an increasing household size may also reflect higher opportunity costs of labour-intensive cultivation techniques, as more mouths have to be fed. Competition between labour for immediate food generating (off-farm) activities and investment in soil and water conservation techniques may then increase. Household labour endowment is measured by labour equivalents ('GEQ_HH')⁶⁸. Furthermore, the access to exchange labour (such as working groups or communal labour) is assumed to increase the probability of technology adoption, as it may relax labour constraints (Lapar and Pandey, 1999; Adesina et al., 2000; Mbagal-Semgalawe and Folmer, 2000). The variable 'CGROUP2' indicates the participation of the farmer in any crop related farmer group, including working groups. Health is assumed to have a negative impact on the adoption incentive of new technologies through its impact on household time constraints and income (Ersado et al., 2004). Health status is represented by the number of compound family members (measured in labour equivalents) helping in lowland rice production who are frequently ill.

Differential access to capital is often cited as factor explaining differential rates of adoption. It is particularly difficult for smallholder farmers to escape poverty because of liquidity constraints to invest in income-enhancing technologies. Access to credit is included by a dummy variable that takes the value one if the farmer ever received credit in the last ten

⁶⁸ Labour equivalents are calculated with the following factors: 0.75 for adult women (14-60 years) and 0.5 for children (younger than 14) and elderly (older than 60 years).

years. According to Salasya et al. (1998), this is a better measure of credit access as simple asking whether the farmer used credit in the current period as this would not distinguish between farmers who chose not to use available credit and farmers who did not have access to credit. With better access to credits, the farmer can afford to purchase production inputs and labour. Furthermore, if the household can smooth consumption through the access to credit the opportunity cost of adoption may be lower than that theoretically implied. Wealth and off-farm income might also provide financial resources for the adoption of new technologies and the purchase of production inputs (Huffman, 1974). To capture wealth effects, assets such as the ownership of tractor and bullocks, as well as the number of bicycles owned are included. Furthermore, the ownership of tractors and bullocks may alleviate the efforts of bund construction. However, these assets may also indicate off-farm income possibilities that may exert a negative impact on adoption probability. In addition, using tractor and bullocks as off-farm income source may result in delayed land preparation on own plots. Previous work has also shown that off-farm and non-farm income availability is negatively related to adoption (Fujiyama, 1993). The positive effect of off-farm income on adoption probability may be offset particularly for labour-intensive technologies by the reduction in the time available for decision making and learning in rice production and the increased opportunity costs of time. Thus, the net effect of off-farm wage income is a-priori unclear.

Social networks are an often-cited factor in the empirical literature to drive adoption probability (Boahene et al., 2000). The social status of the farmer is included and defined as dummy variable that takes the value one if the farmer's compound has a higher social status than average ('STATUS_HH'). Bandiera and Rasul (2006) found that the relationship between the probability of adoption and the number of known adopters is shaped as an inverse-U curve. Thus, the proportion of good results that are reported to the farmer from the farmer's social network is included in the analysis ('REPRES').

The perception of the innovative technology and the perception of the need for technology innovation are often found to be significant in explaining the adoption decision in the empirical technology adoption literature (Adesina and Zinnah, 1993; Shiferaw and Holden, 1999). The adoption decision process of bund technology is expected to be influenced by the perception of bund technology as effective or yield-increasing ('B_EFF'). Similarly, the perception of dibbling as yield-increasing technology ('DIB_Y') is hypothesized to have a positive influence on adoption probability. Moreover, the perception of labour constraints ('CON_L') in rice production and the ranking of weeding activity as most constraining labour

activity in rice cultivation are assumed to determine adoption probability of seed dibbling as it is labour-saving in weeding.

Land quality differentials are found to explain adoption choice and degree (see e.g. Bellon and Taylor, 1993). Due to the fact that 27.49% of farmers in the sample cultivated more than one lowland rice plot, plot characteristics are aggregated for the estimation on farmer level by using the shares of lowland rice area. Plot characteristics included in the estimation are the perception of plot as productive and the perception of water retention status. Better water retention may cause flooding on the plot, which may make dibbling of seed impossible. However, water retention status is not included in the estimation of bund construction as this variable may be influenced by the use of bunds. The benefit of both technologies may be higher on very productive plots thus increasing the adoption probability. On the other hand, investments in water conservation structures may be more likely adopted on marginal land in order to enable rain-fed rice production.

The dummy variable 'BUND_CON' is included to capture exogenous reasons not to use bunds in 2005 that are not controlled by other variables and that should not be confounded with socio-economic characteristics of the farmer and the farm. The variable takes the value one if the farmers stated one of the following reasons for not constructing bunds in 2005: land tenure problems, rain disturbance, flooding at the time of bund construction, no need or abundance of water⁶⁹. Similarly, the variable 'DIB_CON' equals to one, if the farmer indicated that it was not possible for him to dibble seed due to flooding of the plot or due to land tenure problems. In addition, river valley dummies ('KY', 'ZUWARI') are included to capture regional differences such as climatic differences or weather-related weed infestation⁷⁰.

⁶⁹ The variable for water retention status does not capture whether the farm received enough rain.

⁷⁰ Cultivated rice area within the river valleys is quite small. Thus, environmental variables are relatively homogenous, with the same rainfall intensity and little variation in soil types within the river valleys.

7.1.2 Results of Bivariate Adoption Model

The seemingly unrelated bivariate probit estimation was carried out on farmer level using STATA™ statistical software version 9.2 (StataCorp, 2005). The estimates of the maximum likelihood bivariate probit estimation are presented in table 7-3. The estimation is based on 272 observations due to missing values in the explanatory variables. Based on theoretical grounds, every model was estimated as a backward stepwise selection procedure, starting from a full model. This is in line with Hendry's methodology (Maddala, 1992).

The seemingly unrelated bivariate probit model is estimated with the robust option that specifies that the Huber/White/sandwich estimator of the variance (which is a heteroskedasticity consistent estimator) is used (Greene, 2003)⁷¹. Marginal effects of the regressors on the adoption probability indicate the change in the probability of each technology given a one-unit change in the independent variable, respectively. They are obtained by multiplying the coefficient estimates $\hat{\beta}$ by $\phi(\hat{\beta}'Z)$ at the mean values of Z and are reported in table 7-3 (Maddala, 1991).

Overall coefficients were significant ($p < 0.000$). The log-Pseudolikelihood ratio statistic for the bivariate probit estimation is 261.3477 and significant at the 1% level, suggesting that the independent variables taken together influence the adoption probability of bund construction and dibbling. The log-likelihood ratio test is calculated as $LR = 2(L_{\Omega} - L_{\omega})$, where L_{Ω} is the unrestricted maximum likelihood and L_{ω} is the restricted maximum log-likelihood with all slope coefficients set equal to zero (Amemiya, 1981). The McFadden- R^2 , an indicator of goodness of fit, is calculated as $R^2 = 1 - L_{\Omega}/L_{\omega}$ and equals 0.385. The adjusted McFadden- R^2 is calculated as $R^2 = 1 - L_{\Omega} - K/L_{\omega}$, where K is the number of parameters in the model, and equals to 0.253 (Maddala, 1991). The Akaike information criterion (AIC) is 506.8081. The percentage of correct predictions is calculated as the total number of predictions as a percentage of the number of observations. The predictive power is satisfactory and in line with other adoption studies. The level of correct predictions is higher for dibbling technology (82.72%) than for bund construction (73.90%).

The estimate of Rho (correlation between the error terms of the adoption equations) that maximises the bivariate probit likelihood function is 0.851 and is significantly greater than zero at the 1% level. A positive value for Rho indicates that unobserved factors that influence

⁷¹ Heteroskedasticity is frequently encountered in cross-sectional studies and means that the error terms are mutually uncorrelated, while the variance of ε_i may vary over the observations (Verbeek, 2004).

the adoption of bund construction also increase the likelihood of adopting dibbling. This result indicates that the random disturbances of the two adoption decision equations are affected in the same direction by random shocks and that the decision equations are not statistically independent. This emphasizes the importance of a joint estimation.

Table 7-3: Estimated coefficients and marginal effects at the mean for the seemingly unrelated bivariate probit model of adopting bund technology and dibbling method

Variable	Adoption of bunds			Adoption of dibbling		
	Coefficient	Huber/White <i>t</i> -value	Marginal probability	Coefficient	Huber/White <i>t</i> -value	Marginal probability
CONS	-0.133	-0.14	–	-1.858***	-2.88	–
AGE_R	-0.089**	-2.08	-0.033	-0.016	-1.49	-0.006
AGE2	0.001*	1.68	–			
GEQ_HH	0.020*	1.82	0.007	0.032**	2.35	0.011
GEQ_ILL	-0.078***	-2.68	-0.029			
STATUS_HH	0.336	1.49	0.128			
CROP_SZ	-0.034**	-1.64	-0.013			
R_SZ				-0.228***	-2.76	-0.078
AV_FSZ	0.241**	2.19	0.090	0.268**	2.18	0.092
INFS_R	-0.251	-1.26	-0.091	0.547**	2.25	0.174
CREDIT	0.340*	1.65	0.127	0.271	0.98	0.092
OFF_R	-0.101	-0.50	-0.037	-1.060***	-4.58	-0.379
FSRPOP	0.526**	2.18	0.201	1.318***	4.02	0.351
LRDP				0.521**	2.39	0.177
HEAD				1.033***	4.15	0.331
PROJ	0.579**	2.53	0.223			
B_EFF	0.508**	3.00	0.187			
REPRES	0.282**	2.86	0.105			
KY	0.876**	2.54	0.338	-2.313***	-6.43	-0.728
ZUWARI	0.177	0.69	0.067	-0.193	-0.63	-0.068
USE_IMP	0.834**	2.51	0.253	1.052***	2.90	0.399
TRACTOR	1.008*	1.77	0.384	1.037*	1.89	0.242
BULL				-0.309	-1.18	-0.106
CON_L				-0.474*	-2.03	-0.168
DIB_Y				0.550***	2.69	0.192
CGROUP2				0.494**	2.08	0.162

Variable	Adoption of bunds			Adoption of dibbling		
	Coefficient	Huber/White <i>t</i> -value	Marginal probability	Coefficient	Huber/White <i>t</i> -value	Marginal probability
WEED_R				0.529***	4.20	0.181
DIB_CON				-7.517***	-15.91	-0.772
BUND_CON	-8.186***	-24.01	-0.553			
SH_VSOIL	-0.387*	-1.90	-0.144	0.716***	3.06	0.245
SH_VRET				-0.347	-1.56	-0.119
Correct pred. (%)		73.90			82.72	
Obs .			272			
Log- Likelihood Ratio			261.3477 > $\chi^2_{0.99}[42]$)			
Rho			0.851			

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

Source: Own calculation

The effect of the rice farmer's age on the adoption probability of bund technology was found to be nonlinear. As a young farmer ages the adoption probability of bund construction decreases. However, after a minimum adoption probability age starts to contribute to higher adoption rate. This implies that older farmers are less likely to adopt labour-intensive technologies due to the physical effort of bund construction, while this effect seems to be compensated by other effects with increasing age. This result conforms to findings in the empirical adoption literature (Feder et al., 1985; Clay et al., 1998). The effect of age on the adoption probability of dibbling method is also negative but not significant.

Higher labour endowment of the household ('GEQ_HH') significantly increases the likelihood to construct bunds and to use dibbling as seed sowing method. This is in line with empirical literature (e.g., Marenya and Barrett, 2007). In case of bund technology, the number of household members helping in the rice farmer's lowland rice production that are frequently ill ('GEQ_ILL') decreases the probability to use bunds significantly at the 1% level. This result is in line with findings of Ersado and Anmacher (2004). However, this effect is not very strong, with a marginal effect of 3%. Reducing family labour force through frequent illness seems not to be determining the use of dibbling method. This appears plausible as it is more common to use communal labour and non-family labour for dibbling activity than for bund construction,

while bund construction is mainly undertaken by the rice farmer himself. Therefore, illness of family members helping in lowland rice production may be more constraining for the adoption of bund construction than for the adoption decision of dibbling. In line with this argument, the membership of the rice farmer in any crop related farmer group ('CGROUP2') appears to be significant in explaining the adoption probability of dibbling as seed sowing method. This result further supports the importance of the labour exchange systems to overcome labour constraints in working peak periods such as planting, weeding or harvesting. A positive effect of the participation in labour-sharing groups is also found e.g. by Lapar and Pandey (1999) and Mbaga-Semgalawe and Folmer (2000).

Dibbling method appears to be positively related to literacy of the rice farmer ('INFS_R'). In contrast, the educational level of the farmer is not found to be statistically significant in determining the adoption decision on bund technology. Positive education effects are commonly found in the adoption literature (see e.g. Rahm and Huffman, 1984; Feder and Umali, 1993; Bravo-Ureta et al., 2006). These are in contrast to empirical studies that reveal inconclusive or even negative outcomes. Pender et al. (2001) e.g., found no significant effect of education on the adoption of soil bunds, while a negative education effect was estimated for the adoption of stone terraces, and a positive effect was found for the use of manure. One reason for the insignificant relationship may be that the construction of bunds without properly determining the contours is not very knowledge intensive, whereas dibbling may be considered as more knowledge-intensive. This may be due to the fact that dibbling (due to high time-intensiveness) requires timely planning of planting and seeding activities, to organize communal or exchange labour and to train and control them. Furthermore, the variation of the educational level in the sample is quite low, as about 80% of farmers in the sample have no formal schooling. Household heads ('HEAD') are found to be more likely to adopt dibbling method (at a significance level of 1%). The marginal effect implies that the adoption probability increases by 33.1% for household heads. This result suggests that household heads are less constrained in labour and are thus more likely to adopt labour-intensive technologies. The variable representing a higher social status ('STATUS_HH') appears to be positively related with adoption of bunds as expected, *albeit* not significant.

Adoption of both technologies turns out to be determined by an increasing ratio of family land per compound household member ('AV_FSZ'). This finding is in line with other empirical technology adoption studies that found that landholding exerts a positive effect on adoption probability (Honlonkou, 2004; Bravo-Ureta et al. 2006; Kabubo-Mariara, 2007). As expected, the variable representing the size of farmland cultivated with other crops than rice ('CROP_SZ') has a negative and significant effect on the adoption probability of bund

technology. This finding suggests that with increasing importance of other crops, the likelihood of adoption decreases. In case of dibbling method, the variable measuring the rice area cultivated ('R_SZ') turns out to have a negative and significant effect on adoption probability. This result may reflect increasing labour constraints for rice cultivation during planting time of rice. However, both effects appear to be quite small.

Access to credit ('CREDIT') appears to be an important determinant in explaining the adoption of bund technology. The marginal effect implies that credit availability increases adoption of bund construction by 12.7%. Due to reasons of physical efforts and the robustness of the bunds, tractors are preferred for bund construction, which is more capital-intensive than manual construction. The positive relationship also conforms to the findings of previous adoption studies. In contrast, the influence of credit access is not found to be significant in explaining the adoption probability of dibbling method. This may be explained by the fact that labour requirements of dibbling seed are mostly covered by communal labour.

The ownership of tractors appears to be significant in explaining adoption of both technologies at the 10% level. Looking at the adoption decision of bund technology, tractor ownership turns out to have the highest marginal effect with 38.4%, while the marginal effect in case of dibbling method is 24.2%. This effect seems plausible as the use of tractors alleviates bund construction after ploughing. Furthermore, tractor use for land preparation leaves more time for time-intensive planting. The number of bullocks owned ('BULL') is negatively related with the adoption of dibbling method, *albeit* not significant. This finding may be due to the time-intensiveness of bullock ploughing that may delay planting and may thus make seed dibbling impossible. Another explanation is that the ownership of bullocks enables off-farm income possibilities, as oxen are very rare in the study region, reducing the likelihood of adoption of rice-intensifying cultivation practices. This finding is line with the negative effect of off-farm income on the adoption of dibbling method ('OFF_R'). This effect is significant at the 5% level and indicates a decrease in adoption probability by 37.9% if the farmer obtains off-farm wage income. The negative effect is though not significant in case of bund technology. Negative off-farm income effects on adoption have also been found e.g. by Mbagal-Semgalawe and Folmer (2000) for improved conservation measures in Tanzania, and Hagos and Holden (2006) for soil bunds in Ethiopia.

The variables 'LRDP', as well as 'FSRPOP' capture technology extension effects. Participation in the FSRPP ('FSRPOP') exerts a positive and significant effect on the probability to adopt bunds, with a relatively high marginal effect of 20.1%. A positive and significant effect of participation in the FSRPOP is also found for dibbling technology. Here,

the marginal effect is 35.1%. Participation in the LRDP ('LRDP') also appears to be significant in explaining adoption of dibbling, with a marginal effect of 17.7%. However, the coefficient did not appear to be significant in the bund technology equation. It was therefore removed from the estimation of bund technology, following a decreasing Akaike information criterion. This finding implies that formal extension by the LRDP is not important in determining the adoption rate of bund technology. One reason for this may be that nearly all farmers in the sample were advised by the extension agents, who were involved in the dissemination of the technologies by the LRDP⁷². The participation in any other project before the LRDP ('PROJ') increases the likelihood of adopting bund construction significantly at the 5 % level, with a relatively high marginal effect of 22.3%. This positive relationship suggests that farmers who are more innovative are also more likely to use bunds.

Variables measuring the perception of the new technologies are also included in the estimation. The strong perception of bunds as highly effective water conservation method ('B_EFF') increases investments in bund construction significantly at the 1% level, with a marginal effect of 18.7%. Similarly, the proportion of reported good results about the new technology to the farmer ('REPRES') exerts a positive and significant effect on the likelihood of bund construction (at 5% level). However, the marginal effect is quite small with only 10.5%. Likewise, the perception of dibbling as yield-increasing method ('DIB_Y') has the expected positive and significant effect on the adoption probability of dibbling seed, with a marginal effect of 19.2%. The perception of farmer's needs and constraints also turns out to be significantly related with adoption. In case of dibbling, the ranking of weeding activity regarding to labour requirements ('WEED_R') is found to be significant in determining the adoption probability of dibbling (with a marginal effect of 18.1%). Farmers who indicated that weeding is the most constraining labour activity in their lowland rice production are more likely to adopt dibbling as seed sowing method. As dibbling technology is labour-intensive at planting time but labour saving at weeding time, this finding is plausible. Similarly, the adoption of dibbling appears to be significantly correlated (at the 10% level) with the perception that labour is the most constraining production input in the farmer's lowland rice production ('CON_L') (compared to other production inputs such as capital or land). This finding also underlines the importance of labour constraints in the adoption decision of dibbling method.

⁷² 91.67% of farmers in the sample sought advice from extension agents. Referring to the remaining farmers, who did not indicate to have sought advice from extension agents, 38.46% were LRDP project farmers organised in farmer groups advised by extension agents.

The use of improved varieties is found to be an important factor determining adoption of dibbling and bund technology. Using improved varieties increases adoption probability by 25.3%. The marginal effect of improved varieties on the adoption probability of dibbling is even higher with 39.9%.

The significant coefficient of the regional dummy ('KY') indicates that farmers located in Kulda-Yarong valley exhibit a greater probability to adopt bund technology, but a lower likelihood to adopt dibbling as seed sowing method. The reason for this finding is not completely clear, but may be due to different rainfall distribution, weed infestation, or ethnicity of the farmers. The adoption pattern is also significantly affected by field characteristics. This finding demonstrates the importance of land quality in the choice of agricultural technology and is consistent with the results of Caswell and Zilberman (1986) and Pender and Kerr (1998). The share of highly productive rice area ('SH_VSOIL') is found to be negatively associated with bund construction. This indicates that water conservation methods are more likely constructed on marginal lands in terms of soil fertility. Such a relationship was also found in the literature on adoption of soil and water conservation measures (Nyangena, 2006). With regard to dibbling, a higher share of high yielding soils results in a higher adoption probability. While dibbling method has the potential to increase rice output at any level of soil quality, the use of dibbling increases productivity particularly on more fertile plots. On the other hand, a higher share of rice area with very good water retention ('SH_VRET') reduces the adoption probability of dibbling significantly. This may result from the fact that plots with very good water retention are more likely to be flooded during planting time, so that direct seeding by dibbling is not possible.

7.1.3 Concluding Remarks

Results of the bivariate probit model suggest that economic constraints of capital, labour, and land tend to influence adoption decision of bund technology and dibbling method. Alleviating financial constraints by the access to credit turns out to be significant in explaining adoption of bund construction. Labour constraints appear to be a key factor in the adoption decision of dibbling and bund technology. On the one hand, labour constraints may be aggravated by health problems in the compound family, but may be alleviated by the membership in crop related organizations or labour exchange groups, thus influencing the adoption probability. Furthermore, family landholding is found to increase adoption probability.

However, not only economic resource constraints seem to influence the adoption decision. Moreover, factors resulting from the innovation-diffusion paradigm and the perceived-

attributes paradigm turn out to play an important role in the adoption decision process. In line with the factors hypothesized by the innovation-diffusion model, results suggest that the perception and the information about the technology tend to influence the farmer's adoption behaviour. Consistent with adoption literature, the perception of potential benefits of bund construction and dibbling (such as yield increase and effectiveness) appears to be important in explaining adoption decision. In addition, the clear perception of constraints that may be alleviated by the technology adoption determines the adoption decision. Furthermore, participation in projects that are directly related to the technologies (such as FSRPOP and LRDP) but also the participation in other projects that are not directly related to the disseminating technologies seems to be important factors. In agreement with this, the participation in farmer organizations related to crop production was found to have a positive impact on adoption. This further supports the importance of social networks, social learning, and improved access to resources through social networks (such as exchange and communal labour). With regard to bund technology, informal information, social networks, and the perception of the technology seem to be even more important than the initial formal technology extension by the LRDP compared to dibbling method. According to Rogers (1995), many conservation technologies can be classified as 'preventive innovations' that help adopters to keep away from unwelcome future events, e.g. the loss of harvest due to the occurrence of drought. Rogers (1995) hypothesizes that preventive innovations have a low adoption rate because it is hard to demonstrate the benefit of adoption to the farmer since these advantages will occur only in the future. The perception of adoption benefits obtained through the social network may be particularly important for preventive innovations such as bund construction. The use of improved rice varieties tends to drive the adoption pattern of bund technology and dibbling method, implying that the dissemination of interrelated technologies seem to affect adoption rate, which may be either process-induced or due to increasing knowledge and learning effects.

In addition, soil characteristics are found to exert a significant impact on adoption probability. The results suggest that bund technology is more likely adopted on less productive plots while dibbling is more likely adopted on plots that are more productive. Thus, dibbling method seems to be used complementary to productive soils while bund technology appears to be a substitute for productive land. As indicated by the descriptive statistics in section 5.3, negative selection seems to occur in the use of bund technology. This implies that bund construction may be a preventive technology that seems to be a necessary pre-condition for rain-fed rice cultivation on marginal land.

7.2 Determinants of Input Demand, Output Supply, and Net Returns in the Endogenous Switching-regression Framework

The objective of this section is to analyze the impact of the adoption decision on the farmers' demand for farm inputs, output supply, and net returns, controlling for the selection on unobservables, as self-selection of farmers into adoption status might arise.

While the main statistical issue of selection bias in impact evaluation and the econometric framework of the endogenous switching regression model are presented in chapter 6, this section reports the empirical analysis and the results of the impact assessment of technology adoption on outcomes in the framework of the endogenous switching-regression model.

This section is structured as follows: first, it presents the variables included in the models. After that, the estimation results of input demand, rice yields, and net returns for adopters and non-adopters of bund technology and dibbling method are reported. The section then concludes with a discussion and summary of results.

7.2.1 Variables Included in the Model

Net returns are calculated as the revenues minus input costs ('NRET_0') and are measured in GHC per acre⁷³. The nitrogen application rate is given in kg per acre ('N_AC') and is the sum of the nitrogen components of each fertilizer type. Rice yields are measured in bag per acre ('OUT_AC')⁷⁴.

Education is hypothesized to have a positive impact on rice yields, input demand, and net returns by increasing allocative skills. Schultz (1975) argued that education is particularly more likely to be effective under modernizing conditions. However, there is also empirical evidence that education does not contribute to higher crop productivity. Fafchamps and Quisumbing (1998) e.g. show for Pakistan that education raises off-farm productivity and induces rural households to shift labour resources from farm to off-farm activities, while no effect was found on crop and livestock productivity.

The net effect of off-farm activities is a-priori ambiguous, since the participation in off-farm activities may restrict production and decision-making activities. However, off-farm income

⁷³ Input costs include costs for land preparation, fertilizer, herbicides, tarpaulins, sacks and total labour costs (GHC/US\$ (2005) = 9,130.8).

⁷⁴ 1 bag of rice = 82 kg.

may reduce financial constraints, particularly for resource-poor farmers, enabling them to purchase productivity-enhancing inputs, such as nitrogen (Huffman, 1980). Capital constraints may also be alleviated by credit availability. Access to credit permits a farmer to enhance allocative efficiency by enabling him to purchase yield-increasing inputs (such as fertilizer or improved seed). Therefore, credit is assumed to increase net revenue obtained from fixed inputs, market conditions, and individual characteristics (Wozniak, 1993). The variable representing food security of the household is defined as the number of months with food security provided from household's own produce. This variable is included as proxy for the nutrition-related health status, as farmers in the study region are subsistence farmers who primarily try to produce all food they need.

The effect of farm size on productivity is a-priori ambiguous. There is empirical evidence of an inverse farm-productivity relationship such that smaller farms are more productive (see e.g. Byiringiro and Reardon, 1996, for Rwanda; Pender et al., 2004, for Uganda)⁷⁵. The assumption of an inverse relationship between farm size and productivity is commonly based on diminishing returns through a higher family labour endowment per hectare and on more intensive cropping⁷⁶. On the other hand, larger farms could in theory fallow more land and compensate for less family labour per hectare with hired labour, non-labour inputs and capital. Helfand and Levine (2007), e.g., find a non-linear relationship between farm-size and efficiency for Brazil, which is first falling and then rising again. An analysis of Kimhi (2006) shows a monotonic positive relationship between the yield of maize and plot size when considering plot size as an exogenous explanatory variable in Zambia. However, correcting for the endogeneity of plot size results in an inverse relationship in all plots up to 3 ha.

Other explanatory variables include household size, age, plot-level characteristics, distance to the main market Tamale, the use of other technologies (such as improved varieties, intensified weeding), assets, and land preparation method.

7.2.2 Results of the Endogenous Switching-regression Model

The endogenous switching-regression model was estimated with the two-step method using the NLOGIT version 3.0 (Econometric Software, Inc. 2002). The first step was modelled by a univariate probit model of the adoption decision of bund technology and dibbling method to

⁷⁵ Binswanger et al. (1995) provide a very useful survey.

⁷⁶ Other explanations are e.g. size-sensitive cropping pattern, variable soil quality, and temporal price risk (Barrett, 1996).

classify farmers in the regimes of adopters and non-adopters. Results are given in tables 7-4 and 7-5.

The standard errors of adoption decision model are calculated with the Huber/White/sandwich estimator of the variance. To measure the performance of the model, the McFadden- R^2 and the adjusted McFadden- R^2 , as well as the log-likelihood ratio (LR) test are reported in tables 7-4 and 7-5. The adoption probit models for bund construction and dibbling method are significant at the 1% level, suggesting that the regressors as whole influence the adoption probability significantly. Based on theoretical grounds, every model was estimated as a backward stepwise selection procedure, starting from a full model. This is in line with Hendry's methodology (Maddala, 1992). The resulting Akaike information criterion (AIC) is 1.1619 for the estimation of the bund adoption model and AIC equals to 0.8786 for the estimation of the dibbling adoption model.

The univariate adoption decision models of bund technology and dibbling method include the same explanatory variables as the jointly estimated bivariate adoption model that is presented in the previous section does. Comparing the results of the univariate probit model of bund construction with that of the bivariate adoption model shows that the same effects turn out to be significant with the following two exceptions. The signs of the variables related to age ('AGE_R', 'AGE2_R'), which were found to be significant in the bivariate adoption model, are not longer statistically significant at the conventional levels in the univariate adoption model for bund construction. Instead, the positive coefficient of the variable representing the status of the farmer's household ('STATUS_HH'), which was not significant in the bivariate probit model, appears to be significant at the 10% level in the univariate probit model for bund construction. This implies that if the adoption model considers the unobserved effects that may influence both the adoption decision of bund construction and dibbling method, the effect of a higher social status on the adoption probability of bund technology is no longer supported.

Table 7-4: Univariate probit model of the adoption decision of bund construction

Variable	Adoption of bunds		
	Coefficient	Huber/White <i>t</i> -value	Marginal probability
CONS	-0.237	-0.225	
GEQ_HH	0.019*	1.703	0.007
GEQ_ILL	-0.076**	-2.395	-0.028
AGE_R	-0.078	-1.586	-0.029
AGE2	0.001	1.184	0.000
STATUS_HH	0.443*	1.823	0.168
AV_FSZ	0.290**	2.272	0.107
CROP_SZ	-0.049**	-2.234	-0.018
INFS_R	-0.233	-1.139	-0.084
CREDIT	0.402*	1.927	0.149
OFF_R	-0.167	-0.802	-0.061
FSRPOP	0.490**	2.021	0.187
PROJ	0.611**	2.289	0.235
B_EFF	0.521***	2.284	0.191
REPRES	0.255**	2.261	0.094
KY	0.874**	2.414	0.337
ZUWARI	0.181	0.666	0.068
USE_IMP	0.787**	2.365	0.240
TRACTOR	1.144**	2.084	0.429
BUND_CON	-8.518***	-20.623	-0.549
SH_VSOIL	-0.372*	-1.826	-0.137
Obs.		280	
Log-Likelihood Ratio		104.5967 ($\chi^2_{0.99}[20]=37.566$)	
R^2		0.2696	

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

Source: Own calculation

Table 7-5: Univariate probit model of the adoption decision of seed dibbling

Variable	Adoption of dibbling seed		
	Coefficient	Huber/White <i>t</i> -value	Marginal probability
Const	-2.010***	-3.389	
AGE_R	-0.010	-0.846	-0.003
AV_FSZ	0.186	1.526	0.064
FSZ	-0.024	-0.738	-0.008
DIB_CON	-8.727***	19.332	-0.778
CREDIT	0.042	0.154	0.014
FSRPOP	0.903***	3.085	0.263
LRDP	0.683***	2.688	0.231
GEQ_HH	0.025*	1.941	0.009
HEAD	0.622**	2.376	0.207
INFS_R	0.149	0.656	0.051
OFF_R	-0.891***	-4.163	-0.318
CGROUP2	0.501**	2.095	0.166
WEED_R	0.518***	3.817	0.179
CON_L	-0.474**	-2.068	-0.170
DIB_Y	0.751***	3.535	0.264
BULL	-0.359	-1.475	-0.124
SH_VSOIL	0.591***	2.821	0.204
TRACTOR	0.787	1.495	0.207
USE_IMP	0.999***	3.319	0.380
KY	-1.750***	-5.021	-0.616
ZUWARI	-0.419	-1.527	-0.155
Obs.		307	
Log-Likelihood Ratio		159.2090 ($\chi^2_{0.99}[21]=38.932$)	
R^2		0.4124	

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

Source: Own calculation

To shortly summarize the determinants of the adoption of bund construction, the variables representing family land per household member, the participation in the FSRPOP or in other

projects before the LRDP, access to credit, ownership of tractor, use of improved rice varieties, the perception of bunds to be yield-increasing, the share of good experience with the technology reported to the farmer and the above-average social status of farmers' household have the expected positive effect on adoption probability. Area cultivated with other crops indicating opportunity costs of rice cultivation, the number of household members frequently ill and the share of rice area that is high yielding decreases the adoption probability. Furthermore, the indication of farmers to be prevented from bund construction or to have no need for bunds ('BUND_CON') is found to be important in determining the non-adoption of bund technology. In addition, farmers located in Kulda-Yarong valley are less likely to construct bunds. The effects on the adoption decision are discussed in detail in section 7.1.2.

Turning to the results of the adoption decision model of seed-dibbling, findings indicate that the significant effects found in the univariate adoption model of dibbling are the same that turned out to be significant in the bivariate adoption model. Thus, family land per household member, participation in the FSRPOP and LRDP, membership in any crop related group, number of household members, being household head, use of improved rice varieties, the share of rice area that is high yielding, ranking of weeding activity as most constraining labour activity in lowland rice production and the perception of dibbling as yield-increasing are significant in explaining the adoption of dibbling method. On the other hand, off-farm income, ranking of labour as first or second most constraining input in rice production significantly contribute to non-adoption of dibbling. Furthermore, farmers located in Kulda-Yarong valley are less likely to adopt dibbling method. Again, these effects are discussed in detail in section 7.1.2.

The results of the second stage analysis of the switching-regression model for bund adopters and non-adopters are presented in tables 7-6, 7-7, and 7-8. Table 7-6 reports the estimates for nitrogen fertilizer demand, while table 7-7 provides the estimates for output supply. Results of the estimates of net returns are given in table 7-8. Tables 7-9, 7-10 and 7-11 then report the second-stage estimates of the switching-regression model for nitrogen demand, output supply, and net returns for adopters and non-adopters of dibbling seed.

Table 7-6: Switching-regression model of input demand for adopters and non-adopters of bund construction

Variable	Regime 0 (No bunds)		Regime 1 (Bund users)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	16.097***	3.183	32.038***	4.512
AGE_R	0.046	0.649	-0.085	-0.940
EDUC_R	0.049	0.080	1.300	1.318
DEP_HH	-6.724*	-1.788	-0.635	-0.120
STATUS_HH	-0.041	-0.026	6.604**	2.566
HEAD	0.342	0.237	-1.812	-0.813
AV_FSZ	-0.608	-0.599	-0.217	-0.353
R_SZ	-0.757**	-2.058	-1.728**	-2.466
CGROUP	1.857	1.490	1.482	0.759
PROJ	3.095*	1.942	2.137	1.080
CREDIT_05	2.061	1.194	3.385*	1.686
OFF_R	1.298	1.074	0.768	0.381
FOOD_HH	0.611***	2.633	-0.054	-0.179
PRICE_AV	-0.000**	-2.152	-0.000	-1.154
SH_LOAM	-3.659**	-2.504	-3.543*	-1.816
SH_DIB	0.168	0.130	1.779	0.747
DIB_FERT	4.519***	3.205	-0.900	-0.518
CON_FERT	-3.371***	-2.863	-2.621	-1.606
TAMALE	0.142	1.025	-0.377*	-1.659
KY	-6.192**	-2.248	1.014	0.246
ZUWARI	0.638	0.369	-0.772	-0.299
Selectivity terms	0.669	0.496	-5.048**	-2.068
Log-Likelihood Ratio ($\chi^2_{0.99}[21]=38.932$)		100.5316		73.8978
R^2		0.6118		0.4022
Adjusted R^2		0.4687		0.2300
Obs. (selected sample)		79		95

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-7: Switching-regression model of rice yields for adopters and non-adopters of bund construction

Variable	Regime 0 (No bunds)		Regime 1 (Bund users)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	14.392***	3.495	-1.883	-0.496
AGE_R	-0.306	-0.683	0.072*	1.808
GEQ_HH	0.041	0.714	0.004	0.097
DEP_HH	-0.866	-0.363	4.489**	2.025
HEAD	0.697	0.729	-1.699*	-1.901
EDUC_R	-0.032	-0.076	0.956**	2.339
AV_FSZ	2.357***	3.589	-0.154	-0.550
R_SZ	-0.932***	-3.270	-0.984***	-3.330
BULL	2.371**	2.346	0.940	1.231
CGROUP	0.814	1.031	1.198	1.485
CREDIT	1.416*	1.770	0.207	0.262
OFF_SH	-0.045**	-2.426	-0.028	-1.226
PRICE_AV	-0.000*	-1.738	-0.000	-0.223
SH_VSOIL	0.425	0.522	1.869***	2.812
SH_DIB	-0.182	-0.226	-0.011	-0.011
PROJ	-0.037	-0.038	0.492	0.590
MOTOR	-1.685	-0.791	0.332	0.241
TRAC_PL	-1.942*	-1.787	0.242	0.291
USE_WEED	0.550	0.595	2.469***	2.779
DIST_AV	0.031	1.483	0.095**	2.470
TAMALE	-0.065	-0.673	0.245**	2.528
KY	-1.436	-0.758	-4.878**	-2.519
ZUWARI	-0.839	-0.674	0.455	0.432
Selectivity terms	1.220	1.368	-2.005*	-1.697
Log-Likelihood Ratio ($\chi^2_{0.99}[23]=41.638$)	91.2742		89.4780	
R^2	0.5090		0.4222	
Adjusted R^2	0.3353		0.2745	
Obs. (selected sample)	89		114	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-8: Switching-regression model of net returns for adopters and non-adopters of bund construction

Variable	Regime 0 (No bunds)		Regime 1 (Bund users)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	26.704***	3.436	-0.913	-0.127
AGE_R	-0.122	-1.525	0.219***	2.994
DEP_HH	2.378	0.546	8.674	2.145
GEQ_HH	0.080	0.798	-0.047	-0.615
HEAD	2.236	1.284	-2.981*	-1.941
EDUC_R	0.103	0.140	1.964***	2.644
AV_FSZ	3.561***	3.061	-0.423	-0.770
R_SZ	-1.103**	-2.222	-0.630	-1.198
BULL	3.774**	2.156	0.070	0.041
MOTOR	-4.585	-1.052	-4.764	-1.409
CGROUP	-0.151	-0.110	2.209	1.491
PROJ	-0.734	-0.420	-0.586	-0.360
CREDIT	2.869**	1.967	-0.239	-0.166
OFF_SH	-0.082**	-2.282	-0.033	-0.658
PRICE_AV	-0.000***	-2.581	-0.000	-0.282
DIST_AV	0.061	1.624	0.197***	2.914
SH_VSOIL	1.146	0.801	2.243*	1.843
SH_DIB	-0.025	-0.017	-0.415	-0.267
TRAC_PL	-3.607**	-1.911	-2.875*	-1.947
USE_WEED	0.627	0.397	2.466	1.595
TAMALE	-0.327*	-1.921	0.261	0.538
KY	0.411	0.125	-10.037***	-2.873
ZUWARI	-0.792	-0.362	1.717	0.874
Selectivity terms	1.800	1.172	-5.191**	-2.333
Log-Likelihood Ratio ($\chi^2_{0.99}[23]=41.638$)	79.3492		72.8312	
R^2	0.4556		0.3880	
Adjusted R^2	0.2470		0.1841	
Obs. (selected sample)	84		93	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-9: Switching-regression model of input demand for adopters and non-adopters of dibbling

Variable	Regime 0 (No dibbling)		Regime 1 (Use of dibbling)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	0.782	0.109	31.537***	6.424
AGE_R	0.177**	1.997	-0.098	-1.395
EDUC_R	2.840***	2.677	1.511**	2.304
HEAD	-2.073	-1.079	-1.792	-1.155
STATUS_HH	0.539	0.243	5.236	1.035
DEP_HH	-4.829	-0.865	-0.118	-0.030
AV_FSZ	-1.534**	-2.089	-0.234	-0.430
R_SZ	0.097	0.229	-2.305***	-4.230
CGROUP	-1.875	-1.109	3.885***	2.843
PROJ	8.088***	3.981	1.535	1.143
CREDIT_05	8.121***	3.608	1.532	1.035
FOOD_H	0.622**	2.193	0.326	1.423
OFF_R	2.047	1.549	0.244	0.153
PRICE_AV	0.000	0.081	-0.000**	-2.262
SH_LOAM	-1.573	-0.955	-4.141***	-2.837
SH_BUND	2.940*	1.854	-0.304	-0.231
CON_FERT	-3.411***	-2.826	-3.201**	-2.355
TAMALE	0.231	1.081	-0.350**	-2.374
KY	-7.473**	-2.420	5.322	1.243
ZUWARI	2.619	1.131	-0.178	-0.100
Selectivity terms	1.814	1.154	-3.713*	-1.736
Log-Likelihood Ratio ($\chi^2_{0.99}[20]=37.566$)	75.1908		96.0054	
R^2	0.5934		0.4162	
Adjusted R^2	0.3470		0.3147	
Obs. (selected sample)	54		136	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-10: Switching-regression model of rice yields for adopters and non-adopters of dibbling

Variable	Regime 0 (No dibbling)		Regime 1 (Use of dibbling)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	11.106***	2.401	12.153***	3.827
AGE_R	-0.014	-0.345	0.054	0.143
DEP_HH	-4.020	-1.602	5.486***	2.820
GEQ_HH	-0.069	-1.248	0.009	0.211
HEAD	-0.430	-0.469	-0.946	-1.125
EDUC_R	-0.019	-0.038	-0.064	-0.180
AV_FSZ	0.360	0.915	-0.005	-0.17
R_SZ	-0.715***	-3.094	-1.278***	-4.389
CREDIT	1.590**	2.018	0.218	0.305
OFF_SH	-0.060***	-2.651	-0.024	-1.251
MOTOR	3.674	1.505	-2.882**	-2.389
BULL	0.853	0.958	2.920***	3.478
PROJ	1.533*	1.668	0.437	0.653
CGROUP	-0.010	-0.014	0.851	1.224
PRICE_AV	-0.000	-1.320	-0.000**	-1.981
DIST_AV	0.164***	4.010	0.026	1.201
SH_VSOIL	1.356**	1.945	0.605	0.944
SH_BUND	0.424	0.459	-0.371	-0.537
USE_WEED	0.440	0.580	0.589	0.682
TRAC_PL	-3.600***	-3.065	0.724	0.881
TAMALE	0.005	0.046	0.005	0.063
KY	-5.588***	-2.940	1.773	0.888
ZUWARI	-1.237	-1.044	-0.677	-0.679
Selectivity terms	0.998	1.335	-2.840**	-2.333
Log-Likelihood Ratio ($\chi^2_{0.99}[23]=41.638$)	92.0948		90.9070	
R^2	0.6156		0.3418	
Adjusted R^2	0.3999		0.2263	
Obs. (selected sample)	65		155	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-11: Switching-regression model of net returns for adopters and non-adopters of dibbling

Variable	Regime 0 (No dibbling)		Regime 1 (Use of dibbling)	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	20.205***	2.871	22.856***	3.999
AGE_R	-0.067	-1.058	0.036	0.525
DEP_HH	-5.413	-1.417	9.826***	2.794
GEQ_HH	-0.111	-1.344	-0.027	-0.370
HEAD	-0.394	-0.265	-1.146	-0.767
EDUC_R	-0.569	-0.744	-0.099	-0.153
AV_FSZ	0.893	1.503	-0.089	-0.162
R_SZ	-0.768**	-2.158	-1.097**	-2.097
CGROUP	0.259	0.208	0.845	0.678
PROJ	1.210	0.878	0.953	0.808
MOTOR	6.503	1.387	-9.373***	-3.826
BULL	-0.243	-0.181	6.000***	3.451
PRICE_AV	-0.000**	-2.166	-0.000**	-2.092
CREDIT	2.465**	2.109	0.988	0.772
OFF_SH	-0.157***	-4.216	-0.040	-1.107
DIST_AV	0.222***	3.491	0.070*	1.775
SH_VSOIL	2.670**	2.440	-0.036	-0.032
SH_BUND	-0.717	-0.540	-1.905	-1.582
USE_WEED	1.215	1.035	-0.743	0.461
TRAC_PL	-5.051***	-2.959	-1.896	-1.271
TAMALE	-0.305	-1.633	-0.147	-1.039
KY	-4.762	-1.475	1.010	0.288
ZUWARI	-2.683	-1.493	0.302	0.166
Selectivity terms	2.516**	2.042	-5.432**	-2.444
Log-Likelihood Ratio ($\chi^2_{0.99}[23]=41.638$)	93.7506		80.4716	
R^2	0.6455		0.3376	
Adjusted R^2	0.4251		0.1952	
Obs. (selected sample)	61		131	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

The F -test for the joint significance of the explanatory variables shows for all models that regressors are jointly significant (either at the 1% or 5% level). To measure the performance of the models, the adjusted McFadden- R^2 and the log-likelihood ratio are reported. The log-likelihood Ratio (LR) test is calculated as $LR = 2(L_{\Omega} - L_{\omega})$, where L_{Ω} is the unrestricted maximum likelihood and L_{ω} is the restricted maximum log-likelihood with all slope coefficients set equal to zero (Amemiya, 1981). The adjusted McFadden- R^2 is calculated as $R^2 = 1 - L_{\Omega} - K/L_{\omega}$, where K is the number of parameters. Generally, the adjusted McFadden- R^2 is higher for the estimates for the regime of non-adopters than for the regime of adopters in nearly all estimations. Based on theoretical grounds, every model was estimated as a backward stepwise selection procedure, starting from a full model. This is in line with Hendry's methodology (Maddala, 1992).

Identification of the model requires that there is at least one variable in the adoption equation that does not appear in the outcome equations. The use of improved varieties has both a significant and positive effect on the adoption probability of bund technology and dibbling method. This variable is used as identifying instrument and is not included in the outcome equations. Furthermore, the share of reported good results ('REPRES'), that exert a positive and significant effect in the adoption probability of bund technology is used as identifying instruments in estimating fertilizer demand, output supply and net returns for adopters and non-adopters of bunds. In the outcome equations for adopters and non-adopters of dibbling method, the participation in the LRPD, the ranking of weeding activity as most constraining labour activity in lowland rice production and the ranking of labour as first or second most constraining input factor in rice production ('LRDP', 'WEED_R', 'CON_L') are not included, while these variables appear to be significant in explaining the adoption probability of dibbling.

The inverse Mill's ratios (selectivity terms) are found to be significant and negative in all estimations (input demand, rice yields and net returns) for adopters of bund construction and dibbling method. These findings indicate that self-selection occurred in the adoption of the technologies. Hence, adoption of bund technology and adoption of dibbling method may not have the same effect on the non-adopters if they would adopt as it have on adopters. According to Fuglie and Bosch (1995), covariance estimates for non-adopters that are not significantly different from zero imply that prior to adoption there were no significant differences in the average behaviour of the two groups due to unobserved factors. The significance of the inverse Mill's ratio in this analysis suggests that sample selection bias would result if the outcome equations (input demand, yields, and net returns) would be estimated without considering the adoption decision. As Winships and Mare (1992) note, the

signs of covariances between the disturbance term of the selection equation and the outcome equation reveal whether observations are positively or negatively selected into adoption. In case of $\sigma_{AT} > 0$ (covariance between the disturbance term of the selection equation and the outcome equation for adopters), observations are positively selected into adoption. Positive selection implies that those individuals that are most likely to adopt, given the same vector of observed characteristics, have higher outcomes. Hence, negative (unobserved) selection suggests, that those that are most likely to adopt, given that they have the same vector of observed characteristics, have lower outcomes. Furthermore, Fuglie and Bosch (1995) note that alternate signs of the selectivity terms indicate that individuals adopt the new technology based on their comparative advantage: those who adopt have above-average returns from adoption and those who choose not to adopt have above-average returns from non-adoption. If the coefficients have the same sign, it indicates hierarchical sorting: adopters have above-average returns whether they adopt or not, but they are better off adopting, whereas non-adopters have below-average returns in either case, but they are better off not adopting (Maddala, 1991).

The dependency ratio is measured by the proportion of children and elderly living in the compound household. This variable seems to be an important factor in explaining higher rice yields and higher net returns among adopters of dibbling method and bund construction. However, among non-adopters of dibbling method, the effect on rice yields and net returns is found to be negative, *albeit* not significant. The positive relationship for adopters between the proportion of children and elderly in the compound household and rice yields, as well as net returns, reflects that a higher proportion of children and elderly in the household may reduce the labour constraints of dibbling as labour-intensive seed-sowing method. This is because children and elderly are involved particularly in planting (and weeding) activities. Reducing labour constraints of planting also allows investing more time in land preparation and bund construction. This finding is in line with other empirical studies supporting the notion that family labour force increases productivity. Holden et al. (2001) e.g. found that male and female household labour force increases productivity. Household heads seem to have a lower nitrogen application rate than dependent men in the household. However, this effect is not significant in the whole sample. Household heads also tend to have lower yields and net returns than dependent men. However, this effect is only significant for yields and net returns of adopters of bund technology. These results confirm to the expectation that household heads cultivate rice less intensive than dependent men do. It is hypothesized that household heads are less interested in the cultivation of rice as a main cash crop than in production of food staples (such as maize as most important food crop) as they are responsible for feeding

the family, while dependent men are more interested in the cultivation of cash crops (MoFA, 1997). Age exerts a positive and significant impact on rice yields and net returns of adopters of bund technology. For other adopter groups, the age effect is not significant. This contrasts to results of Weir (1999) who found a negative effect of age on productivity in Ethiopia. The coefficient of the educational level turns out to have a positive and significant effect on nitrogen demand in the whole sample, although being only significant for adopters and non-adopters of dibbling method, implying that learning effects are particularly important in the context of interrelated technologies. Furthermore, this result suggests that it is not only literacy but also the level of education that determines demand for nitrogen. With regard to rice yields and net returns, a higher educational level appears to increase these outcomes among adopters of bund technology. This implies that good knowledge and firm understanding of the technology may increase the benefits of bund construction in terms of yields and net returns. The positive impact of education on adoption outcomes is in line with empirical studies (see, e.g., Lockheed et al., 1980). A study of Weir (1999) indicates that level of education contributes to farm productivity in Ethiopia and that returns of education differ between levels of education and between household heads and dependent farmers. A higher status of the farmer's household was found to contribute to a higher nitrogen application rate among adopters of dibbling method. This suggests that higher status may be related to wealth and improved access to information resulting in higher input demand.

The ratio of family land per household member tends to have a negative effect on the demand for fertilizer, although this effect is only significant for non-adopters of dibbling. This finding indicates that a higher family landholding results in a more extensive than intensive rice cultivation, particularly for non-adopters of dibbling. With regard to rice yields and net returns, family landholding per household member appears to contribute significantly to rice yield and net returns of non-adopters of bund construction. However, this effect was not found for other adopter groups. The size of cultivated rice area decreases nitrogen demand in the whole sample. This may be due to the fact that given the constraints in cash availability the fertilizer application rate per acre seems to depend on the size of total rice area. Moreover, farmers cultivating a larger rice area obtain lower rice yields and net returns in all adoption groups. This finding appears to support the inverse relationship between farm size and productivity, which posits that small farms are more productive than large farms, even when the specification accounts for differences in other inputs' use (Binswanger et al., 1995; Barrett, 1996).

Variables indicating wealth and capital constraints are found to influence outcomes, although at varying levels. Access to credit tends to have a positive effect on productivity and net

returns for non-adopting farmers of bund and dibbling technology, though it is not significant for adopters. This suggests that adopters may be less financially constrained such that credits may be simply displaced by another source of financing such as savings. The positive and significant relationship between access to credit and yields is consistent e.g. with the work of Abdulai and Huffman (2000) for Northern Ghana and Abdulai and Binder (2006) for Nicaragua. In case of nitrogen demand, credit received in the cropping season 2005 exerts a positive impact in the whole sample as expected, *albeit* only significant for adopters of bund technology and non-adopters of dibbling method. Among non-adopters of dibbling method, a credit received in the cropping season increases nitrogen demand by 8.121 kg/acre, while nitrogen demand is higher by 3.385 kg per acre among adopters of bund technology. In agreement with this finding, off-farm income tends to increase nitrogen demand in the whole sample, but is not found to be significant. With regard to yields and net returns, the off-farm income share turns out to lower rice yields and net returns among non-adopters significantly, while the off-farm share has a negative but insignificant effect for all adopters. This suggests that non-adopters obtaining off-farm income focus more on off-farm activities than on (intensified) rice production.

This finding is in line with the significant and negative impact of the variable representing access to motorized vehicles on rice yields and net returns for adopters of dibbling method. This indicates that off-farm activities enabled by motorization may decrease time invested in labour-intensive rice cultivation. The variable representing the number of months of food security by the household's own cultivation exerts a positive effect on the nitrogen demand among non-adopters in the sample. This confirms that nitrogen demand seems to be higher with better nutritional status of the household. On the other hand, estimates show that the price of nitrogen fertilizer tends to have a negative impact on nitrogen demand, output supply, and net returns as expected. However, these effects appear to be very small and results are mixed in terms of significance⁷⁷. As expected, weather constraints that prevent farmers from applying the preferred amount of fertilizer (such as flooding or drought) tend to decrease nitrogen demand significantly.

Tractor ploughing appears to decrease rice yields and net returns of non-adopters significantly. This negative relationship suggests that tractor ploughing may postpone land preparation and thus result in late planting due to the limited availability of tractors in the study region. This may in turn decrease productivity. Late planting increases the risk of water

⁷⁷ It is assumed in the analysis that farmers in the study area face the same set of labour prices. Study region is located within a small radius around the regional capital, thus labour wage can be assumed homogenous in the study region.

shortage at the stage of booting, particularly in midlands. In lowlands, late land preparation may face the problem of flooding, which makes planting very difficult. According to the LRDP, timely land preparation is thus a crucial condition for improving rice cultivation (MoFA, 1997). The potential benefits from capital-intensive tractor ploughing do not seem to compensate for the higher costs, resulting in a negative effect on net returns. However, tractor ploughing may be more beneficial for adopters of bund technology, as bunds constructed with tractor during ploughing are more robust than bunds that are constructed manually. For adopters of dibbling method, tractor ploughing may be more rewarding than for non-adopters, as dibbling seed requires a well-prepared seedbed. In contrast, the ownership of bullocks has a positive effect on both yields and net returns, being significant for adopters of dibbling and non-adopters of bund technology. As bunds constructed with bullocks are more robust and have a higher quality, rice yields of farmers who need to construct bunds may be positively affected by the ownership of bullocks. As the use of dibbling as seed-sowing method increases the risk of delays in planting, the ownership of bullock may help to ensure the timeliness of land preparation. A positive effect of animal traction on land and labour productivity was also found in the empirical literature, e.g. by Savadogo et al. (1998).

The participation in any project before the LRDP (being a proxy of motivation and innovativeness of the farmer) has mixed and insignificant effects on rice yields and net returns. For non-adopters of dibbling method however, the effect is found to be positively and significantly related with rice yields. However, this variable exerts a positive relationship to higher nitrogen application among non-adopters in the sample. This may be due to increased understanding and learning effects from previous projects. Similarly, the participation in any crop related farmer group tends to have a positive effect on rice yields and net returns, *albeit* not significant. This implies that farmers participating in farmer groups that focus on other crops than rice may be less interested in rice production.

The use of interrelated technologies appears to impact on outcomes as expected. However, these effects vary according to the type of technology and outcome. Without considering the effects of other determinants, results indicate that adopters of in the whole sample have a higher demand for nitrogen than non-adopters, while rice yields and net returns are higher for the non-adopters of bund technology and the adopters of dibbling method. Among non-adopters of dibbling, bund construction turns out to have a positive and significant effect on nitrogen demand. However, this effect is not significant for adopters of dibbling, implying that bund construction does not have a statistically significant influence on nitrogen demand among adopters of dibbling method who have a higher level of nitrogen demand than non-adopters (without considering other effects). With regard to dibbling, the use of dibbling as

fertilizer application method is found to increase the demand for nitrogen among non-adopters of bund technology, while this effect is not found among adopters of bund technology. With regard to rice yields and net returns, the use of bunds does not appear to be an important factor among adopters and non-adopters of dibbling method. In contrast, looking at yields and net returns, the share of rice area where seed is dibbled is not found to explain variations in these outcomes among both adopters and non-adopters of bund technology. However, farmers who adopted bund technology have higher rice yields and net returns when doing intensified weeding.

Data also reveal that the geographic location of the farm seems to impact on outcomes. The access to the market that is measured by the distance to the main market Tamale exerts a negative and significant effect on nitrogen demand of adopters of bund construction and dibbling method. This finding implies that a better access to the market, resulting in lower transportation costs, increases nitrogen demand among adopters of interrelated technologies. Furthermore, a positive and significant relationship was found between plot distance to the homestead and yields, as well as net returns. This effect is particularly significant for adopters of bund technology and non-adopters of dibbling seed method. This is in line with the fact that as lowland cultivation area was extended with the start of the LRDP, this new lowland area is more distant than traditionally cultivated plots and can be assumed more productive as it was not cultivated before. Furthermore, farmers located in Kulda-Yarong river valley tend to have lower input demand, rice yields, and net returns. Reason for this finding may be due to different climatic conditions between the valleys in 2005 or due to ethnic differences.

Estimates furthermore reveal that plot-level characteristics tend to affect rice yields, net returns, and input demand. A higher share of loamy soil tends to decrease nitrogen application significantly, with this effect on nitrogen demand being more pronounced with adoption than without adoption. Furthermore, a higher share of very fertile rice cropping area has a positive and significant influence on rice yields and net returns among adopters of bund technology and non-adopters of dibbling technology. The positive relationship between fertile soils and rice yields, as well as net returns is as expected. The insignificant effect of fertile soils on rice yields and net returns for adopters of dibbling method suggest that among adopters of dibbling there may be little variation in soil fertility, or other factors may be more important for adopters of dibbling to explain variations in productivity and net returns. The significant influence of soil variables suggests that estimates are likely to be biased if environmental variables are omitted. This finding is in line with the argument put forward by Sherlund et al. (2002).

7.2.3 Concluding Remarks

The results of the two-step endogenous switching regression model suggest that farmers include technology choice in their production decisions. The findings indicate that the adoption decision and the outcomes (net returns, rice yields, and nitrogen demand) are influenced by different variables. Furthermore, different determinants are significant in explaining the outcomes for adopters and non-adopters. The inverse Mill's ratios (selectivity terms) are found to be significant and negative in all outcome estimations for adopters of both bund construction and dibbling method, while selectivity terms appear to be positive but mostly not significant for non-adopters. Thus, sample selection bias would result if the outcome equations are estimated without accounting for self-selection of farmers into adoption status. Hence, the results underline the necessity of accounting for selection bias and for specifying separate equations for adopters and non-adopters.

Data show that economic constraints appear to determine variations in nitrogen demand, yields, and net returns. In particular, capital and labour constraints seem to be important factors in determining these outcomes. In addition, the use of interrelated technologies, as well as learning effects through the dissemination of interrelated technologies turn out to impact on outcomes such as fertilizer demand, output supply, and net returns. Furthermore, social networks such as farmer groups, the availability of land preparation equipment, plot-level characteristics and the distance from the market seem to be significant factors. However, the effects vary in the level and significance according to the type of technology and outcome. Policy implications of the results will be provided in chapter 8.

7.3 Non-parametric Impact Assessment

Based on the results of the adoption decision model given in section 7.1, this section investigates the impact of technology adoption on outcomes in the non-parametric framework of the propensity score matching method. First, this section presents the variables included in the models. After that, the results of impact assessment are reported. The section then concludes with a discussion of results.

7.3.1 Variables Included in the Matching Process

Outcome and treatment variables

Net returns of rice cultivation per acre are calculated as the revenue minus costs for fertilizer (sulphate of ammonia, NPK, urea), herbicides, land preparation, tarpaulins, sacks and total labour costs. Net returns per acre are represented by the variable 'NRET_AC' and measured in GHC per acre⁷⁸. The outcome variable 'OUTP_AC' represents output of lowland rice cultivation and is measured in bags per acre⁷⁹. Furthermore, the nitrogen application rate is represented by the variable 'N_AC' and measured in kg/acre. Treatment variables are 'USE_D' that equals to one if the farmer dibbled seed in 2005 and 'USE_B' that equals to one if the farmer constructed bunds in 2005. The treatment variable 'USE_D_SF' equals to one if the farmer uses dibbling as seed-sowing and fertilizer application method (instead of broadcasting). The variable 'USE_INTEN' takes the value one if dibbling method was combined with intensified weeding (double manual weeding).

Covariates included in the matching process

The propensity scores are estimated by employing probit models that include various household and farm characteristics as regressors. As Heckman et al. (1998) note, in small samples it matters which variables are included in the propensity score matching. As noted by Caliendo and Kopeinig (2008), matching should be based on variables that influence both treatment assignment and outcomes and that are not affected by the treatment to fulfil the conditional independence assumption⁸⁰. To avoid post-treatment bias and overmatching, only variables that are unaffected by the participation decision are included in the model (Baser, 2006; Caliendo and Kopeinig, 2008). However, including variables that are only weakly related to treatment assignment usually reduces bias more than it increases variance (Heckman et al., 1998). Thus, variables affecting outcome even if they are only weakly related to the adoption decision are also included in the matching process. Furthermore, a

⁷⁸ GHC/US\$ (2005) =9,130.8.

⁷⁹ 1bag of rice = 82 kg.

⁸⁰ Bryson et al. (2002) give an intuitive justification, why only those variables that affect participation and outcome should be included: Variables that affect neither participation nor outcome are clearly irrelevant. Variables that influence only participation have not to be included as there is no need to control for the differences between the treatment and the comparison group since the outcome variable of interest is not affected. If a variable influences only the outcome variable, there is no need to control for it since it will not be significantly different between the treatment and comparison groups. Variables that affect both treatment and outcome will differ systematically between the treatment and comparison groups and significantly influence observed outcomes in the two groups. Thus, these variables should enter the matching model (Bryson et al., 2002).

larger set of variables is preferred as it makes it less likely that unobservables remain out of the matching process as omitting important variables could seriously increase bias (Heckman et al., 1997; Dehejia and Wahba, 1999). In practice, empirical evidence found that the bias tends to be higher where cruder sets of conditioning variable are used (Heckman et al., 1998; Lechner, 2000; Smith and Todd, 2005).

The main purpose of the propensity score estimation is not to predict selection into treatment as well as possible but to balance all covariates (Augurzky and Schmidt, 2001)⁸¹. The specification of the propensity score estimation and the choice of the matching algorithm are therefore based on the assessment of the matching quality. The specification of the propensity score model has to be fine-tuned e.g. by including non-linear, higher-order or interaction terms if differences in the covariates in the two groups in the matched sample still remain indicating that the estimated propensity score might not be an adequate balancing score or that a different matching approach should be used (because for a given data set, covariate differences are removed to a different extent by the different approaches of using the propensity score) or both (Caliendo and Kopeinig, 2008; Lee, 2008). The choice of which higher order terms to include is determined solely by the need to obtain an estimate of the propensity score that satisfies the balancing hypothesis (Becker and Ichino, 2002). Thus, the squares of the age of the rice farmer ('AGE2_R'), the farm size ('FSZ2_100'), and of the average family landholding per household member ('AV_FSZ_2_100') are included in propensity score estimations⁸². However, as Mendola (2007) underlines, a 'too good' specification is not helpful for impact assessment (while it is the objective to 'well' specify the propensity scores for adoption) as this makes it more complicated to find matching partners, when the overlap between both groups becomes very limited (Mendola, 2007).

Variables are selected for the estimation of treatment effects based on the results of the bivariate probit model explaining the adoption decision of bund technology and dibbling method. The explaining data set used for impact analysis contains different categories of variables. These include socio-economic characteristics (such as age of the respondent, education, household-headship), resource endowment characteristics and constraints (such as farm size, off-farm income, access to credit, family land holding, assets such as the ownership of bull, tractor or bicycles), institutional characteristics (such as participation in

⁸¹ Including interaction terms should be considered carefully, as adding an inappropriate interaction term could alter the estimated propensity score, possibly introducing bias to the estimate (Baser, 2006).

⁸² The variables 'FSZ2_100' and 'AV_FSZ_2_100' are the squares divided by 100.

LRDP and FSRPOP), as well as plot-level characteristics (such as water retention, soil fertility).

The decisions to use dibbling method and bund technology are not made independently. Thus, the decision to use dibbling as seed sowing method may affect both the adoption decision of bund construction, as well as outcomes. Therefore, the use of dibbling is included in the estimation of the propensity scores of bund technology. Similarly, the use of bund construction is included in the estimation of the propensity scores for the impact analysis of the dibbling method, as the use of bund technology is assumed to influence adoption probability of dibbling, as well as outcomes. The variable 'DROUGHT' indicates whether the farmer has experienced drought during application time of first fertilizer and is assumed to be strongly related with outcome. It is only included in the impact assessment of dibbling technology as the experience of drought may be endogenous to the use of bunds. The price of nitrogen per kg ('PRICE_AV') and the use of improved varieties ('USE_IMP') are assumed to be strongly related with outcomes and are therefore included in all propensity score estimations.

The Mahalanobis metric matching (MMM) is based on the propensity score and a subset of conditioning variables that may be strongly related with the outcome. Including these conditioning variables increases their weight in the matching process. The propensity score is then somehow a 'partial' balancing score that is complemented by an additional set of covariates to obtain perfect matches with respect to specific variables that might be highly correlated with the outcome variables, as well as with selection (Lechner, 1998, 2002). This method is particularly useful in the present analysis with multiple treatments. To assess the unconfounded impact of technology adoption it is necessary to control for the region and the use of other technologies (bund technology or dibbling respectively, use of improved varieties and region, related technologies). Otherwise, observations having similar propensity scores but from different regions or using different interrelated technologies could be matched⁸³. However, Abadie and Imbens (2006) show that using more than one continuous covariate for Mahalanobis metric matching may result in a matching discrepancy. Furthermore, according to Guo et al. (2006), MMM is not good with many covariates. For this reason, the number of variables additional to the propensity score is kept as small as possible and the propensity score is the only continuous variable included.

⁸³ Due to sample size, for evaluating the impact of bund technology observations for which 'BUND_CON' equals to 1 are dropped. For estimations of the treatment effect of dibbling method observations for which 'DIB_CON' equals to 1 are dropped.

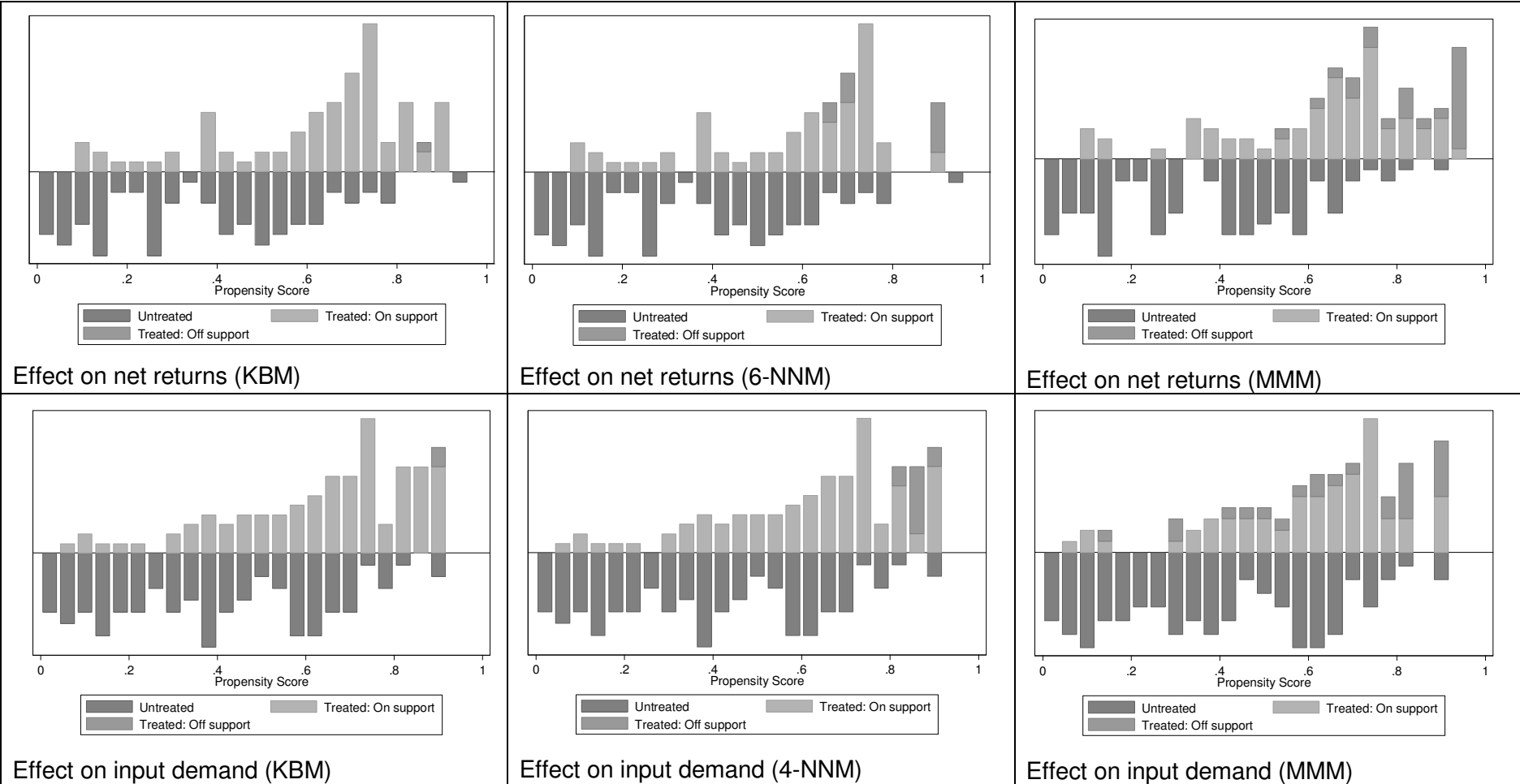
7.3.2 Results of Matching Procedure

The estimation of the average treatment effects and the sensitivity analysis was conducted using the STATA suites 'psmatch2', 'pstest', 'psgraph' (Leuven and Sianesi, 2003) and 'rbounds' (Gangl, 2004). 'Rbounds' calculates the Wilcoxon signrank tests that give the upper and lower bound estimates of significance levels at different levels of hidden bias.

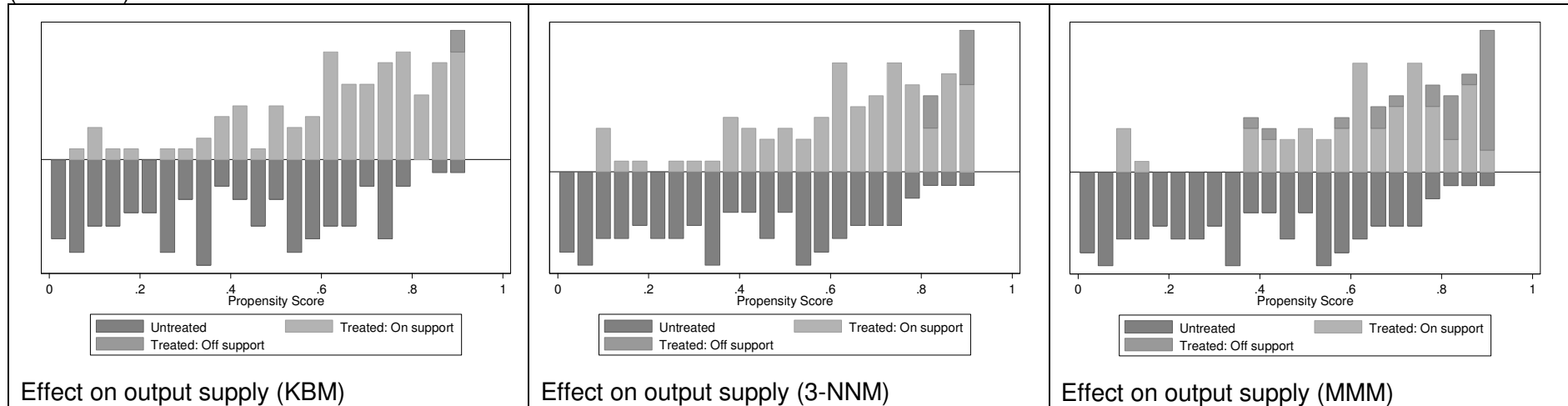
Given that the results of the bivariate probit model indicate a good predictive power of adoption status by explanatory variables and given the rich set of variables included in the matching procedure it seems to be plausible to assume that the CIA holds.

The matching is performed only in the region of common support, which is imposed by dropping observations from the adopter group whose propensity score is higher than the maximum or less than the minimum propensity score of the controls (Leuven and Sianesi, 2003). The distributions of the propensity scores and the regions of common support are presented in figures 7-1, 7-2, 7-3 and 7-4.

Figure 7-1: Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of bund technology

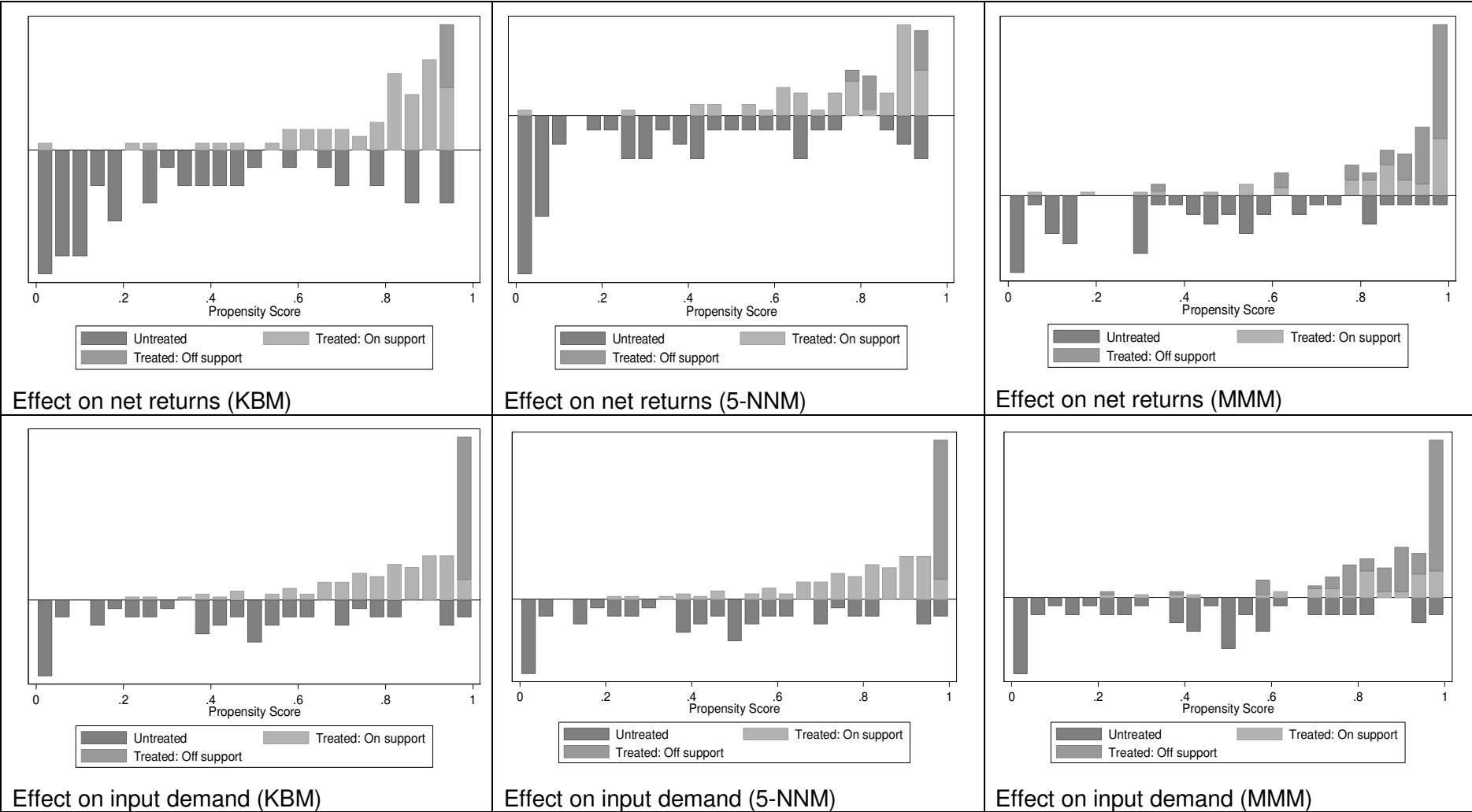


Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of bund technology (continued)

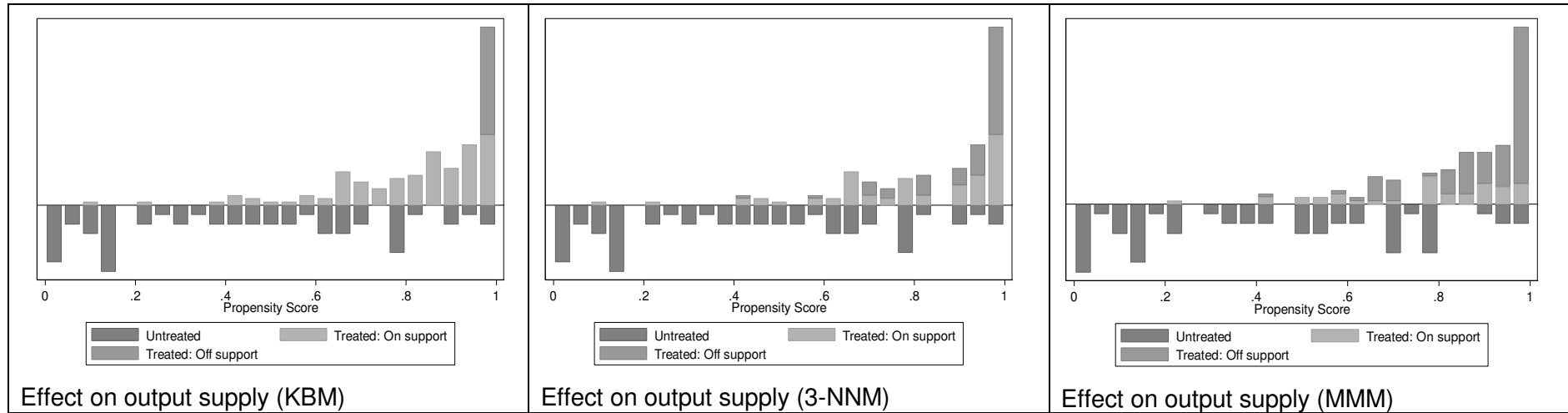


Source: Own calculation

Figure 7-2: Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed

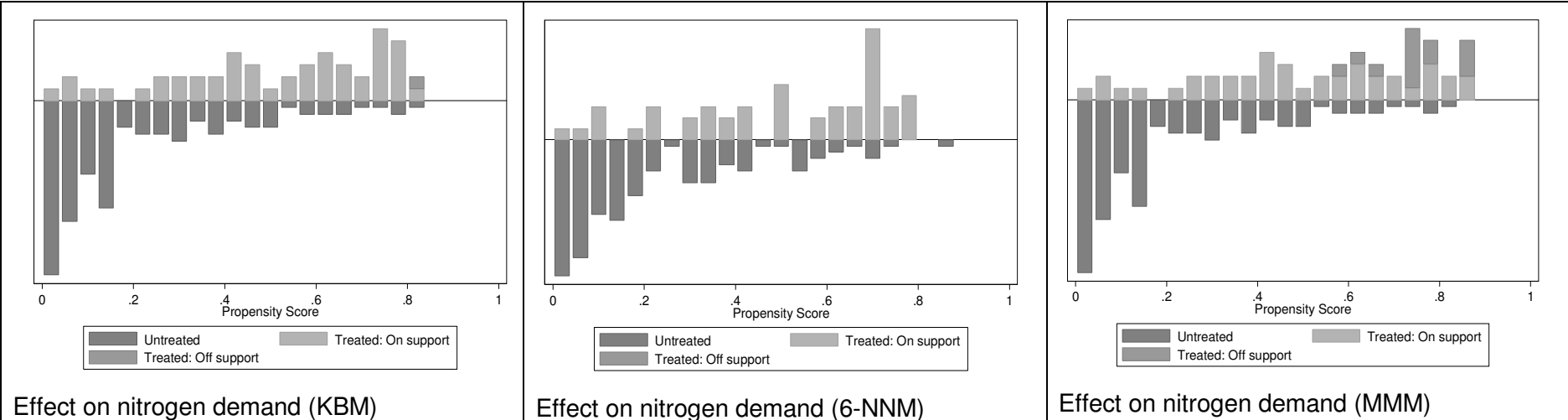


Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed (continued)



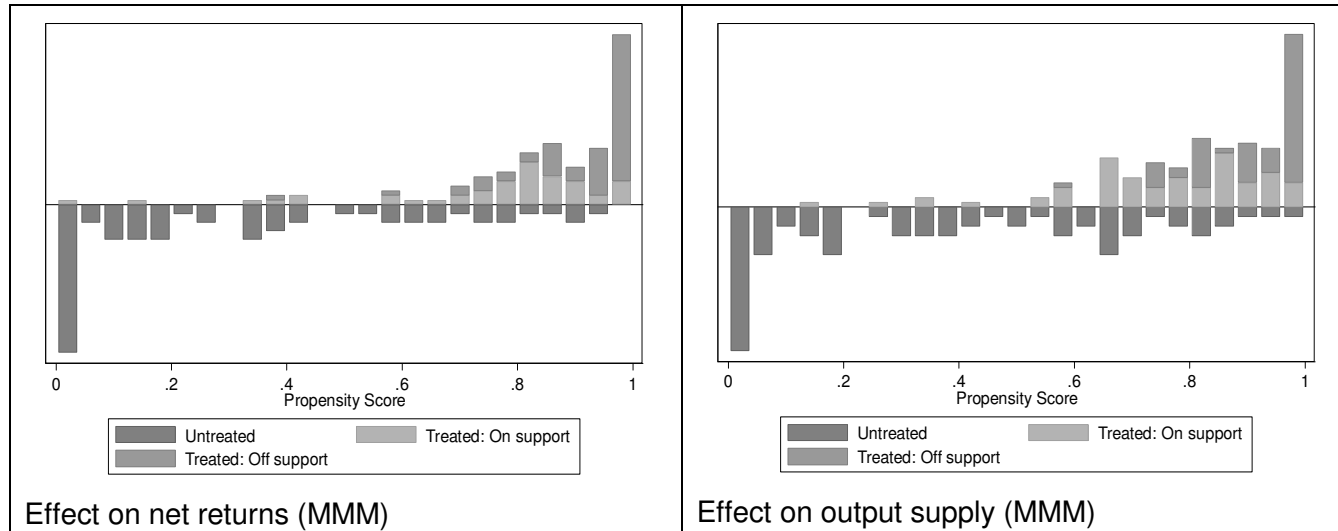
Source: Own calculation

Figure 7-3: Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed and fertilizer



Source: Own calculation

Figure 7-4: Propensity score distribution and common support for propensity score estimation in the estimation of the causal effect of dibbling seed and fertilizer



Source: Own calculation

These figures show the bias in distributions of propensity scores between the treated and untreated groups. They serve to underline the general importance of proper matching, as well as the importance of imposing the common support condition and calipers to avoid bad matches.

Tables 7-12 and 7-14 provide the estimates of the average adoption effects of bund and dibbling technology, while table 7-16 reports the estimated average adoption effects of dibbling both seed and fertilizer and table 7-18 presents the effects for dibbling seed and fertilizer combined with intensified weeding. The number of actual matches of treated and untreated observations and the number of lost observations due to the imposition of the common support condition are given in the last two columns. The propensity score estimations are given in the appendix (tables A. 2 to A. 10). While the Pseudo- R^2 of the propensity score estimates for bund technology ranges between 0.2468 and 0.2558, the Pseudo- R^2 of the propensity score estimates for dibbling method is higher and in the range of 0.3765 and 0.4958 (see tables A. 2 to A. 8).

Since the propensity scores serve only as device to balance the observed distribution of covariates across the treated and the untreated groups, the success of propensity score estimation is assessed by the resultant balance (Lee, 2008). Thus, an interpretation of the propensity score estimations does not need to be undertaken here. Balancing tests are reported in tables 7-13, 7-15, 7-17 and 7-19. Columns 3 and 4 present the median absolute standardized bias before and after matching (taken over all regressors), respectively. In the fifth column, total bias reduction is reported. The bias before matching lies between 18% and 29%. After randomization, the remaining standardized difference in the relevant observable covariates Z lies between 4% and 10% and is quite below the critical level of 20% that is considered as 'large' by Rosenbaum and Rubin (1985). Total bias was more than halved in all estimation indicating a significant reduction, with total bias reduction ranges between 51% and 84%. Additionally, tables 7-13, 7-15, 7-17 and 7-19 show the pseudo- R^2 from the propensity score estimation and the re-estimation of the propensity score after matching on the matched samples in the sixth and seventh column as suggested by Sianesi (2004). The corresponding p -values of the likelihood-ratio test of the joint significance of all the regressors in the probit model before and after matching are presented in columns 8 and 9. In all estimations, the variance of adoption status explained by the covariates declined substantially after matching. The corresponding p -values of the likelihood-ratio test of the joint insignificance of all the regressors before and after matching indicate that after matching, the significance of the regressors on treatment status could always be rejected (Sianesi, 2004). Before matching, the significance of the regressors was never been rejected

at the 1% level. These indicators hence indicate successful randomization. Matching process thus appears to create a high degree of covariate balance between the groups of adopters and non-adopters.

Table 7-12: Average treatment effects for adopters of bund technology and critical levels of hidden bias

Outcome	Outcome difference unmatched	<i>t</i> -stat.	Matching algorithm	Caliper	ATT	<i>t</i> -stat.	Critical level of Γ (hidden bias)	No. Treated No. Controls On support	Loss of observations due to common support
Net returns (GHC per acre)	-55,477.024	-0.62	6- NNM	0.01	76,005.959	0.51	–	65 90	31
			KBM	–	62,983.420	0.43	–	84 90	12
			Mahalanobis	1.0	123,915.467	0.76	–	68 90	28
Demand for N (kg per acre)	1.154	1.11	4-NNM	0.025	2.295	1.63	–	92 98	28
			KBM	–	1.558	0.98	–	101 98	19
			Mahalanobis	0.01	3.045	1.88*	1.45	67 98	53
Average output (bags per acre)	0.013	0.02	3-NNM	0.02	0.554	0.67	–	95 97	24
			KBM	–	0.319	0.36	–	100 97	19
			Mahalanobis	0.05	0.795	0.82	–	75 97	44

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-13: Indicators of covariate balancing, before and after matching (bund technology)

Outcome	Matching algorithm	Median absolute bias (before matching)	Median absolute bias (after matching)	(Total) % bias reduction	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	p -value of LR (unmatched)	p -value of LR (matched)
Net returns (GHC per acre)	6-NNM	18.547	6.808	63.288	0.245	0.067	0.000	0.957
	KBM	18.547	8.925	51.860	0.245	0.062	0.000	0.916
	Mahalanobis	18.547	5.650	69.537	0.247	0.133	0.000	0.309
Demand for N (kg per acre)	4-NNM	20.218	5.106	74.745	0.252	0.033	0.000	0.998
	KBM	20.218	6.839	66.173	0.252	0.032	0.000	0.996
	Mahalanobis	20.072	7.839	60.944	0.252	0.077	0.000	0.857
Average output (bags per acre)	3-NNM	20.533	4.330	78.912	0.256	0.044	0.000	0.978
	KBM	20.032	5.331	73.388	0.256	0.045	0.000	0.975
	Mahalanobis	20.533	5.556	72.941	0.256	0.067	0.000	0.929

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-14: Average treatment effects for adopters of seed dibbling and critical level of hidden bias

Outcome	Outcome difference unmatched sample	<i>t</i> -stat.	Matching algorithm	Caliper	ATT	<i>t</i> -stat.	Critical level of Γ (hidden bias)	No. Treated No. Controls On support	Loss of observations due to common support
Net returns (GHC per acre)	226,956.384	2.19**	5-NNM	0.05	297,170.755	1.85*	1.35	58 50	69
			KBM	–	263,336.593	1.73*	1.50	66 50	61
			Mahalanobis	0.1	149,944.257	0.66	–	48 50	79
Demand for N (kg per acre)	3.562	3.12***	5-NNM	0.05	0.211	0.13	–	106 54	48
			KBM	–	0.238	0.14	–	106 54	48
			Mahalanobis	0.75	1.433	0.52	–	44 54	110
Average output (bags per acre)	1.676	2.72**	3-NNM	0.01	2.440	2.74**	2.15	73 54	79
			KBM	–	1.454	1.55	–	120 54	32
			Mahalanobis	0.075	1.945	2.14**	1.45	44 54	108

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-15: Indicators of covariate balancing, before and after matching (dibbling seed technology)

Outcome	Matching algorithm	Median absolute bias (before matching)	Median absolute bias (after matching)	(Total) % bias reduction	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	p -value of LR (unmatched)	p -value of LR (matched)
Net returns (GHC per acre)	5-NNM	23.309	8.488	63.578	0.490	0.122	0.000	0.807
	KBM	21.493	8.466	60.586	0.496	0.129	0.000	0.546
	Mahalanobis	23.309	10.231	56.107	0.418	0.193	0.000	0.303
Demand for N (kg per acre)	5-NNM	21.160	6.602	68.800	0.380	0.049	0.000	0.806
	KBM	21.160	6.136	71.002	0.380	0.051	0.000	0.785
	Mahalanobis	20.768	4.066	80.422	0.381	0.167	0.000	0.510
Average output (bags per acre)	3-NNM	21.985	9.960	54.696	0.379	0.156	0.000	0.141
	KBM	22.663	8.958	60.473	0.379	0.087	0.000	0.178
	Mahalanobis	22.427	10.251	54.292	0.376	0.149	0.000	0.589

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-16: Average treatment effects for adopters of both dibbling seed and fertilizer and critical value of hidden bias

Outcome	Outcome difference unmatched	<i>t</i> -stat.	Matching algorithm	Caliper	ATT	<i>t</i> -stat.	Critical level of Γ (hidden bias)	No. Treated No. Controls On support	Loss of observations due to common support
			6-NNM	0.1	4.690	2.68**	2.25	49 122	19
Demand for N (kg per acre)	2.902	2.67**	KBM	–	5.183	3.15***	2.60	48 122	20
			Mahalanobis	0.1	5.374	3.19***	2.05	41 122	27

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level
Source: Own calculation

Table 7-17: Indicators of covariate balancing, before and after matching (dibbling seed and fertilizer)

Outcome	Matching algorithm	Median absolute bias (before matching)	Median absolute bias (after matching)	(Total) % bias reduction	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	p -value of LR (unmatched)	p -value of LR (matched)
Demand for N (kg per acre)	6-NNM	22.593	8.053	64.356	0.346	0.088	0.000	0.890
	KBM	19.603	4.523	76.927	0.366	0.054	0.000	0.996
	Mahalanobis	19.603	4.372	77.697	0.366	0.105	0.000	0.918

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-18: Average treatment effects for adopters of intensified technology package

Outcome	Outcome difference unmatched	<i>t</i> -stat.	Matching algorithm	Caliper	ATT	<i>t</i> -stat.	Critical level of Γ	No. Treated No. Controls On support	Loss of observations due to common support
Net returns (GHC per acre)	246,292.360	2.51**	Mahalanobis	0.08	220,406.064	1.71*	1.20	47 61	65
Average output (bags per acre)	1.799	3.16***	Mahalanobis	0.06	1.691	2.05**	1.35	69 70	67

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table 7-19: Indicators of covariate balancing, before and after matching (impact of intensified technology package)

Outcome	Matching algorithm	Median absolute bias (before matching)	Median absolute bias (after matching)	(Total) % bias reduction	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	p -value of LR (unmatched)	p -value of LR (matched)
Net returns (GHC per acre)	Mahalanobis	28.892	4.459	84.563	0.470	0.134	0.000	0.739
Average output (bags per acre)	Mahalanobis	22.569	5.913	73.800	0.394	0.053	0.000	0.986

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

The estimated average treatment effect of bund technology on net returns is in the range of 62,983.420 GHC per acre and 123,915.467 GHC per acre, though not significantly different from zero. This is not surprising, as net returns do not appear to be significantly different between adopters and non-adopters of bund construction in the unmatched sample. In the unmatched sample, the net returns of farmers using bunds is even lower than that of non-adopters (55,477.024 GHC per acre), though not significant. Thus, the causal effect of bund construction found by balancing the distribution of covariates is higher than the effect without controlling self-selection, *albeit* not significant. Using 6-nearest neighbour matching with a very stringent caliper of 0.01, an adoption effect of bund construction on net returns of 76,005.959 GHC per acre is found, *albeit* not significant. An average adoption effect of 62,983.420 GHC per acre was estimated by employing kernel based matching and an effect of 123,915.467 GHC per acre was found with Mahalanobis metric matching and a caliper of 1.0. The calculation of the Mahalanobis distance to estimate the impact of bund technology on net returns is based on the propensity score and the use of dibbling seed, the use of improved varieties, regional dummies, education ('INFS_R') and household headship ('HEAD'). The highest bias reduction was obtained by applying MMM where the bias reduction is 69.53%, while it is slightly lower for 6-NNM (63.29%), compared to 51.86% achieved by KBM. After matching, the variance of the treatment status explained by the regressors declined substantially across all matching algorithms.

With regard to the adoption effect of bund construction on rice yields, the impact of bund technology on output supply was found not to be significant. The ATT estimated with 3-NNM and a caliper of 0.02 suggests that adopters obtain a rice yield that is higher by 0.554 bags per acre than that obtained by non-adopters. Applying the KBM procedure shows that adopters obtain higher yields than non-adopters (with a difference of 0.319 bags per acre). MMM procedure is based on the propensity score and the use of seed dibbling, the use of improved varieties and regional dummies as additional variables. The MMM approach with a caliper of 0.05 results in an estimated ATT of 0.795 bags per acre. This result is consistent with the finding that in the unmatched sample bund technology is not found to be significant in explaining output supply by the *t*-statistic of mean difference. However, in all cases the matching procedure obtained a clear bias reduction in the range of 73% to 79%.

With regard to input demand, estimations show varying results across the applied matching algorithms. Without controlling for other effects, no significant adoption effect of bund construction on demand for nitrogen is found in the unmatched sample. In case of 4-nearest neighbour matching with a caliper of 0.025, an adoption effect of bund technology on nitrogen application rate of 2.295 kg per acre was found, *albeit* not significant. The effect of

bund construction estimated with KBM method is lower (1.558 kg per acre), but was also found not to be significant. The causal effect found by MMM with a caliper of 0.01 (based on the propensity score, regional dummies, and the use of dibbling and improved varieties) equals to 3.045 kg per acre and appears to be significant at the 10% level, suggesting that demand for fertilizer is higher for adopters of bund construction by 3.045 kg per acre. This increase in fertilizer demand may be due to the fact that bund technology reduces the risk of fertilizer to be washed away. This finding implies that the dissemination of technologies seems to affect the extent of adoption of interrelated technologies. The differences in the estimates across the matching algorithms may be due to the fact that the KBM process uses the weighted average of the outcome variable of the whole control group to construct the counterfactual outcome. This may result in estimation bias as matches that are more distant may be accepted. Furthermore, in contrast to Mahalanobis metric matching, KBM and NNM do not specifically control for covariates that may be strongly correlated with the outcome.

Nitrogen demand is not found to be significantly different between adopters and non-adopters of dibbling seed by applying the matching method. The causal effect of adoption estimated employing 5-NNM with a stringent caliper of 0.05 equals to 0.211 bags per acre. Employing KBM results in an adoption effect of 0.238 bags per acre. Using MMM (based on the propensity score, the use of bund technology and improved varieties, occurrence of drought, regional dummies, and membership in a crop related farmer group) with a caliper of 0.75 results in an adoption effect of 1.433 bags per acre. All matching algorithms achieve a significant bias reduction in the range of 69% to 80%. These results suggest that the significant difference in input demand found in the unmatched sample is not due to the adoption of dibbling seed. To further explore the significant difference in nitrogen demand in the unmatched sample, the average adoption effect of dibbling both seed and fertilizer instead of broadcasting is estimated. Contrary to the insignificant adoption effect of dibbling seed, the causal effect of dibbling both seed and fertilizer is found to be significant at the 5% and 1% level in explaining differences in nitrogen demand. Employing 6-NNM with a caliper of 0.1, KBM, and MMM with a caliper of 0.1 suggests an average adoption effect of 4.690 bags per acre, 5.183 bags per acre and 5.374 bags per acre, respectively. A substantial reduction in bias could be obtained in all matching approaches. In case of NNM, the remaining standardized median bias is 8.05%. In case of KBM the standardized bias after matching is 4.52%, while the remaining standardized bias is 4.37% in case of MMM. Controlling for covariates related to adoption decision and nitrogen demand, the use of dibbling as seed sowing and fertilizer application method appears to be an important factor in explaining higher nitrogen demand. While adopting only seed-dibbling does not seem to

increase nitrogen demand, dibbling both seed and fertilizer, instead of broadcasting, increases nitrogen demand by about 4–5 bags per acre. This positive effect may be induced by learning effects and increasing knowledge of interrelated technologies or may be process-induced. Given the very low fertilizer application rate, dibbling fertilizer may require more fertilizer than broadcasting. Furthermore, dibbling fertilizer ensures effective uptake of fertilizer, while top-dressing fertilizer increases the risk that the fertilizer is washed away, increasing the potential benefit of fertilizer application.

Looking at the effect of dibbling seed on rice output, average output tends to be higher for adopters of seed-dibbling than for non-adopters in the matched sample. Applying 3-NNM gives an estimated causal effect of 2.440 bags per acre that is significant at the 5% level. The estimated average treatment effect by employing MMM (based on propensity score, literacy, use of bund technology and improved varieties, occurrence of drought and household headship) with a caliper of 0.075 is significant at the 5% level and equals to 1.945 bags per acre. Contrary to the NNM and MMM approach, KBM indicates an insignificant technology effect on yields with 1.454 bags per acre. As indicated by the number of observations included in the matching process, this difference is because kernel based matching uses more distant observations. This may result in higher estimation bias.

Turning to the adoption effect of dibbling seed on net returns, results indicate that dibbling seed has a significant impact on net returns in the unmatched sample. While 5-NNM and KBM confirm this positive and significant effect in the matched sample, MMM suggests that there is no significant effect of dibbling seed on net returns. The effect found by NNM and KBM is significant at the 10% level and even higher than the adoption effect found in the unmatched sample with $ATT=297,170.755$ GHC per acre in case of NNM and $ATT=263,336.593$ GHC per acre in case of KBM. However, by controlling for other relevant variables, results of MMM indicate that the adoption effect only equals to 149,944.257 GHC per acre, *albeit* not significant. Bias in the distribution of the covariates was more than halved in all matching approaches. The highest reduction was obtained by NNM where bias reduction was 63.58% and bias declined from 23.31% to 8.49%. In case of KBM, the bias declined from 21.49% to 8.47%. The bias reduction of 56.11% in case of MMM results in a decline of the median standardized bias from 23.31% to 10.23%, implying an adequate balancing power.

The adoption of the technological package consisting of dibbling seed and fertilizer (instead of broadcasting) and intensified weeding is found to increase net returns by 220,406.064 GHC per acre by using Mahalanobis metric matching. This effect is found to be significant at the 10% level. The causal adoption effect of this technological intensification package on rice

output is significant at the 5% level and equals to 1.691 bags per acre. Both effects are also found to be significant in the unmatched sample. Balance checks indicate adequate removal of bias by applying MMM; with the median standardized bias decline from 28.89% to 4.46% in case of net returns, while the corresponding reduction for output is from 22.57% to 5.91%.

To check whether unobserved factors can alter inference about adoption effects, column eight of tables 7-12, 7-14, 7-16 and 7-18 presents the critical level of hidden bias (Γ) at which the causal inference of significant adoption effects has to be questioned. As noted by Hujer et al. (2004), sensitivity analysis for insignificant adoption effects is not meaningful and therefore not considered here. Given that the estimated significant adoption effects are positive, the upper bound significance level that is derived under the assumption that the estimated adoption effect overestimates the true adoption effect (due to positive unobserved selection) is critical. Then, the test-statistic is too high and should be adjusted downwards. The lower bounds on the significant level that are derived under the assumption that the true adoption effect has been under-estimated are less interesting in this case and are not reported here (Becker and Ichino, 2007).

The significant positive effect of bund technology on input demand obtained by applying MMM may no longer be significant at a level of Gamma of 1.45. A value of Gamma of 1.45 implies that individuals who have the same z -vector differ in their odds of adopting the technology by a factor of 1.45 or 45% (Hujer et al., 2004). This is the critical level of unobserved heterogeneity at which the conclusion of a positive effect of bund construction on fertilizer demand has to be questioned. This means, that even though adopting and non-adopting individuals are equally distributed in terms of observed variables, if they differ in their odds of adopting the technology by a factor of 1.45 or 45% due to unobserved variables, the causal effect may no longer be significant.

The adoption effect of seed-dibbling on net returns estimated by 5-NNM has to be questioned if an unobserved covariate cause the odds ratio of adopting seed-dibbling to differ between adopter and non-adopter group by a factor of about 1.35. The corresponding critical level of Gamma for applying the Kernel based matching is 1.50. The critical level of Gamma, at which the conclusion of a positive effect of dibbling seed on yields has to be questioned, is just below 1.45 if applying Mahalanobis metric matching. Using the 3-NNM approach, the critical level of unobserved heterogeneity is even higher (Gamma = 2.15).

With regard to the positive and significant adoption effect of dibbling both seed and fertilizer on nitrogen demand, it would even require an unobserved heterogeneity that causes the odds ratio of adoption decision to differ between adopters and non-adopters by a factor of

about 2.25 to render spurious the conclusion of a positive effect in case of 6-NNM. Employing the KBM, it would require an even higher unobserved selection bias to change the causal inference. In this case, a hidden bias of about 2.60 would be required. MMM estimates reveal a critical level of Gamma of 2.05. The adoption effect of the whole intensification technology package on net returns appears to be more sensitive to hidden bias, with a critical value of Gamma of 1.2. The critical level of unobserved selection bias that is required to render spurious the positive adoption effect of the intensification package on rice yields is found to be 1.35 (see table 7-18).

The critical levels of hidden bias for the various adoption effects seem to be similar across matching algorithms. Generally, sensitivity to hidden bias found in the estimates is satisfactory and in the range of what is found in the literature. Overall, robustness to hidden bias varies between critical levels of 1.35 and 2.60, with one exception, where the critical level is 1.2. Thus, the estimated adoption effects appear to be robust to possible presence of hidden bias. It is significant to note that the Rosenbaum bounds are a worst-case scenario (DiPrete and Gangl, 2004). As pointed out by DiPrete and Gangl (2004), a value of Γ of 1.2 does not indicate that there is no true effect of adoption on outcome. This result only indicates that the confidence interval for the treatment effect on the outcome would include zero under two conditions. This is first, if an unobserved variable caused the odds ratio of treatment assignment to differ between treatment and control group by 1.2. Additionally, if this variable's effect on the outcome was so strong as to almost perfectly determine whether the outcome would be bigger for the treatment of the control case in each pair of matched cases in the data. In the case where a confounding variable had an equally strong effect on assignment but only a weak effect on the outcome variable, the confidence interval for the outcome variable would not contain zero (DiPrete and Gangl, 2004).

7.3.3 Summary of Results and Concluding Remarks

Results clearly indicate the presence of bias due to observables in the distribution of covariates between the groups of adopters and non-adopters. This finding underlines the importance for accounting for selection bias. Moreover, balance indicators support the significance of matching as evaluation method in balancing the observed distribution between the groups. The balancing power of estimations is ascertained by considering the reduction in the median absolute standardized bias between the matched and unmatched sample. Sensitivity analysis also indicates that results are relative robust against hidden bias. Furthermore, most adoption effects seem to be robust across matching algorithms. As noted

earlier, kernel based matching and nearest neighbour matching are only based on the single index of the propensity score, but do not account specifically for covariates that may be strongly related with outcomes. Mahalanobis metric matching allows controlling specifically for covariates that may be strongly correlated with outcomes by including these variables in addition to the propensity score. This is particularly useful in the present analysis with multiple treatments. Additionally, kernel based matching uses more distant matches than nearest neighbour matching and Mahalanobis metric matching, where calipers were set. This is particularly critical in small data sets, where fewer matches are available. Thus, kernel based matching may particularly result in increased bias of the estimates.

Although empirical results suggest that technology adoption positively influence output supply, net returns, and fertilizer demand, the effects vary considerably according to the type of technology and outcome. Thus, matching results could help in understanding the different adoption rates of bund technology and dibbling method in the study region. Policy implications derived from the non-parametric impact evaluation are presented in chapter 8.

In particular, estimates of Mahalanobis metric matching method indicate that looking at the improvement of food supply by increasing rice output bund technology does not seem to have a positive effect. Bund construction seems to be more a kind of preventive technology that enables rice cultivation on marginal lands (in terms of water retention status and soil productivity), without increasing output and net returns *per se*. However, output of rice is found to be significantly higher for adopters of dibbling seed method, supporting the assumption that dibbling method is a yield-increasing technique. Furthermore, the use of dibbling method (as seed sowing and fertilizer application method) in combination with intensified weeding (double manual weeding) is not only found to increase output but also yields higher net returns.

Looking at the improvement of soil quality by increasing fertilizer application rate, results reveal that the adoption of dibbling method as seed sowing and fertilizer application method (instead of broadcasting) has a clearly positive impact on nitrogen demand. Results also indicate that bund technology tends to increase nitrogen demand. These findings imply that the dissemination of technologies seem to affect the extent of adoption of interrelated technologies such as fertilizer. This may either be process-induced or result from increased knowledge and understanding of interrelated technologies.

Chapter 8

Summary and Policy Implications

8.1 Summary of Results

The aim of this thesis was to analyze the impact of the adoption of bund construction and dibbling method on outcomes such as net returns, input demand and output supply, and to investigate the determinants explaining adoption decision. The analysis is based on 342 farmers that are located in three river valleys around the regional capital of the Northern Region of Ghana.

The empirical analysis to investigate the determinants of adoption decision was carried out employing maximum-likelihood seemingly unrelated bivariate probit model of the joint adoption probability. Results indicate that adoption decisions are not statistically independent but have to be considered jointly. Economic-resource constraints, as well as factors put forward by the sociological models of technology adoption such as the innovation-diffusion and the perceived attributes paradigm are found to be important factors influencing adoption decision. Specifically, resource endowment and economic constraints of land, capital, and particularly labour turned out to be important factors determining adoption behaviour. In addition, perceived attributes of the technologies appear to be significant factors. Furthermore, the farmer's network appears to be significant in determining adoption by improving access to information and labour, and by constituting the perception of the innovation. While the participation in technology-related projects exerts a significant effect on adoption probability, formal sources of initial information seem to be less important than informal information in case of bund construction compared to dibbling method. In addition, farm characteristics such as soil productivity turned out to be important factors explaining adoption. While dibbling is more likely on productive plots, bund construction is more likely on less productive plots. The construction of bunds thus seems to be more a kind of preventive technology and a pre-condition for rain-fed lowland rice cultivation.

Given the non-experimental nature of the data set used in the analysis, the problem of self-selection bias needed to be addressed in the impact evaluation analysis. Impact assessment

was conducted by the Heckman selection estimator within the endogenous switching-regression framework, as well as by the matching method. Both estimation approaches control for selection bias but impose different assumptions and offer different estimation advantages.

Using the standardized bias method, results indicate that the matching method obtained a clear reduction of the bias in the distribution of covariates across the groups of adopters and non-adopters, supporting the importance of the matching process in reducing selection bias. Mahalanobis metric matching as multivariate matching procedure is particularly useful in the context of multiple treatments, as it specifically accounts for factors that may be strongly related with the outcome. Results indicate that intensification methods (such as dibbling seed, as well as fertilizer, combined with intensified weeding) appear to be important parts of a technology package to be supported, due to their potential to improve rice productivity and net returns. The use of bund technology seems to be more a kind of pre-condition for rain-fed lowland rice cultivation for marginal land, without increasing output supply and net returns. This finding of the matching method is consistent with the results of the bivariate joint adoption model. With regard to the improvement of soil quality, results reveal that the adoption of bund technology, as well as the adoption of dibbling method as seed-sowing and fertilizer application method contribute significantly to an increase of the still extremely low fertilizer application rate in the study region.

The parametric impact evaluation using a two-step endogenous switching-regression model identifies parameters that determine the outcomes of adopters and non-adopters. Results support the notion that self-selection occurs and estimates that do not consider selection-bias would be biased. Results also suggest that adoption decision and outcomes (net returns, rice yields, and nitrogen demand) are influenced by different factors. Furthermore, different determinants are found to be significant in explaining the outcomes for adopters and non-adopters. Thus, the results underline the necessity of specifying separate equations for adopters and non-adopters. Without accounting for other effects, rice yields and net returns seem to be higher for adopters of dibbling relative to non-adopters, while non-adopters of bund construction seem to have higher rice yields and net returns than adopters. Rice size has a negative and significant effect on nitrogen demand, rice productivity, and net returns in the whole sample, supporting an inverse farm-productivity linkage. Education of adopters seems to increase input demand. A higher education level also appears to contribute to higher rice yields and net returns among adopters of bund construction, suggesting that learning effects may be an important issue for adopters. Access to credit tends to have a positive effect on yields and net returns for non-adopters of bunds and dibbling, underlining

the importance of alleviating financial constraints especially for non-adopting farmers. Tractor ploughing tends to have a negative effect on yields and net returns, while the ownership of bullocks has a positive effect on both yields and net returns, supporting the importance of the timely availability of land preparation equipment and the importance of animal traction. A higher share of dependents in the compound household appears to increase rice yields and net returns among adopters of dibbling, indicating the importance of labour endowment for intensification methods.

8.2 Policy Implications

Determinants of farm outcomes and adoption identified in the present thesis do have policy implications. First, results support the notion that technology adoption may indeed increase productivity and net returns. However, the extent of the effect varies by technology and outcome. Furthermore, depending on the adoption status, different factors determine farm outcomes. Thus, policy makers should consider these differing effects when designing development projects to increase agricultural productivity, food security and to reduce soil degradation and poverty.

A major policy implication arises from the evaluation result that efforts to disseminate bund technology may be more rewarding to farmers who cultivate marginal lands (in terms of water retention and soil productivity). Thus, the dissemination of bund technology should be particularly targeted to farmers cultivating less productive plots. Furthermore, the joint adoption of intensification methods appears to be favourable to increase yields and net returns. This implies that joint adoption and dissemination in packages should be focused in projects and programmes.

Depending on the level of fertilizer application, that is still very low in Ghana, it may be important to increase fertilizer application to sustain and improve soil quality. To achieve this, the dissemination and understanding of related technologies such as dibbling as seed sowing and fertilizer application method should be encouraged. However, where fertilizer application is already quite high, the influence of technology adoption on fertilizer demand has to be tracked to avoid adverse effects on soil quality by over-fertilization. Given that the use of bund technology and dibbling method involve higher levels of nitrogen fertilizer, access to credit should be improved to enable farmers facing liquidity constraints to purchase sufficient quantities of fertilizer and other essential farm inputs. This will also enhance technology adoption as financial and labour constraints are found to be main factors contributing to the non-use of technologies. On the other hand, integrated soil fertility

techniques that also deliver micronutrients should be disseminated to avoid soil degradation. Due to its positive effect on input demand, rice productivity, and net returns, education should be improved. Furthermore, the timely availability of land preparation equipment should be enhanced. Thus, the use of draft animals and the training of bullocks should be supported. To increase the adoption rate, the health status of small-scale farmers should be focussed by development policies. Furthermore, due to the significance of technology perception, social learning, and social networks, the implementation of farmer-based groups and farmer-to-farmer learning processes should be focussed by development policies.

References

- Aakvik, A. (2001) Bounding a Matching Estimator: The Case of a Norwegian Training Program. *Oxford Bulletin of Economics and Statistics* 63: 115-143.
- Abadie, A. and Imbens, G. (2001) Simple and Bias-Correct Matching Estimators for Average Treatment Effects. Technical Working Paper 283. National Bureau of Economic Research.
- Abadie, A. and Imbens, G. (2006) Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica* 74: 235-267.
- Abdulai, A. and Binder, C. R. (2006) Slash-and-Burn Cultivation Practice and Agricultural Input Demand and Output Supply. *Environment and Development Economics* 11: 201-220.
- Abdulai, A. and Eberlin, R. (2001) Technical Efficiency during Economic Reform in Nicaragua: Evidence from Farm Household Survey Data. *Economic Systems* 25: 113-125.
- Abdulai, A. and Huffman, W. (2000) Structural Adjustment and Economic Efficiency of Rice Farmers in Northern Ghana. *Economic Development and Cultural Change* 48: 503-520.
- Abdulai, A. and Huffman, W. (2005) The Case of Crossbred-Cow Technology in Tanzania. *American Journal of Agricultural Economics* 87(3): 645-659.
- Abdulai, A., Monin, P. and Gerber, J. (2008) Joint Estimation of Information Acquisition and Adoption of New Technologies under Uncertainty. *Journal of International Development* 20(4): 437-451.
- Abdulai, A. and Regmi, P. P. (2000) Estimating Labour Supply of Farm Households under Nonseparability: Empirical Evidence from Nepal. *Agricultural Economics* 22: 309-320.
- Adégbidi, A., Gandonou, E. and Oostendorp, R. (2004) Measuring the Productivity from Indigenous Soil and Water Conservation Technologies with Household Fixed Effects: A Case Study of Hilly Mountains Areas of Benin. *Economic Development and Cultural Change* 52: 313-346.
- Adelman, I. and Morris, C. (1973) *Economic Growth and Social Equity in Developing Countries*. Stanford, CA: Stanford University Press.
- Adesina, A. A., Mbila, D., Nkamleu, G. B. and Endamana, D. (2000) Econometric Analysis of the Determinants of Adoption of Alley Farming by Farmers in the Forest Zone of Southwest Cameroon. *Agriculture, Ecosystems & Environment* 80(3): 255-265.

- Adesina, A. A. and Zinnah, M. M. (1993) Technology Characteristics, Farmers' Perceptions and Adoption Decisions: A Tobit Model Application in Sierra Leone. *Agricultural Economics* 9: 297-311.
- African Agricultural Market Information Network (2005) The Seeds in Ghana. AFAMIN. Available at: http://www.afamin.net/ghana/seed_dis_gh_en.htm. Retrieved on 30/04/2005.
- Agbola, F. W. (2005) Ghana's Exchange Rate Reform and its Impact on Balance of Trade. Available at: <http://www.saga.cornell.edu/images/agbola.pdf>. Retrieved on 11/10/2007.
- Aikens, M. T., Havens, A. E. and Flinn, W. L. (1975) The Adoption of Innovations: The Neglected Role of Institutional Constraints. Mimeograph, Department of Rural Sociology, Ohio State University. Columbus, OH.
- Alene, A. D. and Manyong, V. M. (2007) The Effects of Education on Agricultural Productivity under Traditional and Improved Technology in Northern Nigeria: An Endogenous Switching Regression Analysis. *Empirical Economics* 32(1): 141-159.
- Al-Hassan, R. and Jatoo, J.B.D. (2002) Adoption and Impact of Improved Cereal Varieties in Ghana. Paper Prepared for the Workshop on the Green Revolution in Asia and its Transferability to Africa. Organised by Foundation for Advanced Studies in International Development (FASID), from 8th to 10th December, 2002, in Tokyo, Japan.
- Amemiya, T. (1981) Qualitative Response Models: A Survey. *Journal of Economic Literature* 19: 1483-1536.
- Amemiya, T. (1984) Tobit Models: A Survey. *Journal of Econometrics* 24: 3-61.
- Amsalu, A. and de Graaff, J. (2007) Determinants of Adoption and Continued Use of Stone-terraces for Soil and Water Conservation in an Ethiopian Highland Watershed. *Ecological Economics* 61: 294-302.
- Araya, B. and Asafu-Adjaye, J. (1999) Returns to Farm-Level Soil Conservation on Tropical Steep Slopes: The Case of the Eritrean Highlands. *Journal of Agricultural Economics* 50: 589-605.
- Asaf, A. and Admassie, A. (2004) The Role of Education on the Adoption of Chemical Fertilizer Under Different Socioeconomic Environments in Ethiopia. *Agricultural Economics* 30: 215-228.
- Asare, I. K. (2000) Characteristics of Commercial Rice Production in Northern Ghana. A Comparative Analysis of Profitability of Indigenous and Improved Rice Varieties. Multiagency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana, November 2000.
- Asenso-Okyere, W. K., Agble, R., Attah-Krah, K., Boakye-Boateng, K., Dittoh, S., van Apt Ham, N. and Nyanteng, V. K. (1998) Country Note for Ghana. IFPRI, 2020 Vision Network for West Africa.
- Asubonteng, K. O., Adiyiah, B., Masunaga, T. and Wakatsuki, T. (2006) Meeting the Rice Production and Consumption Demand of West Africa with Improved Soil and Water

- (Sawah) and Nutrient Management Technologies. Paper presented at 18th World Congress of Soil Science. July 9-15, 2006, Philadelphia, Pennsylvania, USA.
- Asuming-Brempong, S. (1998) Profitability, Competitiveness and Welfare Effects of Trade Liberalization on the Rice Sub-sector in Ghana. In: T. B. Tshibaka, *Structural Adjustment and Agriculture in West-Africa*. Senegal: COPESTRIA Book Series.
- Asuming-Brempong, S. (2003a) Economic and Agricultural Policy Reforms and their Effects on the Role of Agriculture in Ghana. Paper prepared for the Conference on Roles of Agriculture International 20-22 October, 2003 – Rome, Italy. The Roles of Agriculture Project, Agricultural and Development Economics Division (ESA), Food and Agriculture Organization of the United Nations.
- Asuming-Brempong, S. (2003b) National Report Ghana. Paper prepared for the Roles of Agriculture International Conference 20-22 October, 2003 – Rome, Italy. The Roles of Agriculture Project, Agricultural and Development Economics Division (ESA), Food and Agriculture Organization of the United Nations.
- Augurzky, B. and Schmidt, C. M. (2001) The Propensity Score: A Means to An End. IZA Discussion Paper No. 271.
- Baidu-Forson, J. (1999) Factors Influencing Adoption of Land-Enhancing Technology in the Sahel: Lessons from a Case Study in Niger. *Agricultural Economics* 20: 231-239.
- Bam, R. K., Anchirinah, V. M., Manful, J. J., Ansereh-Bio, F. and Agymang, A. (1998) A Preliminary Study of Consumer Preferences and Price. Natural Resources Institute (NRI), Project Report No. 34, Project 6688, UK.
- Bandiera, O. and Rasul, I. (2006) Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal* 116 (514): 869–902.
- Barbier, E. B. (1990) The Farm-level Adoption Economics of Soil Conservation: The Uplands of Java. *Land Economics* 66: 199-211.
- Barnum, H. and Squire, L. (1979) An Econometric Application of the Theory of the Farm Household. *Journal of Development Economics* 60: 79-102.
- Barrett, C. B. (1996) On Price Risk and the Inverse Farm Size-Productivity Relationship. *Journal of Development Economics* 51: 193-215.
- Barrett, C. B., Marenya, P. P., McPeak, J., Minten, B., Murithi, F., Oluoch-Kosura, W., Place, F., Randrianarisoa, J. C., Rasambainarivo, J., Wangila, J. (2006) Welfare Dynamics in Rural Kenya and Madagascar. *Journal of Development Studies* 42 (1): 248–277.
- Barrett, C. B.; Moser, C. M.; McHugh, O. V. and Barison, J. (2004) Better Technology, Better Plots, or Better Farmers? Identifying Changes in Productivity and Risk among Malagasy Rice Farmers. *American Journal of Agricultural Economics* 86(4): 869-888.
- Baser, O. (2006) Too Much Ado about Propensity Score Models? Comparing Methods of Propensity Score Matching. *Value in Health* 9(6): 377-384.
- Batz, F.-J. (1999) Improving Priority Setting for Livestock Research by Using Technology Characteristics for Adoption Assessment. Berlin: Köster.

- BBC Weather (2008) Available at:
http://www.bbc.co.uk/weather/world/city_guides/results.shtml?tt=TT000250. Retrieved on 09/22/2008.
- Becker, S. O. and Caliendo, M. (2007) Mhbounds- Sensitivity Analysis for Average Treatment Effects. Discussion Paper No. 2542. IZA Bonn.
- Becker, S. O. and Ichino, A. (2002) Estimation of Average Treatment Effects Based on Propensity Scores. *The Stata Journal* 2(4): 358-377.
- Becker, M. and Johnson, D. E. (2001) Improved Water Control and Crop Management Effects on Lowland Rice Productivity in West Africa. *Nutrient Cycling in Agroecosystems* 59: 119-127
- Beckman, B. (1981) Ghana: 1951-1978; The Agrarian Basis of the Post-Colonial State. In: J. Heyer, P. Roberts and G. Williams (eds), *Rural Development in Tropical Africa*, London: Macmillan, pp. 143-167.
- Bekele, W. (2005) Stochastic Dominance Analysis of Soil and Water Conservation in Subsistence Crop Production in the Eastern Ethiopian Highlands: The Case of the Hunde-Lafto Area. *Environmental and Resource Economics* 32: 533-550.
- Bekele, W. and Drake, L. (2003) Soil and Water Conservation Decision Behavior of Subsistence Farmers in the Eastern Highlands of Ethiopia: A Case Study of the Hunde-Lafto Area. *Ecological Economics* 46: 437-541.
- Bell, C. and Hazell, P. (1980) Measuring the Indirect Effects of an Agricultural Project on its Surrounding Region. *American Journal of Agricultural Economics* 62: 75-86.
- Bellon, M. R. and Taylor, J. E. (1993) "Folk" Soil Taxonomy and the Partial Adoption of New Seed Varieties. *Economic Development and Cultural Change* 41:763-786.
- Benin, S. (2006) Policies and Programs Affecting Land Management Practices, Input Use and Productivity in the Highlands of Amhara Region, Ethiopia. In: J. Pender, F. Place and S. Ehui, S. (eds), *Strategies for Sustainable Land Management in the East African Highlands*, Washington, D.C.: International Food Policy Research Institute.
- Benjamin, D. (1992) Households Composition, Labour Markets, and Labour Demand: Testing for Separation in Agricultural Households Models. *Econometrica* 60: 287-322.
- Benjamin, D. (1995) Can Unobserved Land Quality Explain the Inverse Productivity Relationship? *Journal of Development Economics* 46: 51-84.
- Besely, T. and Case, A. (1993) Modelling Technology Adoption in Developing Countries. *American Economic Review* 83: 396-402.
- Binswanger, H., Deininger, K and Feder, G. (1995) Power, Distortions, Revolt and Reform in Agricultural Land Relations. In: J. Behrman and T. N. Srinivasan (eds), *Handbook of Development Economics*, vol. 3B, Amsterdam: Elsevier Science.
- Boahene, K., Snijder, Tom A. B. and Folmer, H. (1999) An Integrated Socioeconomic Analysis of Innovation Adoption: The Case of Hybrid Cocoa in Ghana. *Journal of Policy Modelling* 21: 167-184.
- Boserup, E. (1965) *The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure*. London: Earthscan Publications Ltd.

- Blackman, A. (1999) The Economics of Technology Diffusion: Implications for Climate Policy in Developing Countries. Discussion Paper 99-42, Resources for the Future, Washington.
- Bloomberg (2008) Available at:
<http://www.faz.net/s/Rub58BA8E456DE64F1890E34F4803239F4D/Doc~EB3202D1741CA4705AA72A86814124CB0~ATpl~Ecommon~Scontent.html>. Retrieved on 04/15/2008.
- Blundell, R., Dearden, L. and Sianesi, B. (2005) Evaluating the Impact of Education on Earning in the UK: Models, Methods and Results from the NCDS. *Journal of the Royal Statistical Society, Series A* 168(3): 473-512.
- Blundell, R. and Dias, M. C. (2000) Evaluation Methods for Non-Experimental Data. *Fiscal Studies* 21(4): 427-468
- Bøjø, J. (1996) The Costs of Land Degradation in Sub-Saharan Africa. *Ecological Economics* 16: 161-173.
- Bravo-Ureta, B. E., Solís, D., Cocchi, H. and Quiroga, R. E. (2006) The Impact of Soil Conservation and Output Diversification on Farm Income in Central American Hillside Farming. *Agricultural Economics* 35: 267-276.
- Bryson, A., Dorsett, R. and Purdon, S. (2002) The Use of Propensity Score Matching in the Evaluation of Active Labour Market Policies. Working Paper Number 4, London: Policy Studies Institute and National Centre for Social Research.
- Bumb, et al. (1992) Fertilizer Policy Research in Africa: An Assessment of the Policy Environment and Fertilizer Sector Development in Ghana. Accra, Ghana: International Fertilizer Development Center (IFDC) and Institute of Statistics, Social, and Economic Research (ISSER).
- Byiringiro, F. and Reardon, T. (1996) Farm Productivity in Rwanda: Effects of Farm Size, Erosion, and Soil Conservation Investments. *Agricultural Economics* 15: 127-136.
- Caliendo, M. and Kopeinig, S. (2008) Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys* 22(1): 31–72.
- Cameron, L. A. (1999) The Importance of Learning in the Adoption of High-Yielding Variety Seeds. *American Journal of Agricultural Economics* 81: 83-94.
- Carter, M. R. (1989) The Impact of Credit on Peasant Productivity and Differentiation in Nicaragua. *Journal of Development Economics* 31: 13–36.
- Caswell, M. F., Fuglie, K. and Ingram, C., Jans, S. and Kascak, C. (2001) Adoption of Agricultural Production Practices: Lessons Learned from the US Department of Agriculture Area Studies Project. Economic Research Service, AER-792, ERS Agricultural Economic Report No. 792:116.
- Caswell, M. F. and Zilberman, D. (1986) The Effects of Well Depth and Land Quality on the Choice of Irrigation Technology. *American Journal of Agricultural Economics* 68(4): 798-811.
- Cary, J. W. and Wilkinson, R. L. (1997) Perceived Profitability and Farmers' Conservation Behaviour. *Journal of Agricultural Economics* 48(1): 13-21.
- Central Intelligence Agency (2006) The World Factbook 2006. Available at <http://www.cia.gov/cia/publications/factbook/index.html>. Retrieved on 10/14/2007.

- Chambers, R. (1994) The Origins and Practice of Participatory Rural Appraisal. *World Development* 22(7):953-969.
- Chambers, R. G. (1998) *Applied Production Analysis, A Dual Approach*. New York: Cambridge University Press.
- Clay, D., Reardon, T., and Kangasniemi, J. (1998) Sustainable Intensification in the Highland Tropics: Rwandan Farmers' Investments in Land Conservation and Soil Fertility. *Economic Development and Cultural Change* 45(2): 351-378.
- Cochran, W. G. (1968) The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. *Biometrics* 24: 295-313.
- Cochran, W. and Rubin, D. (1973) Controlling Bias in Observational Studies: A Review. *Sankhya, Series A*, 35: 417-46.
- Conley, T. G. and Udry, C. R. (2001) Social Learning through Networks: The Adoption of New Agricultural Technologies in Ghana. *American Journal of Agricultural Economics* 83(3): 668-673.
- Conley, T. G. and Udry, C. R. (2005) Learning about a New Technology: Pineapple in Ghana. Working Papers Series No. 817. Economic Growth Center, Yale University.
- Cragg, J. (1971) Some Statistical Models for Limited Dependent Variables with Application the Demand for Durable Goods. *Econometrica* 39: 829-844.
- Cramer, G. L., Wailes, E. J. and Shui, S. (1993) Impacts of Liberalizing Trade in the World Rice Market. *American Journal of Agricultural Economics* 75: 219-226.
- Dalton, T. J., Masters, W. A. and Foster, K. A. (1997) Production Costs and Input Substitution in Zimbabwe's Smallholder Agriculture. *Agricultural Economics* 17: 201-209.
- Dapaah, S. K. (1995) Empirical Analysis of the Likely Future Evolution of Agriculture in Ghana and How it Will Affect the Prospects for Longer Term Growth of Agriculture, the Food System and Broader Economy. Paper presented at the Workshop on Agricultural Transformation in Africa. Abidjan, Cote d'Ivoire, 26.-29.09.1995.
- Dasgupta, S., Meisner, C. and Wheeler, D. (2007) Is Environmentally-Friendly Agriculture Less Profitable for Farmers? Evidence on Integrated Pest Management in Bangladesh. *Review of Agricultural Economics* 29(1): 103-118.
- David, C.C. and Otsuka, K. (eds) (1994) *Modern Rice Technology and Income Distribution in Asia*. Boulder, CO: Lynne Rienner Publishers.
- Dawe, D. (2002) The Changing Structure of the World Rice Market, 1950-2000. *Food Policy* 27: 355-370.
- Deaton, A. (1997) *The Analysis of Household Surveys. A Microeconometric Approach to Development Policy*. Published for the World Bank. Baltimore: The John Hopkins University Press.
- Defoer, T., Wopereis, M. C. S., Jones, M. P., Lançon, F., Erenstein, O. and Guei, R. G. (2004) Rice-based Production Systems for Food Security and Poverty Alleviation in Sub-Saharan Africa. Proceedings of the FAO Rice Conference. FAO International Rice Commission Newsletter 53.

- Dehejia, R. H. and Wahba, S. (2002) Propensity Score-Matching Methods for Nonexperimental Causal Studies. *The Review of Economics and Statistics* 84(1): 151-161.
- DeJanvry, A., Fafchamps, M. and Sadoulet, E. (1991) Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained. *The Economic Journal* 101: 1400-1417.
- DeJanvry, A. and Sadoulet, E. (2002) World Poverty and the Role of Agricultural Technology: Direct and Indirect Effects. *Journal of Development Studies* 38(4): 1-26.
- Delgado, C. L., Hopkins, J. and Kelly, V. A. (1998) *Agricultural Growth Linkages in Sub-Saharan Africa*. Washington, D. C.: International Food Policy Research Institute, Research Report 107.
- Demeke, A. B. (2003) Factors Influencing the Adoption of Soil Conservation Practices in Northwestern Ethiopia. Discussion Papers No. 37, Institute of Rural Development, University of Goettingen.
- De Nigris, M. (2005) Defining and Quantifying the Extent of Import Surges: Data and methodologies. FAO Import Surge Project Working Paper, FAO Rome.
- Deutsche Botschaft Accra (2006) Jahreswirtschaftsbericht Ghana 2005. Accra, Ghana.
- Diagana, B., Akindès, F., Savdogo, K., Reardon, T. and Staatz, J. (1999) Effects of the CFA Franc Devaluation on Urban Food Consumption in West Africa: Overview and Cross Country Comparison. *Food Policy* 24: 465-478.
- Diewert, W. E. (1973) Functional Forms for Profit and Transformation Functions. *Journal of Economic Theory* 6: 284-316.
- DiNardo, J. and Tobias, J. L. (2001) Nonparametric Density and Regression Estimation. *Journal of Economic Perspectives* 15(4): 11-28.
- DiPrete, T.A. and Gangl, M. (2004) Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. *Sociological Methodology* 34: 271-310.
- Dittoh, S., Yeboah, R. and Kranjac-Berisavljevic, G. (1997) Socio-Economic Factors Influencing Soil and Water Conservation Practices in the Nabogu Valley of the Northern Region of Ghana. In: Proceedings of the International Seminar on Sustainable Rural Development in Sub-Saharan Africa. 21-25 July 1997, Kumasi, Ghana.
- Doll, J. and Orazem, F. (1984) *Production Economics: Theory with Applications*, 2nd Edition, New York: Wiley.
- Dong, D. and Saha, A. (1998) He Came, He Saw, (and) He Waited: An Empirical Analysis of Inertia in Technology Adoption. *Applied Economics* 30(7): 893-905.
- Donya, D. (2000) Characteristics of Traditional Rice Production in Ghana. Multi-Agency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana, November 2000.
- Doss, C. R. (2002) Men's Crop? Women's Crop? The Gender Patterns of Cropping in Ghana. *World Development* 30(11): 1987-2000.

- Doss, C. R. (2003) Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. CIMMYT Economics Working Paper 03-07. Mexico, D.F: CIMMYT.
- Doss, C. R. (2006) Analyzing Technology Adoption Using Microstudies: Limitations, Challenges, and Opportunities for Improvement. *Agricultural Economics* 34(3): 207-219.
- Doss, C. R. and Morris, M. L. (2001) How does Gender Affect the Adoption of Agricultural Innovations? The Case of Improved Maize Technology in Ghana. *Agricultural Economics* 25: 27-39.
- Dregne, H. E. (1990) Erosion and Soil Productivity in Africa. *Journal of Soil and Water Conservation* 45: 432-436.
- Econometric Software Inc. (2002) LIMDEP and NLOGIT Software. www.limdep.com and www.nlogit.com.
- Ellis, F. (1988) Household Strategies and Rural Livelihood Diversification. *Journal of Development Studies* 35(1): 1-38.
- Ersado, L. Anmacher, G. and Alwang, J. (2004) Productivity and Land Enhancing Technologies in Northern Ethiopia: Health, Public Investments, and Sequential Adoption. *American Journal of Agricultural Economics* 86: 321-331.
- Ervin, C. A. and Ervin, D. E. (1982) Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications. *Land Use Policy* 58(3): 276-292.
- Evenson, R. E. and Gollin, D. (2003) Assessing the Impact of the Green Revolution, 1960 to 2000. *Science* 300 (5620): 758-762.
- Fafchamps, M. and Quisumbing, A. R. (1998) Human Capital, Productivity, and Labor Allocation in Rural Pakistan. FCND Discussion Paper No. 48, Washington, D.C.: IFPRI.
- Falcon, W. P. and Naylor, R. L. (2005) Rethinking Food Security for the Twenty-First Century. *American Journal of Agricultural Economics* 87(5): 1113-1127.
- Fan, S. and Rao, N. (2003). Public Spending in Developing Countries: Trends, Determination and Impact. *EPTD Discussion Paper No. 99*. Washington, D.C.: IFPRI.
- Fan, S. and Saurkar, A. (2006) Public Spending in Developing Countries: Trends, Determination and Impact (mimeo).
- Feder, G. (1980) Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty. *Oxford Economics Papers* 32: 263-283.
- Feder, G. (1982) Adoption of Interrelated Agricultural Innovations: Complementarity and Impact of Risk, Scale, and Credit. *American Journal of Agricultural Economics* 64: 94-101.
- Feder, G., Just, E and Zilberman, D. (1985) Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change* 33: 255-298.
- Feder, G. and Umali, D. (1993) The Adoption of Agricultural Innovations: A Review. *Technological Forecasting and Social Change* 43: 215-239.
- Fisher, R. A. (1935) *The Design of Experiments*. London: Boyd.

- Food and Agriculture Organization of the United Nations (1999) FAOSTAT database.
- Food and Agriculture Organization of the United Nations (2002) FAO/WFP Crop and Food Supply – Assessment Mission to Northern Ghana, Special Report. FAO Global Information and Early Warning System on Food and Agriculture, World Food Programme.
- Food and Agriculture Organization of the United Nations (2003) Compendium of Agricultural – Environmental Indicators: 1989-91 to 2000. Statistics Analysis Service, Statistics Division, Rome.
- Food and Agriculture Organization of the United Nations (2005a) Ghana. Aquastat, FAO. Available at: <http://www.fao.org/nr/water/aquastat/countries/ghana/index.stm>. Retrieved on 05/08/2005.
- Food and Agriculture Organization of the United Nations (2005b) Fertilizer Use By Crop in Ghana. Land and Plant Nutrition Management Service. Land and Plant Development Division. FAO, Rome.
- Food and Agriculture Organization of the United Nations (2005c) Statistical Yearbook.
- Food and Agriculture Organization of the United Nations (2005d) On the Extent and Impact of Food Import Surges: The Case of Rice in Ghana. FAO Statement by Mr. Oloche Anebi Edache. National Dissemination Workshop, 01.09.2005, Accra, Ghana.
- Food and Agriculture Organization of the United Nations (2006) FAO Briefs on Import Surges No. 5. Ghana: Rice, Poultry and Tomato Paste. Rome, Italy.
- Food and Agriculture Organization of the United Nations (2007) FAO Briefs on Import Surges - Commodities, No. 2: Import Surges in Developing Countries: The Case of Rice. Rom, Italy.
- Forman, C. and Goldfarb, A. (2006) Diffusion of Information and Communication Technologies to Business. In: T. Hendershott (eds), *Handbook in Information Systems*, vol.1, Elsevier
- Fuglie, K. O. and Bosch, D. J. (1995) Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis. *American Journal of Agricultural Economics* 77: 891-900.
- Fujisaka, S. (1993) A Case of Farmer Adaptation and Adoption of Contour Hedgerows for Soil Conservation. *Experimental Agriculture* 29: 97-105.
- FSRPOP (2005) Yield Survey 2005, unpublished.
- Gangl, M. (2004) RBOUNDS: Stata Module to Perform Rosenbaum Sensitivity Analysis for Average Treatment Effects on the Treated. Version 1.1.6. Available at: <http://ideas.repec.org/c/boc/bocode/s438301.html>.
- Garbers, F., Hirsch, T. and Paasch, A. (2007) Die Auswirkungen der Liberalisierung des Reismarkts auf das Recht auf Nahrung. Fallstudien zu Ghana, Honduras und Indonesien. Hrsg.: 'Brot für die Welt' - Kampagne für Ernährungssicherheit 'Niemand isst für sich allein', Stuttgart 2007.
- Gebremedhin, B. and Swinton, S. M. (2003) Investment in Soil Conservation in Northern Ethiopia: The Role of Land Tenure Security and Public Programs. *Agricultural Economics* 29(1): 69-84.

- Gerken, A., Sugo, J. and Braun, M. (2001) Pesticides Use and Policies in Ghana - An Economic and Institutional Analysis of current Practice and Factors Influencing Pesticide Use. Publication Series No. 10. Pesticide Policy Project Publication Series. MoFA, PPSD, GTZ.
- Geroski, P. A. (2000) Models of Technology Diffusion. *Research Policy* 29: 603-625.
- Ghanaian-German Agricultural Development Project, Northern and Upper Regions of Ghana, GGADP (1977) Agricultural Extension Handbook, Tamale, Ghana.
- Goody, J. R. (1980) Rice Burning and the Green Revolution in Northern Ghana. *The Journal of Development Studies* 16(2): 136-155.
- Gould, B. W., Saupe, W. E. and Klemme, R. M. (1989) Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion. *Land Economics* 65(2): 167-182.
- Greene, W. H. (2002) *Limdep Version 8.0. Econometric Modeling Guide Vol. 2*. Plainview, NY: Econometric Software, Inc.
- Greene, W. H. (2003) *Econometric Analysis*. 5th ed. Upper Saddle River: Prentice Hall.
- Grepperud, S. (1996) Population Pressure and Land Degradation: The Case of Ethiopia. *Journal of Environmental Economics and Management* 30: 18-33.
- Griliches, Z. (1957) Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica* 25(4): 501-522.
- Gunneweg, H. A. M. I., Evers, A. and Huizing, A. (1986) A Model to Assess Proposed Procedures for Water Control: Application and Results for Two Small Inland Valleys. In: A. S. R. Juo and J. A. Lowe (eds), *The Wetlands and Rice in Sub-Saharan Africa*, Ibadan, Nigeria: IITA.
- Guo, S., Barth, R. P. and Gibbons, C. (2006) Propensity Score Matching Strategies for Evaluating Substance Abuse Services for Child Welfare Clients. *Children and Youth Services Review* 28: 357-383.
- Haggblade, S. and Hazell, P.B.R. (1989) Agricultural Technology and Farm-Non-Farm Growth Linkages. *Agricultural Economics* 3: 345-64.
- Hagos, F. and Holden, S. (2006) Tenure Security, Resource Poverty, Public Programs, and Household Plot-level Conservation Investments in the Highlands of Northern Ethiopia. *Agricultural Economics* 34: 183-196.
- Hayes, J., Roth, M. and Zepeda, L. (1997) Tenure Security, Investment and Productivity in Gambian Agriculture: A Generalised Probit Analysis. *American Journal of Agricultural Economics* 79: 369-382.
- Hazell, P. B. R. and Hojjati, B. (1995) Farm/Non-farm Growth Linkages in Zambia. *Journal of African Economies* 4(3): 406-435.
- Heckman, J. J. (1979) Sample Selection Bias as a Specification Error. *Econometrica* 47: 153-161.
- Heckman, J. J., Ichimura, H., Smith, J. and Todd, P. (1998) Characterization of Selection Bias Using Experimental Data. *Econometrica* 66: 1017-1098.

- Heckman, J. J., Ichimura, H. and Todd, P. (1997) Matching as an Econometric Evaluation Estimator. *Review of Economic Studies* 65 (2): 261–294.
- Heckman, J. J., LaLonde, R. and Smith, J. A. (1999) The Economics and Econometrics of Active Labour Market Programs. In: A. Ashenfelter and D. Card (eds), *Handbook of Labour Economics*, vol. 3, Amsterdam: Elsevier Science.
- Heckman, J. J. and Navarro-Lozano, S. (2004) Using Matching, Instrumental Variables and Control Functions to Estimate Economic Choice Models. *Review of Economics and Statistics* 86(1): 30-57.
- Heckman, J. J. and Robb, R. (1985) Alternative Methods for Evaluating the Impact of Interventions: An Overview. *Journal of Econometrics* 30 (1-2): 239-267.
- Helfand, S. M. and Levine, E. S. (2007) Farm Size and the Determinants of Productive Efficiency in the Brazilian Center-West. *Agricultural Economics* 31(2-3): 41–249.
- Herbst, J. (1993) *The Politics of Reform in Ghana 1982-1991*. University of California Press.
- Heltberg, R. (1998) Rural Market Imperfections and the Farm Size-Productivity Relationship: Evidence from Pakistan. *World Development* 26: 1807-1826.
- Hiebert, D. (1974) Risk, Learning and the Adoption of Fertilizer Responsive Seed Varieties. *American Journal of Agricultural Economics* 56: 764-768.
- Hintze, L. H., Renkow, M. and Sain, G. (2003) Variety Characteristics and Maize Adoption in Honduras. *Agricultural Economics* 29: 307-317.
- Holden, S., Shiferaw, B. and Pender, J. (2001) Market Imperfections and Land Productivity in the Ethiopian Highlands. EPTD Discussion Paper No. 76. Washington, D.C.: IFPRI.
- Honlonkou, A. N. (2004) Modelling Adoption of Natural Resources Management Technologies: The Case of Fallow Systems. *Environment and Development Economics* 9: 289-314.
- Hooks, G. M., Napier, T. L. and Carter, M. V. (1983) Correlates of Adoption Behaviour: The Case of Farm Technologies. *Rural Sociology* 48(2): 308-323.
- Hotelling, H. (1932) Edgeworth Taxation Paradox and the Nature of Demand and Supply Functions. *Journal of Political Economy* 40: 577-616.
- Huang, C. and Raunikar, R. (1991) The Application and Economic Interpretation of Selectivity Models. *American Journal of Agricultural Economics* 73: 496-501.
- Huffman, W. E. (1974) Decision Making: The Role of Education. *American Journal of Agricultural Economics* 56: 85-97.
- Huffman, W. E. (1977) Allocative Efficiency: The Role of Human Capital. *Quarterly Journal of Economics* 91: 59-77.
- Huffman, W. E. (1980) Farm and Off-farm Work Decisions: The Role of Human Capital. *The Review of Economics and Statistics* 62: 14-23.
- Huffman, W. E. (2001) Human Capital: Education and Agriculture. In: B. L. Gardner and G. Russer (eds), *Handbook of Agricultural Economics*, vol. 1B, New York: Elsevier Science-North Holland, pp.438-45.

- Hujer, R., Caliendo, M. and Thomsen, S. L. (2004) New Evidence on the Effects of Job Creation Schemes in Germany – A Matching Approach with Threefold Heterogeneity. *Research in Economics* 58(4): 257-302.
- Imbens, G. W. (2004) Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *The Review of Economics and Statistics* 86(1): 4-29.
- International Monetary Fund (2008a) A Factsheet – The Poverty Reduction and Growth Facility (PRGF). Available at: <http://www.imf.org/external/np/exr/facts/prgf.htm>. Retrieved on 10/18/2008.
- International Monetary Fund (2008b) A Factsheet – Debt Relief Under the Heavily Indebted Poor Countries (HIPC) Initiative. Available at: <http://www.imf.org/external/np/exr/facts/hipc.htm>. Retrieved on 10/18/2008.
- Institute of Statistics, Social, and Economic Research (2004) The State of The Ghanaian Economy in 2003. Legon, Ghana: ISSER, University of Ghana.
- Institute of Statistics, Social, and Economic Research (2006) The State of the Ghanaian Economy Report 2005 - Presentation, ISSER, University of Ghana, Legon.
- Isham, J. (2000) The Effect of Social Capital on Technology Adoption: Evidence from Rural Tanzania. IRIS Working Paper No. 235, University of Maryland.
- Issah, M. (2007) Right to Food of Tomato and Poultry Farmers – Report of an Investigative Mission to Ghana. FIAN, Send Foundation, Both Ends, Germanwatch & UK Food Group (Hg.): Heidelberg.
- Jacoby, H. G. (1993) Shadow Wages and Peasant Family Labour Supply: An Econometric Application to the Peruvian Sierra. *Review of Economic Studies* 60: 903-921.
- Jagger, P. and Pender, J. (2003) Impacts of Programs and Organizations on the Adoption of Sustainable Land Management Technologies in Uganda. Environment and Production Technology Division Discussion Paper No. 101, Washington, DC: International Food Policy Research Institute.
- Jenin, L. and Awuni, J. (2001) LRDP Mission 1 Report – Monitoring and Evaluation. Draft Final Report. AFD, MoFA.
- Johnson, N. L. and Kotz, S. (1970) *Distributions in Statistics: Continuous Univariate Distributions, Volume I and II*. Boston: Houghton Mifflin.
- Johnson, M. E. and Masters, W. A. (2004) Complementarity and Sequencing of Innovations: New Varieties and Mechanized Processing for Cassava in West Africa. *Economics of Innovation and New Technology*. 13: 19-31.
- Johnson, M. E., Masters, W. A. and Preckel, P. V. (2007) Diffusion and Spillover of New Technology: A Heterogeneous-agent Model for Cassava in West Africa. *Agricultural Economics* 35(2): 119-129.
- Kabubo-Mariara, J. (2007) Land Conservation and Tenure Security in Kenya: Boserup's Hypothesis Revisted. *Ecological Economics* 64(1): 25-35.
- Kabubo-Mariara, J., Mwabu, G. and Kimuyu, P. (2006) Farm Productivity and Poverty in Kenya: The Effect of Soil Conservation. *Journal of Food Agriculture and Environment* 4(2): 291-297.

- Kaliba, A. R. M. and Rabele, T. (2001) Impact on Adopting Soil Conservation Practices on Wheat Yield in Lesotho. Paper presented at the 8th AFNET meeting, May 7-10, 2001, Arusha, Tanzania.
- Kaliba, A. R. M., Verkuijl, H. and Mwangi, W. (2000) Factors Affecting Adoption of Improved Maize Seeds and Use of Inorganic Fertilizer for Maize Production in the Intermediate and Lowland Zones of Tanzania. *Journal of Agricultural and Applied Economics* 32: 35-47.
- Kalirajan, K. P. and Shand, R. T. (2001) Technology and Farm Performance: Paths of Productive Efficiencies over Time. *Agricultural Economics* 24: 297-306.
- Karanja, D. D., Renkow, M. and Crawford, E. W. (2003) Welfare Effects of Maize Technologies and Marginal and High Potential Regions of Kenya. *Agricultural Economics* 29: 331-341.
- Karshenas and Stoneman, (1993) Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model. *The RAND Journal of Economics* 24(4): 503-528.
- Kassie, M. and Holden, T. S. (2006) Parametric and Non-parametric Estimation of Soil Conservation Adoption Impact on Yield. Contributed Paper Prepared for Presentation at the International Association of Agricultural Economists (IAAE) Conference, Gold Coast, Australia, August 12-18, 2006.
- Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R. and Mulugeta E. (2008) Estimating Returns to Soil Conservation Adoption in the Northern Ethiopian Highlands. *Agricultural Economics* 38(2): 213-232.
- Kazianga, H. and Masters, W. A. (2002) Investing in Soils: Field Bunds and Micro Catchments in Burkina Faso. *Environment and Development Economics* 7: 571-591.
- Kebbeh, M., Miezán, K. and Camara, M. (2004) Developing Technology Options for Rice Integrated Crop Management in the Sahel Zone of West Africa: *Uganda Journal of Agricultural Sciences* 9(11): 425-432.
- Khanna, M. (2001) Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity: A Double Selectivity Model. *American Journal of Agricultural Economics* 83: 35-51.
- Kijima, Y., Otsuka, K. and Sserunkuuma, D. (2008) Assessing the Impact of NERICA on Income and Poverty in Central and Western Uganda. *Agricultural Economics* 38: 327-337.
- Kimhi, A. (2006) Plot Size and Maize Productivity in Zambia: Is there an Inverse Relationship? *Agricultural Economics* 35(5):1-9.
- Knight, J., Weir, S. and Woldehanna, T. (2003) The Role of Education in Facilitating Risk-Taking and Innovation in Agriculture. *The Journal of Development Studies* 39(6): 1-22.
- Knowler, D. and Bradshao, B. (2007) Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research. *Food Policy* 32: 25-48.
- Kosarek, J L., Garcia, P., Morris, M. L. (2002) Factors Explaining the Diffusion of Hybrid Maize in Latin America and the Caribbean region. *Agricultural Economics* 26(3): 267-280.

- Koundouri, P., Nauges, C., and Tzouvelekas, V. (2006) Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics* 88(3): 657-670.
- Kranjac-Berislavjevic, G. (2000) Some Features of Rice Production in Ghana. Multi-Agency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana.
- Kranjac-Berislavjevic, G., Bayorbor, T. B. and Abdulai, A. S. (2000) in International Workshop on Soil and Water Conservation in Sub-Saharan Africa, 15th-17th February 2000, ODI, UDS.
- Kranjac-Berislavjevic, G., Bayorbor, T. B., Abdulai, A. S., Obeng, F., Blench, R. M., Turton, C. N., Boyd, C. and Drake, E. (1999) Rethinking Natural Resource Degradation in Semi-Arid Sub-Saharan Africa: The Case of Semi-Arid Ghana, University for Development Studies, Tamale and ODI, London.
- Kranjac-Berislavjevic, G., Blench, R. M. and Chapman, R. (2003) Multi-Agency Partnerships (MAPS) for Technical Change in West African Agriculture. Rice Production and Livelihoods in Ghana. ODI, UDS.
- Kranjac-Berislavjevic, G., Laryea, K. B., Abenney-Mickson, S., Mahama, S. and Alhassan, R. (2000?) A Study of Appropriate Bunding Methods for Rain fed Rice in Northern Ghana.
- Krummacher, A. (2004) Der Participatory Rural Appraisal (PRA)-Ansatz aus ethnologischer Sicht. PRA – a quick and dirty anthropology? Working Papers Nr. 36, Institut für Ethnologie und Afrikastudien, Mainz: Johannes Gutenberg Universität.
- Lançon, F. and Benz, H. D. (2007) Rice Imports in West Africa: Trade Regimes and Food Policy Formulation. Poster prepared for Presentation at the 106th Seminar of the EAAE, 25-27.10.2007, Montpellier, France.
- Langyintuo, A. S., Gyasi, K. O., Abatania, L. N. and Terbobri, P. (2002) Determinants of the Adoption of Improved Rice Varieties in the Inland Valleys of Northern Ghana. A Tobit Model Application. Paper submitted to the SADAOC Foundation for the SACAOC International Conference (Bamako, September 2002).
- Lapar, M. L. A. and Pandey, S. (1999) Adoption of Soil Conservation: The Case of the Philippine Uplands. *Agricultural Economics* 21: 241-256.
- Larson, B. A. and Frisvold, G. B. (1996) Fertilizers to Support Agricultural Development in Sub-Saharan Africa: What is Needed and Why. *Food Policy* 21: 509-525.
- Lau, L. J. (1971) Applications of Profit Functions. In: D. L. McFadden (eds), *An Econometric Approach to Production Theory*, Amsterdam, North-Holland Pub.Co.
- Lau, L. J. (1976) A Characterization of the Normalized Restricted Profit Function. *Journal of Economic Theory* 12: 131-163.
- Lau, L. J. and Yotopoulos, P. A. (1972) Profit, Supply, and Factor Demand. *American Journal of Agricultural Economics* 54:11-18.
- Leathers, H. D. and Smale, M. (1991) A Bayesian Approach to Explaining Sequential Adoption of Components of a Technological Package. *American Journal of Agricultural Economics* 73(3): 734-742.

- Lechner, M. (2002) Some Practical Issues in the Evaluation of Heterogenous Labour Market Programmes by Matching Methods. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 165(1): 59–82.
- Lee, D. R. (2005) Agricultural Sustainability and Technology Adoption: Issues and Policies for Developing Countries. *American Journal of Agricultural Economics* 87(5): 1325-1334.
- Lee, D. R., Barrett, C. B. and McPeak, J. G. (2006) Policy, Technology, and Management Strategies for Achieving Sustainable Agricultural Intensification. *Agricultural Economics* 34(2):123–127.
- Lee, L. F. (1982) Some Approaches to the Correction of Selectivity Bias. *Review of Economic Studies* 82: 355-37.
- Lee, L. F., Maddala, G. S. and Trost, R. P. (1980) Asymptotic Covariance Matrices of Two-Stage Probit and Two-Stage Tobit Methods for Simultaneous Equations Models with Selectivity. *Econometrica* 46: 491-503.
- Lee, L. F. and Trost, R. P. (1978) Estimation of Some Limited Dependent Variable Models with Application to Housing Demand. *Journal of Econometrics* 8: 355-382.
- Lee, W. (2008) Propensity Score Matching and Variations on the Balancing Test. 3rd Conference on Policy Evaluation, ZEW, Mannheim (Germany), 27-28 October.
- Leuven, E. and Sianesi, B. (2003). "PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing". Available at <http://ideas.repec.org/c/boc/bocode/s432001.html>. Retrieved on 07/17/07.
- Lockheed, M. E., Jamison, D. T. and Lau, L. J. (1980) Farmer Education and Farm Efficiency: A Survey. *Economic Development and Cultural Change* 29:37-76.
- López-Pereira, M. A., Sander, J. H., Baker, T. G. and Preckel, P. V. (1994) Economics of Erosion-control and Seed-fertilizer Technologies for Hillside Farming on Honduras. *Agricultural Economics* 11: 271-288.
- Maatman, A., Sawadogo, H., Schweigman, C. and Ouedraogo, A. (1998) Application of Zai and Rock Bunds in the Northwest Region of Burkina Faso: Study of its Impact on Household Level by Using a Stochastic Linear Programming Model. *Netherlands Journal of Agricultural Science* 46(1): 123-136.
- Maddala, G. S. (1986) Disequilibrium, Self-selection, and Switching models. In: Z. Griliches and M. D. Intriligator (eds), *Handbook of Econometrics*, vol. 3: 1634-1688.
- Maddala, G.S. (1991) *Limited Dependent and Qualitative Variables in Econometrics*. New York, Cambridge University Press.
- Maddala, G. S. (1992) *Introduction to Econometrics*. New York, NY: Macmillan Publishing Company.
- Mahama, I. (2004) *History and Traditions of Dagbon*. Tamale, Ghana: Gillbt Printing Press.
- Mansfield, E. (1961) Technical Change and the Rate of Imitation. *Econometrica* 29: 741-765.
- Manski, C. F. (1989) Anatomy of the Selection Problem. *Journal of Human Resources* 24: 341-360.

- Marenya, P. P. and Barrett, C. B. (2007) Household-level Determinants of Adoption of Improved Natural Resources Management Practices among Smallholder Farmers in Western Kenya. *Food Policy* 32(4): 51-536.
- Marra, M., Pannell, D. and Abadi Ghadim, A. (2003) The Economics of Risk, Uncertainty and Learning in the Adoption of new Agricultural Technologies: Where are we on the Learning Curve? *Agricultural Systems* 75: 215–234.
- Mazzucato, V. and Niemeijer, D. (2000) The Cultural Economy of Soil and Water Conservation: Market Principles and Social Networks in Eastern Burkina Faso. *Development and Change* 31: 831-855.
- Mbaga-Semgalawe, Z. and Folmer, H. (2000) Household Adoption Behaviour of Improved Soil Conservation: The Case of the North Pare and West Usambara Mountains of Tanzania. *Land Use Policy* 17: 321-336.
- McFadden, D. L. (1971) Cost, Revenue, and Profit Functions. In: D. L. McFadden (eds), *An Econometric Approach to Production Theory*, Amsterdam, North-Holland Pub.Co.
- McKay, A. and Aryeetey, E. (2004) Operationalizing Pro-Poor Growth: A Country Case Study of Ghana. 'Operationalizing Pro-Poor Growth' Initiative from AFD, BMZ (GTZ, KfW Development Bank), DFID and the World Bank.
- Mekuria, M. and Waddington, S.R. (2002) Initiatives to Encourage Farmer Adoption of Soil-fertility Technologies for Maize-based Cropping Systems in Southern Africa. In: C. B. Barrett, F. Place and A. A. Abound (eds), *Natural Resource Management in African Agriculture: Understanding and Improving Current Practices*. Oxford: CABI Publishing.
- Mellor, J. W. (1976) *The New Economics of Growth: Strategy for India and the Developing World*. Ithaka: Cornell University Press.
- Mendola, M. (2007) Agricultural Technology Adoption and Poverty Reduction: A Propensity-Score Matching Analysis for Rural Bangladesh. *Food Policy* 32 (3): 372-393.
- Mercer-Quarshie, H. (2000) The Lowland Rice Development Project. Multiagency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana, November 2000.
- Ministry of Food and Agriculture, Ghana (1991) Agriculture in Ghana, Facts and Figures. Policy Planning, Monitoring and Evaluation (PPMED), MoFA.
- Ministry of Food and Agriculture, Ghana (1997) Final Report of Feasibility Study: Rice Development Project in the Northern Region of Ghana. AFD, MoFA.
- Ministry of Food and Agriculture, Ghana (1999) Task Force Report on Proposals for Improving Rice Production Technology and Quality in Ghana. MoFA.
- Ministry of Food and Agriculture, Ghana (2001) Accelerated Agricultural Growth and Development Strategy in Support of Ghana's Vision 2020. Republic of Ghana.
- Ministry of Food and Agriculture, Ghana (2002) LRDP External Evaluation. Final Report, AFD, MoFA.
- Ministry of Food and Agriculture, Ghana (2004a) Agriculture in Ghana. Facts and Figures 2003. Statistics, Research and Information Division, MoFA.

- Ministry of Food and Agriculture, Ghana (2004b) LRDP End Report. AFD, MoFA.
- Ministry of Food and Agriculture, Ghana (2005a) Talking Points of the 2005 Budget. Accra, Ghana: Government of Ghana.
- Ministry of Food and Agriculture, Northern Region, Ghana (2005b) Mid-Term Report 2005.
- Ministry of Food and Agriculture, Ghana (2006a) Speech Delivered By Hon. Ernest A. Debrah (MP), Minister for Food and Agriculture at the Ministry of Information and National Orientation Conference Room On Tuesday, 11th July 2006, Ghana.
- Ministry of Food and Agriculture, Ghana (2006b) Annual Progress Report: Jan. – Dec. 2005, Policy Planning Monitoring and Evaluation Directorate, MoFA, Ghana.
- Ministry of Information and National Orientation, Ghana (2007) Available at: http://www.ghana.gov.gh/ghana_map. Retrieved on 07/18/2008.
- Minten, B. and Barrett, C. B. (2008) Agricultural Technology, Productivity, and Poverty in Madagascar. *World Development* 36 (5): 797-822.
- Monge, M., Hartwich F. and Halgin, D. (2008) How Change Agents and Social Capital Influence the Adoption of Innovations among Small Farmers Evidence from Social Networks in Rural Bolivia. IFPRI Discussion Paper 00761, Washington, D.C.: International Food Policy Research Institute.
- Morris, M. L., Tripp, R. and Dankyi, A. A. (1999) Adoption and Impacts of Improved Maize Production Technology: A Case Study of the Ghana Grains Development Project. Economics Program Paper 99-01, Mexico, D. F.: CIMMYT.
- Moser, C. M., and Barrett, C. B. (2003) The Disappointing Adoption Dynamics of a Yield-increasing, Low External Input Technology: The Case of SRI in Madagascar. *Agricultural Systems* 76: 1085–1100.
- Moser, C. M. and Barrett, C. B. (2006) The Complex Dynamics of Smallholder Technology Adoption: The Case of SRI in Madagascar. *Agricultural Economics* 35(3): 373-388.
- Mundlak, Y. (1978) On the Pooling of Time-Series and Cross-section Data. *Econometrica* 64(1): 69-85.
- Namara, R., Weligamage, P. and Barker, R (2003) Prospects for Adopting System of Rice Intensification in Sri Lanka: A Socioeconomic Assessment. IWMI Research Report No. 75.
- Ndiaye, S. M. and Sofranko, A. J. (1994) Farmers' Perceptions of Resource Problems and Adoption of Conservation Practices in a Densely Populated Area. *Agriculture, Ecosystems and Environment* 48(1): 35-47.
- Negatu, W. and Parikh, A. (1999) The Impact of Perception and Other Factors on the Adoption of Agricultural Technology in the Moret and Jiru *Woreda* (district) of Ethiopia. *Agricultural Economics* 21: 205-216.
- Neill, S. P. and Lee, D. R. (2001) Explaining the Adoption and Disadoption of Sustainable Agriculture: The Case of Cover Crops in Northern Honduras. *Economic Development and Cultural Change* 49: 793-820.

- Neyman, J. (1923) On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9. Translated in: *Statistical Science* 5(4) (1990): 465–480.
- Nkonya, E., Pender, J., Jagger, P., SSerunkuuma, D., Kaizzi, C. and SSali, H. (2004) Strategies for Sustainable Land Management and Poverty Reduction in Uganda. Research Report 133, Washington, D.C.: IFPRI.
- Nkonya, E., Schroeder, T. and Norman, D. (1997) Factors Affecting Adoption of Improved Maize Seed and Fertiliser in Northern Tanzania. *Journal of Agricultural Economics* 48: 1-12.
- Norman, J. C. and Otoo, E (2002) Rice Development Strategies for Food Security in Africa. In: Sustainable Rice Production for Food Security. Proceedings of the 20th Session of the International Rice Commission. Bangkok, Thailand, 23-26 July 2002.
- Nwanze, K. F., Mohapatra, S., Kormawa, P., Keya, S. and Bruce-Oliver. S. (2006) Perspective – Rice Development in Sub-Saharan Africa. *Journal of Science of Food and Agriculture* 86: 675-677.
- Nyangena, W. (2006) Essays on Soil Conservation, Social Capital and Technology Adoption. Economic Studies 148. Department of Economics. School of Economics and Commercial Law, Göteborg University.
- Nyangena, W. (2008) Social Determinants of Soil and Water Conservation in Rural Kenya. *Environment, Development and Sustainability* 10(6): 745-767.
- Nyanteng, V. K. (1987) *Rice in West Africa. Consumption, Imports and Production with Projections to the Year 2000*. Monrovia, Liberia: WARDA.
- Obare, G. A., Omamo, S. W. and Williams, J. C. (2003) Smallholder Production Structure and Rural Roads in Africa: The Case of Nakuru District, Kenya. *Agricultural Economics* 28: 245-254.
- Obeng, J. W. (1994) Research Strategies for Improved Rice Production in Ghana. Paper presented at the International Seminar, Towards Rice Self-Sufficiency in Ghana, 6-7 June, 1994, Akosombo, Ghana.
- OECD (2003) Ghana. African Economic Outlook AfDB, OECD.
- OECD/FAO (2007) OECD-FAO Agricultural Outlook 2007-2016.
- Okike, M.A., Manyong, V. M., Smith, J. W. and Ehui, S. K. (2004) Factors Affecting Farm-Specific Production Efficiency in the Savanna Zones of West Africa. *Journal of African Economics* 13: 134-165.
- Oladele, O. I. and Sakagami, J. I. (2004) Impact of Technology Innovation on Rice Yield Gap in Asia and West Africa: Technology Transfer Issues. Presented at Deutscher Tropentag 2004 (Rural Poverty Reduction through Research for Development and Transformation) October 5 - 7, 2004, Berlin.
- Oomen, J. M. V., De Wolf, J. and Jobin, W. R. (1990) Health and Irrigation: Incorporation of Disease-Control Measures in Irrigation, a Multi-Faceted Task in Design, Construction and Operation. Publication 45, Wageningen: ILRI.
- Oteng, J. W. (1997) Rice Production and Development in Ghana. *International Rice Commission Newsletter* 46: 38-42.

- Overseas Development Institute (2000) Multi-Agency Partnerships in West Africa: Rice Production in Ghana. Available at: <http://www.odi.org.uk/plag/PROJECTS/multi-agency-partnerships.html>. Retrieved on 03/23/2005.
- Oxford Policy Management (2007) The Decline in Public Spending to Agriculture – Does it Matter? OPM Briefing Notes, UK.
- Pattanayak, S. and Mercer, D. E. (1998) Valuing Soil Conservation Benefits of Agroforestry: Contour Hedgerows in the Eastern Visayas, Philippines. *Agricultural Economics* 18(1):31-46.
- Pearce, R. (1990) Traditional Food Crops in Sub-Saharan Africa: Potentials and Constraints. *Food Policy* 15: 374-395.
- Pender, J., Gebremedhin, B., Benin, S. and Ehui, S. (2001) Strategies for Sustainable Agricultural Development in the Ethiopian Highlands. *American Journal of Agricultural Economics* 83: 1231-1240.
- Pender, J. and Kerr, J. (1998) Determinants of Farmers' Indigenous Soil and Water Conservation Investments in India's Semi-Arid Tropics. *Agricultural Economics* 19: 113-125.
- Pender, J., Nkonya, E., Jagger, P., Sserunkuuma, D., Henry Ssali, H. (2004) Strategies to Increase Agricultural Productivity and Reduce Land Degradation: Evidence From Uganda. *Agricultural Economics* 31: 181-195.
- Pinstrup-Andersen, P. and Pandya-Lorch, R. (1995) Agricultural Growth is the Key to Poverty Alleviation in Low-Income Developing Countries. 2020 Vision Brief 15, Washington, D.C.: IFPRI.
- Pitt, M. M. and Sumodiningrat, G. (1991) Risk, Schooling and the Choice of Seed Technology in Developing Countries: A Met-Profit Function Approach. *International Economic Review* 32(2): 457-473.
- Place, F., Franzel, S., Noordin, Q. and Jama, B. (2004) Improved Fallows in Kenya: History, Farmer Practice, and Impacts. EPTD Discussion Paper No. 115, Washington, D.C.: IFPRI.
- Place, F. and Hazell, P. (1993) Productivity Effects of Indigenous Land Tenure Systems in Sub-Saharan Africa. *American Journal of Agricultural Economics* 75: 10-19.
- Powell, J. (1986) Symmetrically Trimmed Least Squares Estimation for Tobit Models. *Econometrica* 54: 1435-1460.
- Pretty, J. N., Morison, J. I. L. and Hine, R. E. (2003) Reducing Food Poverty by Increasing Agricultural Sustainability in Developing Countries. *Agriculture, Ecosystems and Environment* 95: 217-234.
- Rahim, A. H., Ruben, R. and Ierland, E. C. (2008) Examining Disadoption of Gum Arabic Production in Sudan. *Agroforestry Systems* 73(2): 115-126.
- Rahm, M. and Huffmann, W. (1984) The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *The American Journal of Agricultural Economics* 66: 405-413.

- Ransom, J. K., Paudyal, K. and Adhikari, K. (2003) Adoption of Improved Maize Varieties in the Hills of Nepal. *Agricultural Economics* 29: 299-305.
- Rauniyar, G. P. and Goode, F. M. (1992) Technology Adoption on Small Farms. *World Development* 20: 275-282.
- Ravallion, M. and Datt, G. (1996) How Important to India's Poor Is the Sectoral Composition of Economic Growth? *The World Bank Economic Review* 10(1): 1-25.
- Reardon, T., Crawford, E. and Kelly, V. (1994) Links between Nonfarm Income and Farm Investment in African Households: Adding the Capital Market Perspective. *American Journal of Agricultural Economics* 76:1172-1176.
- Reinganum, J. F. (1981) Market Structure and the Diffusion of New Technology. *Bell Journal of Economics* 12: 618-624.
- Republic of Ghana (2005) Growth and Poverty Reduction Strategy (GPRS II) (2006-2009). National Development Planning Commission. Published as IMF Country Report No. 06/225. Ghana: Poverty Reduction Strategy Paper.
- Rhodes, E. R. (1995) Nutrient Depletion by Food Crops in Ghana and Soil Organic Nitrogen Management. *Agricultural Systems* 48: 101-118.
- Rogers, E. M. (1995) *Diffusion of Innovations*. New York: Free Press.
- Rogers, E. M. and Shoemaker, F. F (1971) *Communication of Innovations: A Cross-Cultural Approach*. New York: Free Press.
- Rosenbaum, P. R. (2002) *Observational Studies*. New York: Springer.
- Rosenbaum, P. R. and Rubin, D. B. (1983b) The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70(1): 41-50.
- Rosenbaum, P. R. and Rubin, D. B. (1985) Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician* 39: 33-38.
- Rosenzweig, M. R. and Wolpin, K. I. (1993) Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India. *Journal of Political Economy* 101 (2): 223-244.
- Roy, A. D. (1951) Some Thoughts on the Distribution of Earnings. *Oxford Economics Paper* 3: 135-146.
- Rubin, D. B. (1973) Matching to Remove Bias in Observational Studies. *Biometrics* 29: 159-183.
- Rubin, D. B. (1974) Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology* 66: 688-701.
- Rubin, D. B. (1976a) Multivariate Matching Methods that are Equal Percent Bias Reducing I: Some Examples. *Biometrics* 32: 109-120.
- Rubin, D. B. (1976b) Multivariate Matching Methods that are Equal Percent Bias Reducing II: Maximums on Bias Reduction for Fixed Sample Sizes. *Biometrics* 32: 121-132.

- Rubin, D. B. (1979) Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observation Studies. *Journal of the American Statistical Association* 74: 318-328.
- Rubin, D. B. (1980) Bias Reduction Using Mahalanobis Metric Matching. *Biometrics* 36: 293-298.
- Rubin, D. B. and Thomas, N. (2000) Combining Propensity Score Matching with Additional Adjustments for Prognostic Covariates. *Journal of the American Statistical Association* 95(450): 573-585.
- Runge-Metzger, A. and Diehl, L. (1993) Farm Household Systems in Northern Ghana. A Case Study in Farming Systems Oriented Research for the Development of Improved Crop Production Systems. NAES-Research Report, GTZ.
- Sadoulet, E. and de Janvry, A. (1995) *Quantitative Development Policy Analysis*. Baltimore, M.D.: John Hopkins University Press.
- Saha, A., Love, H. A. and Schwart, R. (1994) Adoption of Emerging Technologies Under Output Uncertainty. *American Journal of Agricultural Economics* 76: 836-846.
- Sakurai, T. (2002) Adoption of Modern Rice Variety and Water Control Technology in West Africa's Rainfed Lowland. WARDA, JIRCAS. Paper presented at the Workshop on the Green Revolution in Asia and its Transferability to Africa. December 8-10, 2002, Tokyo, Japan.
- Salasya, B. D. S., Mwangi, W. M., Verkuijl, H., Odendo, M. A. and Odenya, J. O. (1998) An Assessment of the Adoption of Seed and Fertilizer Packages and the Role of Credit in Smallholder Maize Production in Kakamega and Vihiga Districts, Kenya. Mexico, DF: CIMMYT/Kenya Agricultural Research Institute.
- Savadogo, K., Reardon, T. and Pietola, K. (1998) Adoption of Improved Land Use Technologies to Increase Food Security in Burkina Faso: Relating Animal Traction, Productivity, and Non-Farm Income. *Agricultural Systems* 58(3): 441-464.
- Schultz, T. W. (1975) The Value of the Ability to Deal with Disequilibria. *Journal of Economic Literature* 13: 827-46.
- Schumpeter, J. A. (1934) *The Theory of Economic Development*. Cambridge, MA: Harvard University Press.
- Seini, A. W. (2002a) Political Instability and Agricultural Policy Dynamics in Ghana. *Journal of Law Politics in Africa, Asia and Latin America*. 35(3): 414-430.
- Seini, A. W. (2002b) Agricultural Growth and Competitiveness under Policy Reforms in Ghana. Technical Publication 61.2002. Accra, Ghana: ISSER, University of Legon.
- Seini, A. W. and Asante, F. A. (1998) Rice Production in Ghana – A Policy Analysis Matrix (PAM) Assessment, Improving the Competitiveness and Marketability of Locally Produced Rice in Ghana. NRI/DFID.
- Seini, A. W. and Nyanteng, V. K. (2003) Afrint Macro Study: Ghana Report (Revised). ISSER, University of Ghana, Legon.

- Senauer, B., Sahn, D. and Alderman, H. (1986) The Effect of the Value of Time on Food Consumption Patterns in Developing Countries: Evidence from Sri Lanka. *American Journal of Agricultural Economics* 68(4): 920-927.
- Senayah, J. K. and Dedzoe, C. D. (1997) Potentials and Constraints on Productivity of Inland Valleys in Ghana: A Reconnaissance Study of the Forest Zone for Rice-based Systems. In: Proc. Soil Sci. Soc. Ghana. Vols. 14 & 15: 127-136.
- Sherlund, S. M., C. B. Barrett and Adesina, A. A. (2002) Smallholder Technical Efficiency Controlling for Environmental Production Conditions. *Journal of Development Economics* 69: 85-101.
- Shiferaw, B. and Holden, S. (1999) Soil Erosion and Smallholders' Conservation Decisions in the Highlands of Ethiopia. *World Development* 27(4): 739-752.
- Shively, G. E. (1997) Consumption Risk, Farm Characteristics, and Soil Conservation Adoption among Low-income Farmers in the Philippines. *Agricultural Economics* 17 (2-3): 165-177.
- Shively, G. E. (1998a) Impact of Contour Hedgerow on Upland Maize Yields in the Philippines. *Agroforestry Systems* 39: 59-71.
- Shively, G. E. (1998b) Modelling Impacts of Soil Conservation on Productivity and Yield Variability: Evidence from a Heteroskedastic Switching Regression. Selected paper at the Annual Meeting of the American Agricultural Economics Association 2-5 August 1998, Salt Lake City, Utah.
- Shively, G. E. (1999) Risks and Returns from Soil Conservation: Evidence from Low-Income Farms in the Philippines. *Agricultural Economics* 21(1): 53-67.
- Shively, G. E. (2001) Poverty, Consumption Risk and Soil Conservation. *Journal of Development Economics* 65: 267-290.
- Sianesi, B. (2004) An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s. *The Review of Economics and Statistics* 86: 133-155.
- Sidhu, S. S. and Baanante, C. A. (1979) Farm-level Fertilizer Demand for Mexican Wheat Varieties in the Indian Punjab. *American Journal of Agricultural Economics* 61(3): 455-462.
- Sidibe, A. (2005) Farm-level Adoption of Soil and Water Conservation Techniques in Northern Burkina Faso. *Agricultural Water Management* 71(3): 211-224.
- Simtowe, F. P. (2006) Can Risk-Aversion towards Fertilizer Explain Part of the Non-Adoption Puzzle for Hybrid Maize? Empirical Evidence from Malawi. *Journal of Applied Sciences* 6(7): 1490-1498.
- Singh, I. J., Squire, L. and Strauss, J. (eds) (1986) *Agricultural Household Models: Extensions, Applications, and Policy*. Baltimore, M.D.: Johns Hopkins University Press.
- Solh, M. (2002) Keynote address: Issues and Challenges in Rice Technological Development for Sustainable Food Security. In Proceedings of the 20th Session of the International Rice Commission, Bangkok, Thailand, 23-26 July 2002.
- Solivas, E. S., Ramirez, G. M. and Manalo, A. N. (2007) The Propensity Score Matching for Correcting Sample Selection Bias. 10th National Convention on Statistics (NCS), October

- 1 -2, 2007, Available at:
<http://www.nscb.gov.ph/ncs/10thNCS/papers/invited%20papers/ips-15/ips15-03.pdf>.
Retrieved on 06/14/2008.
- Somda, J., Nianogo, A. J., Nassa, S. and Sanou, S. (2002) Soil Fertility Management and Socio-Economic Factors in Crop-Livestock Systems in Burkina Faso: A Case Study of Composting Technology. *Ecological Economics* 43: 175-183.
- Smith, J. and Todd, P. (2005) Does Matching Overcome LaLonde's Critique of Non-experimental Estimators? *Journal of Econometrics*, 125(1): 305-353.
- Staal, S. J., Baltenweck, I., Waithaka, M. M., deWolff, T. and Njoroge, L. (2002) Location and Uptake; Integrated Household and GIS Analysis of Technology Adoption and Land Use, with Application to Smallholder Dairy Farms in Kenya. *Agricultural Economics* 27(3): 295-315.
- StataCorp (2005) Stata Statistical Software: Release 9. College Station, TX: StataCorp LP.
- Stoneman, P. (2002) *The Economic of Technological Diffusion*. Oxford, UK: Blackwell Publishers
- Sunding, D. and Zilberman, D. (2001) The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector. In: B. Gardner and G. Rausser (eds), *Handbook of Agricultural Economics*, vol. 1A: 207-261, Amsterdam: Elsevier.
- Teklewold, H., Dadi, L., Yami, A. and Dana, N. (2006) Determinants of Adoption of Poultry Technology: a Double-hurdle Approach. *Livestock Research for Rural Development* 18, No. 40.
- The World Bank (1989) *World Bank Report 1989*. New York: Oxford University Press.
- The World Bank (2003) Ghana Living Standards Survey 1998/99. Standardized Survey Bulletin 1. World Bank, Africa Region.
- The World Bank (2005a) World Development Indicators (WDI) 2005. Available at <http://go.worldbank.org/TSL3CROL30>. Retrieved on: 02/19/2008.
- The World Bank (2005b) IMF and World Bank Support US\$3.5 Billion in Debt Service Relief for the Republic of Ghana. News Release No: 2005/21/PREM.
- The World Bank (2007a) World Development Indicators (WDI) 2007. Available at: <http://web.worldbank.org/WBSITE/EXTERNAL/DATASTATISTICS/0,,contentMDK:21298138~pagePK:64133150~piPK:64133175~theSitePK:239419,00.html>. Retrieved on 06/08/2008.
- The World Bank (2007b) Ghana at a Glance. http://devdata.worldbank.org/AG/gha_aag.pdf. Retrieved on 01/04/2008.
- Todd, P. E. (2006) Matching Estimators. *Palgrave Dictionary of Economics*. Available at: <http://athena.sas.upenn.edu/~petra/papers/mpalgrave2.pdf>. Retrieved on 07/02/2008.
- Trost, R. P. (1981) Interpretation of Error Covariances with Nonrandom Data: An Empirical Illustration of Returns to College Education. *Atlantic Economic Journal* 9(3):85-90.

- Tunali, I. (1986) A General Structure for Models of Double-selection and an Application to a Joint Migration and Wage Process with Remigration. In: R. Ehrenberg (eds), *Research in Labour Economics: A Research Manual*, vol. 8 Part B, Greenwich, CT.: JAI Press.
- Tsikata, Y. M. (1999) Aid and Reform in Ghana. Econometric and Social Research Foundation (ESRF), Dar es Salaam, Tanzania. In: S. Devarajan, D. R. Dollar and T. Holmgren (eds), *Aid and Reform in Africa*, 45-100.
- Tsur, Y., Sternberg, M., and Hochman, E. (1990) Dynamic Modelling of Innovation Process Adoption with Risk Aversion and Learning. *Oxford Economic Papers* 42: 326-355.
- Udry, C. (1996) Gender, Agricultural Production, and the Theory of the Household. *Journal of Political Economy* 104: 1010-1046.
- United Nations Conference on Trade and Development (2008) Available at: <http://r0.unctad.org/infocomm/anglais/rice/market.htm>. Retrieved on 05/15/2008.
- United Nations Development Programme (2001) Human Development Report 2001, UNDP, New York.
- United Nations Development Programme (2005) Human Development Report 2005, UNDP, New York.
- United Nations Development Programme (2007) Human Development Report 2007/2008, UNDP, New York.
- United Nations (2007) World Population Prospects: The 2006 Revision and World Urbanization Prospects: The 2007 Revision. United Nations Secretariat, Department of Economic and Social Affairs, Population Division. Available at: <http://esa.un.org/unup>. Retrieved on 02/06/2008.
- United States Department of Agriculture (2006) Rice Backgrounder. Outlook Report from the Economic Research Service. RCS-2006-01, ERS, USDA.
- United States Department of Agriculture (2008a) Ghana – Grain and Feed Update 2008. Gain Report Number GH8001. FAS, USDA.
- United States Department of Agriculture (2008b) USDA Agricultural Projections to 2017. Long-term Projections Report, OCE-2008-1, USDA.
- Vella, F. (1998) Estimating Models with Sample Selection Bias: A Survey. *The Journal of Human Resources* 33(1): 127-169.
- Verbeek, M. (2004) *A Guide to Modern Econometrics*. New York: John Wiley and Sons.
- Voortman, R. L., Sonneveld, B. G. J. S. and Keyzer, M. A. (2000) African Land Ecology: Opportunities and Constraints for Agricultural Development. CID Working Paper No. 37.
- WARDA (1986) *Rice Statistics Yearbook*. Monrovia, Liberia: WARDA.
- WARDA (1997) Annual Report 1997. Bouaké, Côte d'Ivoire: WARDA.
- Weir, S. (1999) The Effects of Education on Farmer Productivity in Rural Ethiopia. CSAE Working Paper Series No. 99-7. Oxford: Centre for the Study of African Economies.
- Weir, S. and Knight, J. (2000) Adoption and Diffusion of Agricultural Innovations in Ethiopia: The Role of Education. CSAE Working Papers Series 2000-5. Oxford: Centre for the Study of African Economies.

- Willis, R. J. and Rosen, S. (1979) Education and Self-Selection. *Journal of Political Economy* 87: S7-S36.
- Winship, C. and Mare, R. D. (1992) Models for Sample Selection Bias. *Annual Review of Sociology* 18: 327-350.
- Wooldridge, J. M. (2002) *Econometric Analysis of Cross-Section and Panel Data*. Cambridge, M.A.: MIT Press.
- World Food Programme (2008) Where We Work – Ghana. Available at: http://www.wfp.org/country_brief/indexcountry.asp?country=288. Retrieved on 06/18/2008.
- World Trade Organization (2001) Document G/AG/N/GHA/2, 21 August 2001.
- World Trade Organization (2007) Trade Policy Review - Ghana. Document WT/TPR/S/194. Report of the WTO Secretariat.
- Wozniak, G. D. (1984) The Adoption of Interrelated Innovations: A Human Capital Approach. *The Review of Economics and Statistics* 66: 70-79.
- Wu, J. J. and Babcock, B. A. (1998) The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications. *American Journal of Agricultural Economics*: 494-511.
- Xu, X. and Jeffrey, S. (1998) Efficiency and Technical Progress in Traditional and Modern Agriculture: Evidence from Rice Production in China. *Agricultural Economics* 18: 117-165.
- Yesuf, M. (2004) Risk, Time and Land Management under Market Imperfections: Applications to Ethiopia. Economic Studies No. 139. Department of Economics, Göteborg University. Sweden.
- Zeller, M., Diagne, A. and Mataya, C. (1998) Market Access by Smallholder Farmers in Malawi: Implications for Technology Adoption, Agricultural Productivity and Crop Income. *Agricultural Economics* 19 (1-2): 219-229.

Appendices

Appendix 1: Background information

Table A. 1: Ghana's post-independence regimes

Year	Regime		
1957-1966	Convention People's Party (CPP) Government under Nkrumah	Socialist	Civilian
1966-1969	National Liberation Council (NLC)	Capitalist	Military
1969-1972	Progress Party (PP) Government under Busia	Capitalist	Civilian
1972-1975	National Redemption Council (NRC) Government under Acheampong	State-led / socialist	Military
1975-1979	Supreme Military Council (SMC) Government under Acheampong (SMC I), from 1978 under Akuffo (SMC II) after coup	State-led / socialist	Military
1979	Armed Forces Revolutionary Council (AFRC) Government under Rawlings	Capitalist	Military
1979-1981	People's National Party (PNP) Government under Liman	Capitalist	Civilian
Dec 1981	Coup		
1982-1992	Provisional National Defence Council (PNDC) Government under Rawlings	Capitalist	Military
1992-2000	National Democratic Congress (NDC) Government under Rawlings, re-election in 1993 and 1996	Capitalist	Civilian
2000-present	New Patriotic Party (NPP) Government under Kufuor, re-election in 2004	Capitalist	Civilian

Source: Asuming-Brempong (2003a); Seini and Nyanteng (2003)

Appendix 2: Econometric Estimations

Table A. 2: Estimation of propensity scores: treatment effects of bund adoption on net returns

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.004	-0.32	-0.004	-0.32	-0.003	-0.22
GEQ_HH	0.023	1.48	0.023	1.48	0.024	1.53
GEQ_ILL	-0.057	-1.48	-0.057	-1.48	-0.057	-1.48
PRICE_AV	-0.000	-0.49	-0.000	-0.49	-0.000	-0.51
HEAD	0.172	0.55	0.172	0.55	0.175	0.56
BULL	-0.570	-1.44	-0.570	-1.44	-0.568	-1.44
BIKE	-0.059	-0.26	-0.059	-0.26	-0.071	-0.31
CROP_SZ	-0.145	-1.11	-0.145	-1.11	-0.149	-1.14
FSZ	0.091	0.83	0.091	0.83	0.094	0.85
AV_FSZ	0.274*	1.79	0.274*	1.79	0.289*	1.87
INFS_R					0.157	0.62
EDUC_R	0.025	0.18	0.025	0.18		
OFF_R	-0.242	-0.92	-0.242	-0.92	-0.255	-0.96
CREDIT	0.341	1.11	0.341	1.11	0.336	1.10
TRACTOR	1.261	1.26	0.261	1.26	1.241	1.26
FSRPOP	0.078	0.26	0.078	0.26	0.072	0.24
LRDP	0.033	0.12	0.033	0.12	0.039	0.14
USE_IMP	0.866	1.54	0.866	1.54	0.856	1.53
USE_D	1.289***	4.29	1.289***	4.29	1.291***	4.29
CGROUP2	-0.024	-0.09	-0.024	-0.09	-0.009	-0.03
SH_VSOIL	-0.449*	-1.78	-0.449*	-1.78	-0.445*	-1.76
SH_LOAM	-0.409	-1.34	-0.409	-1.34	-0.405	-1.33
SH_VRET	-0.153	-0.60	-0.153	-0.60	-0.153	-0.60
KY	1.620***	3.20	1.620***	3.20	1.653***	3.25
CONST	-1.531	-1.49	-1.531	-1.49	-1.624	-1.59
Obs.	186		186		186	
Pseudo- R^2	0.2454		0.2454		0.2468	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 3: Estimation of propensity scores: treatment effects of bund adoption on output supply

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	0.001	0.08	0.001	0.10	0.001	0.08
GEQ_HH	0.023	1.48	0.023	1.50	0.023	1.48
GEQ_ILL	-0.058	-1.59	-0.058	-1.58	-0.058	-1.59
PRICE_AV	-0.000	-0.09	-0.000	-0.10	-0.000	-0.09
HEAD	0.001	0.03	0.023	0.08	0.001	0.03
BULL	-0.237	-0.76	-0.227	-0.72	-0.237	-0.76
CROP_SZ	-0.111	-0.89	-0.118	-0.93	-0.111	-0.89
FSZ	0.064	0.60	0.057	0.51	0.064	0.60
FSZ2_100			0.043	0.24		
AV_FSZ	0.270*	1.82	0.265*	1.79	0.270*	1.82
EDUC_R	-0.022	-0.16	-0.023	-0.17	-0.022	-0.16
OFF_R	-0.176	-0.70	-0.171	-0.68	-0.176	-0.70
CREDIT	0.371	1.25	0.363	1.22	0.371	1.25
TRACTOR	0.924	1.53	0.895	1.46	0.924	1.53
FSRPOP	0.225	0.79	0.230	0.81	0.225	0.79
LRDP	0.169	0.56	0.173	0.57	0.169	0.56
USE_IMP	0.512	1.04	0.512	1.04	0.512	1.04
USE_D	1.445***	5.04	1.446***	5.05	1.445***	5.04
CGROUP2	-0.105	-0.44	-0.107	-0.44	-0.105	-0.44
SH_LRDP	-0.246	-0.65	-0.248	-0.65	-0.246	-0.65
SH_VSOIL	-0.543**	-2.32	-0.540**	-2.30	-0.543**	-2.32
SH_LOAM	-0.315	-1.11	-0.322	-1.13	-0.315	-1.11
SH_VRET	-0.136	-0.57	-0.131	-0.55	-0.136	-0.57
KY	1.508***	3.18	1.523***	3.19	1.508***	3.18
CONST	-1.664*	-1.81	-1.625*	-1.75	-1.664*	-1.81
Obs.	216		216		216	
Pseudo- R^2	0.2556		0.2558		0.2556	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 4: Estimation of propensity scores: treatment effects of bund adoption on input demand

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.000	-0.02	-0.000	-0.02	-0.001	-0.04
GEQ_HH	0.025*	1.66	0.025*	1.66	0.025*	1.66
GEQ_ILL	-0.054	-1.48	-0.054	-1.48	-0.055	-1.49
PRICE_AV	-0.000	-0.22	-0.000	-0.22	-0.000	-0.11
HEAD	0.075	0.26	0.075	0.26	0.078	0.27
BULL	-0.234	-0.76	-0.234	-0.76	-0.229	-0.75
BIKE	-0.083	-0.40	-0.083	-0.40	-0.084	-0.41
CROP_SZ	-0.122	-0.99	-0.122	-0.99	-0.124	-1.01
FSZ	0.074	0.70	0.074	0.70	0.077	0.73
AV_FSZ	0.261*	1.77	0.261*	1.77	0.259*	1.76
EDUC_R	-0.014	-0.11	-0.014	-0.11	-0.013	-0.10
OFF_R	-0.132	-0.53	-0.132	-0.53	-0.125	-0.51
CREDIT	0.184	0.19	0.184	0.19	0.404	1.55
CREDIT*PRICE	0.000	0.24	0.000	0.24		
TRACTOR	1.016*	1.68	1.016*	1.68	1.024*	1.70
FSRPOP	0.234	0.81	0.234	0.81	0.248	0.88
SH_LRDP	-0.075	-0.22	-0.075	-0.22	-0.072	-0.21
USE_IMP	0.498	1.02	0.498	1.02	0.506	1.04
USE_D	1.430***	5.03	1.430***	5.03	1.435***	5.07
CGROUP2	-0.059	-0.25	-0.059	-0.25	-0.058	-0.25
SH_VSOIL	-0.533**	-2.24	-0.533**	-2.24	-0.541**	-2.30
SH_VRET	-0.119	-0.51	-0.119	-0.51	-0.116	-0.50
KY	1.540***	3.20	1.540***	3.20	1.554***	3.26
CONST	-1.560	-1.58	-1.595	-1.58	-1.687*	-1.82
Obs.	218		218		218	
Pseudo- R^2	0.2520		0.2520		0.2518	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 5: Estimation of propensity scores: treatment effects of dibbling seed on input demand

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.003	-0.16	-0.003	-0.16	-0.000	-0.13
AGE2_R					0.006	0.08
GEQ_HH	0.007	0.31	0.007	0.31	0.009	0.39
PRICE_AV	-0.000	-0.33	-0.000	-0.33	-0.000	-0.37
HEAD	0.418	1.23	0.418	1.23	0.441	1.26
FSZ	-0.052*	-1.75	-0.052*	-1.75	-0.048	-0.72
FSZ2_100					-0.015	-0.09
AV_FSZ	0.016	0.11	0.016	0.11	0.171	0.52
AV_FSZ2_100					-2.641	-0.55
INFS_R	0.208	0.70	0.208	0.70	0.249	0.81
OFF_R	-0.855***	-2.71	-0.855***	-2.71	-0.891***	-2.74
CREDIT	0.296	0.92	0.296	0.92	0.322	0.99
TRACTOR	0.820	1.01	0.820	1.01	0.902	1.03
FSRPOP	0.721*	1.86	0.721*	1.86	0.711*	1.82
SH_LRDP	-0.193	-0.39	-0.193	-0.39	-0.241	-0.47
USE_IMP	0.850	1.34	0.850	1.34	0.844	1.31
SH_BUND	1.111***	3.43	1.111***	3.43	1.141***	3.38
CGROUP2	0.297	0.94	0.297	0.94	0.281	0.88
SH_VSOIL	0.961***	3.12	0.961***	3.12	0.961***	3.10
SH_VRET	-0.083	-0.71	-0.083	-0.71	-0.103	-0.35
DROUGHT	0.536*	1.75	0.536*	1.75	0.543*	1.75
KY	-2.373***	-3.96	-2.373***	-3.96	-2.348***	-3.82
ZUWARI	-0.237	-0.63	-0.237	-0.63	-0.253	-0.67
CONST	-0.764	-0.71	-0.764	-0.71	-1.056	-0.59
Obs.	208		208		208	
Pseudo- R^2	0.3799		0.3799		0.3811	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 6: Estimation of propensity scores: treatment effects of dibbling seed on output supply

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.002	-0.03	-0.002	-0.03	-0.000	-0.00
AGE2_R	-0.000	-0.00	-0.000	-0.00		
GEQ_HH	0.022	0.97	0.022	0.97	0.022	0.99
PRICE_AV	0.000	0.39	0.000	0.39	0.000	0.40
HEAD	0.248	0.71	0.248	0.71	0.266	0.77
BULL	-0.595	-1.40	-0.595	-1.40	-0.532	-1.29
bike	0.473*	1.67	0.473*	1.67	0.483*	1.72
R_SZ	-0.149	-0.97	-0.149	-0.97	-0.112	-0.78
FSZ	0.053	0.61	0.053	0.61	-0.004	-0.11
FSZ2_100	-0.140	-0.76	-0.140	-0.76		
AV_FSZ	-0.015	-0.10	-0.015	-0.10	-0.017	-0.12
INFS_R	0.103	0.36	0.103	0.36	0.098	0.34
OFF_R	-0.621**	-2.09	-0.621**	-2.09	-0.609**	-2.08
CREDIT	-0.224	-0.56	-0.224	-0.56	-0.244	-0.61
TRACTOR	0.430	0.53	0.430	0.53	0.284	0.37
FSRPOP	0.600	1.58	0.600	1.58	0.596	1.59
LRDP	0.712*	1.81	0.712*	1.81	0.719*	1.84
USE_IMP	0.715	1.25	0.715	1.25	0.742	1.30
SH_BUND	0.905***	3.11	0.905***	3.11	0.903***	3.13
SH_LOAM	0.402	1.10	0.402	1.10	0.391	1.08
SH_VRET	0.302	1.15	0.302	1.15	0.333	1.28
DROUGHT	0.508*	1.69	0.508*	1.69	0.503*	1.71
KY	-2.431***	-4.08	-2.431***	-4.08	-2.337***	-4.13
ZUWARI	-0.309	-0.89	-0.309	-0.89	-0.288	-0.83
CONST	-1.667	-1.00	-1.667	-1.00	-1.612	-1.54
Obs.	206		206		206	
Pseudo- R^2	0.3789		0.3789		0.3765	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 7: Estimation of propensity score: treatment effects of dibbling seed on net returns

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.008	-0.40	-0.001	-0.07	0.002	0.13
GEQ_HH	0.012	0.44	0.014	0.52	0.021	0.84
GEQ_ILL	0.021	0.38	0.019	0.36	0.027	0.51
PRICE_AV	-0.000	-0.44	-0.000	-0.13	0.000	0.78
HEAD	0.361	0.87	0.430	1.05	0.243	0.62
BULL	-0.031	-0.05	-0.312	-0.58	-0.532	-1.00
BIKE	0.342	1.05	0.395	1.22	0.581*	1.88
R_SZ	-0.285	-1.49	-0.170	-0.96	-0.019	-0.11
FSZ	0.290	1.55	-0.020	-0.34	-0.049	0.92
FSZ2_100	-1.266	-1.50				
AV_FSZ	-0.118	-0.71	-0.124	-0.78	0.090	0.26
AV_FSZ_2_100					-1.758	-0.37
EDUC_R	-0.045	-0.23	-0.096	-0.51	-0.071	-0.38
OFF_R	-0.958***	-2.69	-0.814**	-2.32	-0.850**	-2.53
CREDIT	0.380	0.94	-0.201	-0.44	-0.136	-0.33
TRACTOR	-0.508	-0.49	-0.353	-0.34	-0.098	-0.11
FSRPOP	0.676	1.35	0.740	1.52	0.589	1.33
LRDP			1.020**	2.34	0.913**	2.26
SH_LRDP	0.179	0.30				
USE_IMP	1.046	1.44	0.811	1.17	0.736	1.19
USE_B	1.284***	3.74	1.309***	3.87		
SH_BUND					0.793***	2.62
CGROUP3	0.340	0.63	0.290	0.56	0.121	0.24
SH_VSOIL	0.863**	2.34	0.849**	2.30		
SH_LOAM	0.342	0.80	0.283	0.67	0.243	0.62
SH_VRET	0.067	0.19	0.075	0.22		
DROUGHT	0.818**	2.23	0.786**	2.22	0.597*	1.89
KY	-3.296***	-3.83	-3.164***	-4.07	-2.628***	-3.88
ZUWARI	-0.450	-1.05	-0.357	-0.83	-0.334	-0.89
CONST	-1.742	-1.25	-1.149	-0.88	-1.772	-1.44
Obs.	177		177		177	
Pseudo- R^2	0.4898		0.4958		0.4184	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 8: Estimation of propensity score: treatment effects of dibbling seed and fertilizer on input demand

Variable Name	Nearest Neighbour		Kernel based		Mahalanobis	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
AGE_R	-0.018	-1.09	0.025	0.33	0.025	0.33
AGE2_R			0.001	-0.61	-0.001	-0.61
GEQ_HH	-0.006	-0.36	-0.013	-0.67	-0.013	-0.67
PRICE_AV	0.000	1.63	0.000*	1.79	0.000*	1.79
HEAD	0.096	0.29	-0.107	-0.31	-0.107	-0.31
FSZ	-0.054*	-1.79	0.128	0.88	0.128	0.88
FSZ2_100			-0.767	-0.98	-0.767	-0.98
AV_FSZ	0.122	0.88	0.156	1.00	0.156	1.00
EDUC_R	0.197	1.33	0.224	1.45	0.224	1.45
OFF_R	-0.843***	-2.77	-0.944***	-2.95	-0.944***	-2.95
CREDIT	0.884***	2.85	0.937***	2.96	0.937***	2.96
TRACTOR	2.136**	3.04	2.475***	2.97	2.475***	2.97
FSRPOP	0.777**	2.49	0.673**	2.13	0.673**	2.13
SH_LRDP	-0.696	-1.60	-0.745*	-1.72	-0.745*	-1.72
USE_IMP	0.953	1.34	0.829	1.17	0.859	1.17
SH_BUND	0.386	1.26	0.447	1.42	0.447	1.42
CGROUP2	0.004	0.01	0.012	0.04	0.012	0.04
SH_VSOIL	0.190	0.70	0.188	0.68	0.188	0.68
SH_VRET	-0.516*	-1.75	-0.613**	-2.00	-0.613**	-2.00
DROUGHT	-1.026***	-3.48	-1.075***	-3.54	-1.075***	-3.54
ZUWARI	-1.426***	-3.66	-1.403***	-3.64	-1.403***	-3.64
CONST	-1.140	-1.02	-2.479	-1.33	-2.479	-1.33
Obs.	190		190		190	
Pseudo- R^2	0.3456		0.3656		0.3656	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 9: Estimation of propensity score: treatment effect of intensified package on net returns

Variable Name	Mahalanobis	
	Coefficient	<i>t</i> -value
AGE_R	-0.001	-0.50
AGE2_R	0.039	0.43
GEQ_HH	0.029	1.17
PRICE_AV	-0.000	-0.15
BULL	0.312	0.49
HEAD	0.262	0.68
FSZ	0.100	0.59
FSZ2_100	-0.891	-1.05
AV_FSZ	0.471	1.22
AV_FSZ_2_100	-6.313	-1.21
EDUC_R	-0.067	-0.37
OFF_R	-0.769**	-2.18
CREDIT	-0.169	-0.39
FSRPOP	0.536	1.32
LRDP	1.080***	2.60
USE_IMP	0.268	0.39
USE_B	1.106***	3.36
CGROUP3	0.031	0.06
SH_VSOIL	0.543*	1.71
SH_LOAM	0.452	1.15
SH_VRET	0.619*	1.84
DROUGHT	1.240***	3.41
KY	-3.753**	-4.12
ZUWARI	-0.539	-1.48
CONST	-2.894	-1.34
Obs.	173	
Pseudo- R^2	0.4702	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Table A. 10: Estimation of propensity score: treatment effect of intensified package on output

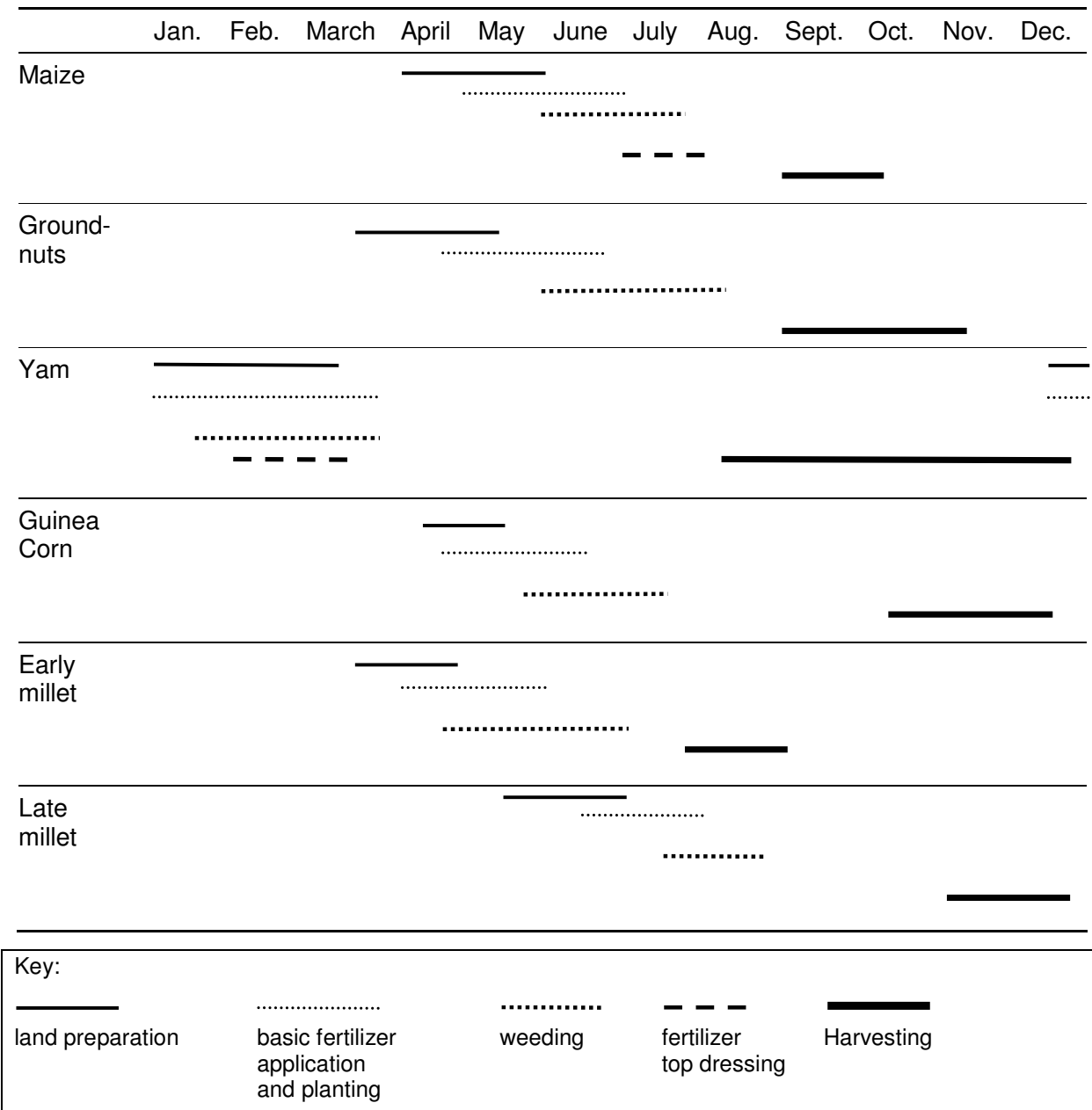
Variable Name	Mahalanobis	
	Coefficient	<i>t</i> -value
AGE_R	-0.020	-1.24
GEQ_HH	0.012	0.58
PRICE_AV	-0.000	-0.16
BULL	0.647	1.38
BIKE	0.090	0.37
HEAD	0.286	0.84
FSZ	0.125	0.91
FSZ2_100	-1.031	-1.48
AV_FSZ	0.055	0.34
EDUC_R	-0.079	-0.53
OFF_R	-0.490*	-1.67
CREDIT	-0.030	-0.08
TRACTOR	-0.806	-1.43
FSRPOP	-0.009	-0.03
LRDP	0.821**	2.14
USE_IMP	0.259	0.45
USE_B	0.912***	3.30
CGROUP3	0.152	0.32
SH_VSOIL	0.525*	1.85
SH_VRET	0.618**	2.12
DROUGHT	1.014***	3.39
KY	-3.238	-1.15
ZUWARI	-0.378	-1.15
CONST	-0.906	-0.81
Obs.	206	
Pseudo- R^2	0.3943	

Note: Coefficients followed by *, ** and *** are significant at the 10%, 5%, and 1% level

Source: Own calculation

Appendix 3: Calendar of Cropping Activities, Northern Region Ghana

Figure A. 1: Cropping calendar of principal food crops



Source: Ghanaian-German Agricultural Development Project (1977)

Table A. 11: Rice cropping calendar

Activity	Focus group discussion	Recommendations according to MoFA (2004b)
Ploughing, bund construction	April - May	When soil becomes moist enough, depending on first rains
Harrowing	End of May	About two weeks after ploughing to ensure that all weeds are desiccated
Planting	First week of June	Before middle of June to obtain good yields
First fertiliser application	First week of July	Fertilizer applied three weeks after planting, second 50 days later
First manual weeding / herbicides	Middle – end of July	Three weeks after planting
Second weeding	August	Four weeks after first weeding, if herbicide was applied, light weeding may be required 6 weeks later
Second fertiliser	Late August / September	The second fertilizer is top-dressed 6-7 weeks after first fertilizer
Harvesting	November	Maturity

Source: Focus group discussion, Touroyili (Kulda-Yarong valley); MoFA (2004b)

Appendix 4: Farmer-level Questionnaire

Water harvesting methods and intensive practices in Lowland rice cultivation in Northern Region, Ghana

University of Kiel, Germany (Prof. Dr. Abdulai)
in collaboration with
Savannah Agricultural Research Institute (SARI), Tamale

I. INDIVIDUAL RICE FARMER QUESTIONNAIRE

QUESTIONNAIRE №.: _____

Questionnaire № of related compound household: _____

Name of household head: _____

House name: _____

District: _____ Village: _____ Sub-quarter: _____

BEFORE STARTING THE QUESTIONNAIRE:

➤ **Were you a LRDP farmer?**

Was a LRDP member

Was not a LRDP member

➤ Did you ever make bunds by your own (small field bunds, intermediary bunds, contour bunds on own lowlands or LRDP)?

NO, never → Non-adopter of self bunds (never used self made bunds)

YES → Do you still use / maintain / reconstruct the self made bunds?

Yes → Adopter of self bunds (currently use self made bunds)

No → **Do you want to continue next cropping season with construction / maintenance of the self made bunds?**

Yes → Adopter of self made bunds

No → Dis-adopter of self made bunds (don not want to continue self made bunds)

Still use self-made bunds

Never used self-made bunds

Does not want to continue with self-made bunds

Still dibbling

Never dibbled

Stopped dibbling

COMPARE WITH LIST! ONLY IF FARMER BELONGS TO CORRECT GROUP, CONTINUE WITH THE QUESTIONNAIRE

Date of interview: [_ / _ / _] (DD/MM/YY)	
Time started: _____	Time ended: _____
Reviewed by: _____	Date: [_ / _ / _]
Name of Interviewer: _____	

A. INFORMATION ABOUT RICE FARMER

1. Name of **respondent (rice farmer)**: _____
2. Respondent's relation to the household head:

1 = Household head himself <input type="checkbox"/>	4 = Daughter <input type="checkbox"/>
2 = Wife to household head <input type="checkbox"/>	5 = Other (specify) _____ <input type="checkbox"/>
3 = Son <input type="checkbox"/>	<input type="checkbox"/>
3. Sex of respondent: _____
4. Age of respondent: _____ (If given age is doubted: **estimated age**: _____)
5. Religion: (Tick)

1 Muslim <input type="checkbox"/>	3 Indigenous <input type="checkbox"/>
2 Christian <input type="checkbox"/>	4 _____ <input type="checkbox"/>
6. Marital status of respondent: (Tick)

1 Married (monogamous) <input type="checkbox"/>	4 Widowed <input type="checkbox"/>
2 Married (polygamous) <input type="checkbox"/> → No of current wives: _____	5 Divorced <input type="checkbox"/>
3 Single (unmarried) <input type="checkbox"/>	
7. Number of children of respondent:

≤16 years _____	
Adult children _____	
8. Number of children (≤16 years) sent to school: _____
9. Highest educational level of **farm family**: (Codes below)

Male _____	1 None	5 Primary school 1-3	9 Senior Secondary School
Female _____	2 Adult literacy education	6 Primary school 3-6	10 Technical college
Children _____	3 Dabani literacy	7 Middle School	11 Training college
	4 Korani	8 Junior Secondary School	12 University

B. GENERAL FARMING INFORMATION


10. Means of transport:

	Means of transport (more than one possible)	Location (name of market / farmgate)	Means of transport 1 foot 2 bicycle 3 motorbike 4 car	5 market truck 6 market women 7 _____
Transport of harvest to compound	_____	XXXXXXXXXXXX		
Selling rice	_____	_____		
Selling other agricultural output	_____	_____		
Buying agricultural inputs	_____	_____		

11. **Farm family (husband + wife(s) + children):** № of livestock owned

- | | | | |
|------------|-------|-----------|-------|
| a) Cattle | _____ | g) Pigeon | _____ |
| b) Sheep | _____ | h) Donkey | _____ |
| c) Goat | _____ | i) Horse | _____ |
| d) Poultry | _____ | j) _____ | _____ |

12. Respondent: № of equipment owned and access to equipment:

	№ owned by respondent	If not owned, possible source of use
Radio	_____	_____
Bicycle	_____	_____
Motorbike	_____	_____
Push cart	_____	_____
Animal drawn cart	_____	_____
Wheelbarrow	_____	_____
Bullock plough	_____	_____
Tractor plough / harrower	_____	_____
Bullock (pair)	_____	_____
Car / Pick-up	_____	_____
Tractor	_____	_____

Source:
1 Household
2 Borrow / use without payment
3 Hire

13. Total size of land owned by the respondent: _____ (acres)

14. **Plots** of rice farmer (except of lowland / midland rice) 2005: Indicate (intercropped) crop(s) per plot and size of plot:

Plot	Crop(s): ¹	Size (acres):	Plot	Crop(s): ¹	Size (acres):
1	_____	_____	5	_____	_____
2	_____	_____	6	_____	_____
3	_____	_____	7	_____	_____
4	_____	_____	8	_____	_____

15. Rank crops according importance as cash crop for respondent (plots of respondent: output of crops 2005). **Indicate for each crop, whether it is cultivated for own purpose or family feeding.**

Type of crop	Quantity harvested by respondent (2005)	Unit Code	O=own purpose F=family feeding	Rank after importance as cash crop for respondent (normal year)
1 Maize	_____	_____	_____	_____
2 Lowland / midland rice	_____	_____	_____	_____
3 Upland rice	_____	_____	_____	_____
4 Cassava	_____	_____	_____	_____
5 Millet	_____	_____	_____	_____
6 Guinea corn	_____	_____	_____	_____
7 Groundnut	_____	_____	_____	_____
8 Yam	_____	_____	_____	_____
9 Cowpea	_____	_____	_____	_____
10 Beans	_____	_____	_____	_____
11 Soybean	_____	_____	_____	_____
12 Bambara Beans	_____	_____	_____	_____
13 Pidgeon pea (Cajanus)	_____	_____	_____	_____
14 Sheanut	_____	_____	_____	_____
15 Sweet potatoe	_____	_____	_____	_____
16 Tomato	_____	_____	_____	_____
17 Okro	_____	_____	_____	_____
18 Pepper	_____	_____	_____	_____
19 Tobacco	_____	_____	_____	_____
20 Mango	_____	_____	_____	_____
21 Papaw	_____	_____	_____	_____
22 Watermelon	_____	_____	_____	_____

Unit Codes

1 Bowl

2 Maxi Bags

3 Mini Bags

4 Kg

5 Tubers

6 Calabash

7 Crate(s)

8 Bail(s)

9 Bundles

16. How many hours per week do you usually work on your **own farms**? _____ (hours / week)

C. LOWLAND RICE PRODUCTION OF RESPONDENT

17. When did you start operating your own rice production in lowlands / midlands?
_____ (year)

18. Were you a **LRDP / FSRPOP** project farmer? Yes → a) No → b)

a) **IF LRDP farmer**: Year of starting: _____ Year of leaving: _____

If farmer left: why did you leave?

b) **IF NO LRDP farmer:** Why did you not participate in the project?

→ If farmer did not get a LRDP plot, when did you try to participate and apply:

_____ (year)

19. Did you **abandon** any plot in lowlands / midlands? Yes No → Question № 20

IF YES:

	Acres	Year	Reason:
LRDP rice plots	_____	_____	_____
Self banded other lowlands / midlands	_____	_____	_____
Non-banded other lowlands / midlands	_____	_____	_____

20. Use of improved lowland rice cropping practices in lowlands / midlands

	C=still used N=never used S=not continue	IF EVER USED: year of starting (and ending*)	IF NOT OR NOT ANYMORE USED, why not?
Intermediary bunds	_____	_____ - _____	_____
Self 'contour' bunds	_____	_____ - _____	_____
Levelling	_____	_____ - _____	_____
Dibbling seed	_____	_____ - _____	_____
Using fertilizer	_____	_____ - _____	_____
Improved varieties	_____	_____ - _____	_____

21. Total size of **lowlands / midlands** hold by respondent in **2005**: _____ (acres)

22. Number of **acres in LRDP** of respondent in **2005**: _____ (acres)

23. Characteristics of **lowland and midland rice plots** of respondent cultivated in **2005**:

(Name)	LRDP project bunds	Size of cultivated plot (acre)	Distance to compound (bike min)	Number of years plot is cultivated by respondent	Intercropping of rice with other crops?	Type of tenure arrangement	IF NOT OWN: for how long is land given to you?
LRDP rice plots	1 _____	_____	_____	_____	_____	_____	_____
	2 _____	_____	_____	_____	_____	_____	_____
Other lowlands / midland rice plots	3 _____	_____	_____	_____	_____	_____	_____
	4 _____	_____	_____	_____	_____	_____	_____

Plot No.	Position in valley	Field type	Soil type	Soil fertility	Water retention without bunds (end of season)
1	Entry of water flow	1 Midland	1 Clay	1 High (or yield <3- 4 bags)	1 Very good (< 1 week)
2	Exit of water flow	2 Lowland	2 Gravel	2 Middle (or yield <2-3 bags)	2 Good (< 4 days)
3	Middle	3 Upland	3 Loam	3 Low (or yield <1-2 bags)	3 Middle (< 2,3 days)
			4 Silt	4 Very low (or yield <0.5-1 bag)	4 Bad (< 1 day)
			5 Sandy Loam		
1	_____	_____	_____	_____	_____
2	_____	_____	_____	_____	_____
3	_____	_____	_____	_____	_____
4	_____	_____	_____	_____	_____

IF RESPONDENT EVER USED BUNDS OR DIBBLING
--

24. If any self made bunds on own lowlands:

Bunds constructed in straight line along contours

25. Estimated height and width of **self made bunds**, equipment and maintenance: (*Codes below*)

	(last) height	(last) width	(last) length	Equipment for construction	Maintenance (Codes !)	Equipment for raising, reshaping, reconstruction
'Contour' bunds	_____	_____	_____	_____	_____	_____
Intermediary bunds	_____	_____	_____	_____	_____	_____

Codes for maintenance (*more than one possible*)

- | | | |
|----------------------------|-------------------------------------|--------------------|
| 1 Uprooting weeds | 4 Reshaping / raising | 7 No maintenance |
| 2 Spraying / cutting weeds | 5 Reconstruction (partial) | 8 Use of sand bags |
| 3 Planting cover crops | 6 Complete reconstruction | 9 _____ |

If no maintenance; why?

26. Reasons to make **self-bunds**: (**Rank**)

Water retention	_____	Foot path	_____
Conservation of fertilizer	_____	Marking field	_____
Conservation of soil fertility	_____	_____	_____

27. From whom did you learn most about **bunds/dibbling** and its benefit? (**Rank**)

Project	_____	Family members	_____
Extension agents	_____	Friends	_____
Other LRDP farmer	_____	Radio	_____
Fellow farmers	_____	_____	_____
Farmer group	_____		

28. What was the **average yield** of lowland rice in a normal year before adoption of self-made bunds / dibbling? _____ (**bags / acre**)

29. **Use of revenues** from rice production in lowlands / midlands: (Tick, **rank only if any expenditure**)

- | | | | |
|---|-------|---|-------|
| <input type="checkbox"/> Food purchases | _____ | <input type="checkbox"/> Education | _____ |
| <input type="checkbox"/> Basic needs, clothing, health | _____ | <input type="checkbox"/> Others (stop migration, Marriage, own household) | _____ |
| <input type="checkbox"/> Farming activities (hiring labour, inputs, tractor / bullock services) | _____ | | |
| <input type="checkbox"/> Family / own assets : | _____ | <input type="checkbox"/> | _____ |
| _____ | | | |

30. Was there any change in size in upland cultivation after adoption of bunds / dibbling?
 Yes No

IF YES:

- Increase** by _____ acres
 Decrease by _____ acres

31. *Did you receive any credit before adoption of **any** bunds / dibbling? Yes No

IF RESPONDENT HAD BUNDS IN 2005

32. Condition of self made bunds of responding rice farmer in **2005**:

If hired tractor- / bullock services for reconstruction and maintenance of all bunds 2005:

Additional costs of tractor- / bullock services for bund construction / maintenance 2005 _____

IF RESPONDENT HAS LRDP BUNDS

33. **Height and condition** of LRDP bunds:

34. Maintenance of LRDP bunds: (Tick)

- | | | |
|--|--|--|
| <input type="checkbox"/> <i>Uprooting weeds</i> | <input type="checkbox"/> <i>Reshaping / raising</i> | <input type="checkbox"/> <i>No maintenance</i> |
| <input type="checkbox"/> <i>Spraying / cutting weeds</i> | <input type="checkbox"/> <i>Reconstruction (partial)</i> | <input type="checkbox"/> <i>Use of sand bags</i> |
| <input type="checkbox"/> <i>Planting cover crops</i> | <input type="checkbox"/> Complete reconstruction | <input type="checkbox"/> _____ |

If no maintenance; why?

IF RESPONDENT HAD NO SELF BUNDS in 2005:

35. Do you plan to construct bunds? No

Yes → when? _____

- type: intermediary bunds
 self contour bunds

IF RESPONDENT DIBBLES SEED

36. Why do you dibble seed? (*Rank*)

Easy weeding	___	Save seed	___
Yield increase	___	_____	___
Easy fertilizer application	___	_____	___

37. IF not dibbling all plots: why?

IF RESPONDENT DOES NOT DIBBLE SEED / FERTILIZER:

38. Why did you not dibble seed / fertilizer in 2005?

39. Will you dibble next cropping season? Yes No

QUESTIONS FOR EVERY RESPONDENT

40. Land preparation activities and equipment in lowland / midland plots:

	Manual	Bullock	Tractor
Ploughing	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Harrowing	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Levelling (not harrowing!)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Stamping	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

41. Were there any constraints by weather conditions in applying the **usual rate of fertilizer** in lowlands / midlands in **2005**?

Drought Over flooding No constraints

42. * Which other crops do you normally also use fertilizer for? _____


43. Were there any constraints by weather conditions for the **number of weeding** in **2005**?

Drought Over flooding No constraints

44. № of acres where farmer removes the off-types **before maturity**? _____ (acres)

Inputs in lowland / midland rice production 2005

45. Indicate quantity of inputs used in this cropping season **(2005)** and the price per unit:

	Lowland / midland rice	IF NO Cooperative member:	Other crops*
	Quantity <u>used</u> in 2005	price / unit for purchased inputs	Quantity <u>used</u> 2005
15-15-15 NPK (kg)	_____	_____	_____
Other NPK: _____ (kg)	_____	_____	_____
Urea (kg)	_____	_____	_____
Sulphate of Ammonia (kg)	_____	_____	_____
Herbicides (litres)	_____	_____	_____
Sacks	_____	_____	_____
Tarpaulins	_____	_____	_____
Ploughing: _____	_____ acres	_____ / acre	_____ acres
Harrowing: _____	_____ acres	_____ / acre	_____ acres
Machine / bullock levelling	_____ acres	_____ / acre	_____ acres
Hired land	_____ acres	_____ / acre	_____ acres

* **other crops: upland rice, maize,**

46. Rice varieties, quantity and source of seed in lowland / midland rice production 2005:

Rice varieties	Type of plot	Total seed quantity	Source
_____	_____	_____	_____
_____	_____	_____	_____
_____	_____	_____	_____

Type of plot:	Source:
3 LRDP plot	1 own
4 Self banded	2 exchange
5 Non banded	3 purchased

47. **All individual farms** (not only rice production) of **respondent**:

№ of household members **(including respondent)** usually working there?

	№ usually working	How many of them suffer of <u>any frequent illness?</u> (Guinea worm, Malaria and others)	Source:
Men (16-60)	_____	_____	1 Hired daily labourer
Women (16-60)	_____	_____	2 Communal labour
Children (7-16)	_____	_____	3 Working group (Darikpariba)

49. Which activity in lowland rice production is the biggest problem **for you** referring to **labour requirement?** (*Rank*)

Land preparation _____
 Planting _____
 Weeding _____
 Harvesting _____

Output of lowland / midland rice production

50. Share of rice of lowlands / midlands usually sold: _____ %

51. Use of lowland / midland rice this cropping season **(2005):** (*bags*)

Given to landowner	Given for threshing	Given for labour help	Seed	For consumption	Other
_____	_____	_____	_____	_____	_____

52. Cash revenue of rice production from lowlands / midlands this harvest **(2005 / 2006):**

Quantity sold _____ (maxi) bags Price per bag sold: _____ Cedi / bag
 Quantity left for
 selling _____ (maxi) bags

53. What **yield per acre** of lowland rice did / do you **expect because of adoption** before **self-made bunds / dibbling?** _____ (**bags / acre**)

54. **Average output** of rice production in lowlands / midlands:

Year	Total output (plots with LRDP bunds)	Acres	Total output (other lowlands with self made bunds)	Acres	Total output (other lowland without self made bunds)	Acres
2005	_____	_____	_____	_____	_____	_____
2004	_____	_____	_____	_____	_____	_____
2003	_____	_____	_____	_____	_____	_____
2002	_____	_____	_____	_____	_____	_____

55. Reason for any change in yield in last years:

56. Reason for differences in yield between different plot types:

SOCIOECONOMIC CHARACTERISTICS

57. **Farm family:** income sources besides crop and livestock production?

Male _____
 Female _____
 Children _____

58. Usual sources of cash income of farm family (husband + wives + own children)

	Amount	Share
Lowland / midland rice production	_____	_____
Other cash crops:	_____	_____
Livestock production	_____	_____
Off-Farm activities¹	_____	_____
		¹ e.g. bullock ploughing service, food preparing and selling, trading, processing, weaving, making ropes
Others:	_____	_____

59. Did you receive any credit by LRDP / FSRPOP? Yes No

If yes, Year of last credit: _____ (year)

IF LRDP / FSRPOP CREDIT 2005:

Acres on credit 2005	Purpose of credit 2005			Duration of credit 2005
	fertilizer	ploughing	harrowing	
_____	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	_____

60. Did you receive any other formal or informal credit for agricultural production in the last 10 years?
Yes → a) No → b)

a) If yes, Source of credit: (*Tick*)

Bank	<input type="checkbox"/>	Savings groups / farmer group	<input type="checkbox"/>
Traders	<input type="checkbox"/>	Relatives, neighbours or friends	<input type="checkbox"/>
Local moneylenders	<input type="checkbox"/>	_____	<input type="checkbox"/>
Government institutions, NGO's	<input type="checkbox"/>		<input type="checkbox"/>

Was credit granted in full amount? Yes No

IF ANY CREDIT in 2005 for lowland / midland rice production (other than LRDP/FSRPOP):

Principal	Interest rate	Duration
_____	_____	_____

- b) If no, Why not? (*Tick, more than one possible*)
- No credit available
 - Credit was not granted: where did s/he apply?
 - High interest rate
 - Lack of awareness
 - Fear of indebtedness
 - Lack of previous experience in using formal credit
 - Others (specify): _____
 - No need

61. How often have you sought advice on your lowland / midland rice production? (*Tick, if applicable*)

	Extension agents	Fellow farmer
Very often (4-7 times per week)	<input type="checkbox"/>	<input type="checkbox"/>
Often (1-3 times per week)	<input type="checkbox"/>	<input type="checkbox"/>
Sometimes (1-3 times per month)	<input type="checkbox"/>	<input type="checkbox"/>
Seldom (1-5 times per year)	<input type="checkbox"/>	<input type="checkbox"/>
Never	<input type="checkbox"/>	<input type="checkbox"/>

62. How often did you participate in field days related to lowland rice production **in 2005**? _____

63. Did you participate in any other project activity except of LRDP / FSRPOP (**farming, health and others**) before using bunds / dibbling? Yes No

64. Do you know the current price of paddy rice at the main markets? Yes No

If yes, from which source?

- Own / family project farmer group
 fellow farmer radio traders (**not family**)

65. How often do you go to the main market? _____ per _____

66. **Farm family:** does anybody belong to any organization / farmer group? (*more than one possible, codes below*)

Male _____
 Female _____
 Children _____

1 Political party	5 Crop farmer group
2 Rice Cooperative (FSRPOP)	6 Livestock farmer group
3 Farmer working group ('Darikpariba')	7 Village committee
4 Rice processing group	8 Other Organization

67. Before using self made bunds / dibbling:

How many of your friends, fellow farmers and relatives in your community reported good results about bunds / dibbling? <25% 25% - 50% 50% - 75% 75% - 100%

68. Which factors are the most important constraints not to expand lowland rice production? (Rank)

Lowlands _____ Tractor / bullock services _____
 Labour _____ Inputs (fertilizer,) _____
 Credit _____

Appendix 5: Compound Section of the Farmer-level Questionnaire

Water harvesting methods and intensive practices in Lowland rice cultivation in Northern Region, Ghana

**University of Kiel, Germany (Prof. Dr. Abdulai)
in collaboration with
Savannah Agricultural Research Institute (SARI), Tamale**

II. COMPOUND HOUSEHOLD INFORMATION

HOUSEHOLD SECTION
Questionnaire № _____

RICE FARMER
Questionnaire Numbers: _____

District: _____ Village: _____

Sub-quarter: _____

Date of interview: [__ __/__ __/ __ __] (DD/MM/YY)

Time started: _____

Time ended: _____

Reviewed by: _____

Date: [__ / __ / __]

Name of Interviewer: _____

2. RESPONDENT (= HOUSEHOLD HEAD OR SENIOR MAN):

3. Name of household head: _____ House name: _____

4. IF HOUSEHOLD HEAD NOT QUESTIONED AS RICE FARMER:

Sex of household head: _____

5. IF HOUSEHOLD HEAD NOT QUESTIONED AS RICE FARMER:

Age of household head: _____

6. Ethnic group: _____

7. Are you a native in the community? Yes No

IF NO, for how long do you live in the community? _____

IF NO, from which region do you come from? _____

8. What is the household head's relationship to traditional authority?

9. IF HOUSEHOLD HEAD NOT QUESTIONED AS RICE FARMER: Education of household head:
_____ (Use codes below)

10. Number of compound family members (living permanently on compound) and education. (Use codes below)

	No living in compound	Highest Educational level		
Adult male (14-60)	_____	_____	1 None	7 Middle School
Adult female (14-60)	_____	_____	2 Adult literacy education	8 Junior Secondary School
Elderly male (> 60)	_____	_____	3 Dabani literacy	9 Senior Secondary School
Elderly female (> 60)	_____	_____	4 Koranic	10 Technical / Training college
Children (7-13)	_____	_____	5 Primary school 1-3	11 University
Children (0-6)	_____	_____	6 Primary school 3-6	

11. No of members of the compound household who do any activities outside from crop and livestock production as income source (also business related with agriculture, e.g. processing, food selling, shoe repairing, tractor services,)

12. Does / did any member of your household belong to any group or organization? (**crop, livestock and others**) Yes, currently Yes, in the past No

IF YES:	No	Focus	No. of executive members
Adult men	_____	_____	_____
Adult women	_____	_____	_____

Focus (more than one possible)

<i>Political party</i>	1	<i>Farmer group</i>	2
<i>Rice Cooperative</i>	3	<i>Agricultural organization</i>	4
<i>Religious</i>	5	_____	6

13. How many compound family members suffer of any frequent illness? (Guinea worm, Malaria and others)

Men (16-60) _____
 Women (16-60) _____
 Children (7-16) _____

14. Size of family owned land: _____

15. What is the total size of lowlands / midlands cultivated by household members 2005?

16. Number of rice farmer in lowlands / midlands in the household: _____

17. IF HOUSEHOLD HEAD NOT QUESTIONED AS RICE FARMER:

Household farms: Output of crops 2005

Type of crop	Output of household farm 2005	Unit Code
1 Maize	_____	_____
2 Lowland / midland rice	_____	_____
3 Upland rice	_____	_____
4 Cassava	_____	_____
5 Millet	_____	_____
6 Guinea corn	_____	_____
7 Groundnut	_____	_____
8 Yam	_____	_____
9 Cowpea	_____	_____
10 Beans	_____	_____
11 Soybean	_____	_____
12 Pidgeon Pea	_____	_____
13 Bambara Beans	_____	_____
14 Sheanut	_____	_____
15 Sweet potatoe	_____	_____
16 Tomato	_____	_____
17 Okro	_____	_____
18 Pepper	_____	_____
19 Tobacco	_____	_____
20 Mango	_____	_____
21 Papaw	_____	_____
22 Watermelon	_____	_____
23 _____	_____	_____

Unit Codes

- | |
|------------|
| 1 Bowl |
| 2 Bags |
| 3 Kg |
| 4 Tubers |
| 5 Calabash |
| 6 Crate(s) |
| 7 Bail(s) |
| 8 Bundles |

18. IF HOUSEHOLD HEAD NOT QUESTIONED AS RICE FARMER: Livestock of household head

Livestock type	Number	Livestock type	Number
a) Bullock	_____	c) Donkey	_____
b) Cattle	_____	d) Horse	_____

19. Number of months the family's food stock last /in a good year? _____

Appendix 6: Village-level Questionnaire

Water harvesting methods and intensive practices in Lowland rice cultivation in Northern Region, Ghana

**University of Kiel, Germany (Prof. Dr. Abdulai)
in collaboration with
Savannah Agricultural Research Institute (SARI), Tamale**

COMMUNITY LEVEL

District : _____ Village: _____

1. **How many people are living in the community?** _____
(if estimation → tick here:)

→ **how many households?** _____ (if estimation → tick here:)

2. How were the yields for most “good farmers” (*Tick appropriately*)

	Good (>16 bags)	Average (11-15 bags)	Below average (7-11 bags)	Bad (≤6)
2005	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2004	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2003	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2002	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2001	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2000	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

3. Infrastructure in the village: Is there any of the following in the village?

Number of Dagbani literates	[_____]	(number)
Number of English literates	[_____]	(number)
Permanent Shops (excl. restaurants, food selling)	[_____]	(number)
Houses with zinc	[_____]	(number)
Bullocks	[_____]	(number)
Number of field days related to lowland rice production	[_____]	(number)
Primary school	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Junior Secondary school	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Clinics / health facility	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Pipe water / borehole (working most time of year)	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Electricity (working most time of year)	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Credit facility (moneylenders / institutions)	Yes <input type="checkbox"/>	No <input type="checkbox"/>
Market truck coming to community	Yes <input type="checkbox"/>	No <input type="checkbox"/>

Key:

Not countable NA

4. How far is it to:

	Distance
Local (daily) market: _____	[] miles
Main (periodical) market: _____	[] miles
Next main community	[] miles
District capital: _____	[] miles
Regional capital: Tamale	[] miles
Next input supplier (seed, fertilizer)	[] miles
Fuel supplier	[] miles
Rice farmers' group	[] miles
Primary school: _____	[] miles
Secondary School: _____	[] miles
Clinic / health care centre: _____	[] miles
Main road	[] miles
Small road open to vehicles all year	[] miles
Small road open only during the dry season	[] miles
A tard road	[] miles
Drinking water source in <u>dry season</u> (walking time)	[] _____
Firewood source (walking time)	[] _____

5. **All Programs, organizations and groups - committee in the community (except of LRDP) in the last 10 years:**

Programs / organization	purpose	Still there?	If already stopped → when (rough estimation)
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
Types of farmer groups	purpose		
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____
_____	_____	<input type="checkbox"/>	_____

Curriculum Vitae

Liane Faltermeier

geboren am 05.05.1978 in Regensburg

AUSBILDUNG

1997	Allgemeine Hochschulreife <i>Werner-von-Siemens-Gymnasium, Regensburg</i>
1997 – 2003	Studium der Volkswirtschaftslehre: Abschluss als Diplom-Volkswirtin <i>Universität Regensburg</i>
06/2004 – 02/2009	Promotion <i>Lehrstuhl für Ernährungsökonomik, Christian-Albrechts-Universität zu Kiel</i>

BERUFLICHE ERFAHRUNGEN

06/2004 – 02/2009	Wissenschaftliche Mitarbeiterin <i>Lehrstuhl für Ernährungsökonomik, Christian-Albrechts-Universität zu Kiel</i>
10/2003 – 03/2004	Wissenschaftliche Mitarbeiterin <i>Lehrstuhl für Volkswirtschaftslehre (Regionalökonomie und Empirische Makroökonomie), Universität Regensburg</i>
09/1999 – 05/2000	Studentische Hilfskraft <i>Lehrstuhl für Volkswirtschaftslehre (Regionalökonomie und Empirische Makroökonomie), Universität Regensburg</i>