Improving the social welfare of rural households in South Asia and Africa through effective rural development interventions

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Abbreviations

ADB	Asian Development Bank
ADBI	Asian Development Bank Institute
AI	Artificial Intelligence
BCA	Benefit-cost analysis
BCR	Benefit-cost ratio
BIGD	BRAC Institute of Governance and Development
BMA	Bayesian Model Average
CCT	Conditional cash transfers
CD	Compact disk
CEGIS	Centre for Geographic and Information Services
CGAP	Consultative Group to Assist the Poor
CIAT	International Center for Tropical Agriculture
CIDA	Canadian International Development Agency
CIWF	Compassion in World Farming
CPI	Consumer Price Index
DFID	Department for International Development
FAO	Food and Agriculture Organization
FE	Fixed effects
GHG	Greenhouse Gas
GIS	Geographic Information System
GMS	Greater Mekong Subregion
GTZ	The Deutsche Gesellschaft für Technische Zusammenarbeit
HCPR	Head-count poverty reductions
HIES	Household Income and Expenditure Survey
ICEM	International Centre for Environmental Management
IFAD	International Fund for Agricultural Development
IFC	International Finance Corporation
IFPRI	International Food Policy Research Institute

IFRC	International Federation of Red Cross
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental Variable
LASSO	Least absolute shrinkage and selection operator
MINAGRI	Ministry of Agriculture and Animal Resources
MLE	Maximum likelihood estimation
MRC	Mekong River Commission
ODA	Official Development Assistance
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PDF	Probability density function
PDR	People's Democratic Republic
PFC	Present value fixed cost
PIP	Posterior inclusion probabilities
PSM	propensity score matching
PV	Present value
PVB	Present value benefit
RGB	Rwanda Governance Board
SDSN	Sustainable Development Solutions Network
UN	United Nations
UNDP	United Nations Development Programme
UNICEF	United Nations International Children's Fund
UNUWIDER	UN University World Institute for Development Economics Research
USD	United States dollar
VIF	Variance inflation factor
WB	World Bank
WHO	World Health Organization

Glossary

Aid effectiveness	Aid effectiveness is the effectiveness of development aid in achieving economic or human development (or development targets)
Benefit-cost ratio	Ratio of the benefits of a project or proposal, expressed in monetary terms, relative to its costs
Bilateral aid flows	Bilateral concession loans and grants between governments
Biogas plant	An anaerobic digester that uses farm wastes to produce biogas for energy
Break-even probability	The cumulative probability of realising net revenues equal to or greater than zero
Climate-smart technologies	Clean low greenhouse gas emission technologies to facilitate climate change adaptation and mitigation
Common support problem	When households that are unlikely to be in the treatment group, when estimated based on observed covariates, are included in the treatment group in the actual observations due to the influence of an unobserved variable
Endogeneity	The existence of unobserved time-invariant factors that jointly influence the treatment variable and the dependent variable
Extensive margin	A binary indicator for participation or no participation typically measured using a dummy variable
Girinka	A livestock donation program in Rwanda involving distribution of a heifer to the poorest members of a community in a village
Head-count poverty ratio	The proportion of a population that exists, or lives, below the poverty line
Information communication technology	Technology used to transfer information, including mobile phones, radio, and television
Instrumental Variable	Variables used in regression to address endogeneity. An instrumental variable, z, is used to identify the causal effect of the explanatory variable, x, on the dependent variable, y. The two requirements for a valid instrumental variable are $\mathrm{cov}(z,x)\neq 0$ (the instrument relevance condition) and $\mathrm{cov}(z,u)=0$ (the exclusion restriction).
Intensive margin	A measure of the extent or degree of participation typically measured using a continuous numerical variable
Microcredit income	The amount of microcredit loan income received by a rural household in one year
Microcredit participation	Access and utilisation of microcredit programs by getting loans to increase production and/or consumption
Model robustness	Occurs when model results are not sensitive to variability in model assumptions
Monte Carlo simulation	A technique used to randomly sample values from a range of probable parameter values
Off support	When there is biased sampling of households in the treatment and control groups due to an unobserved variable
Official development assistance	Foreign aid cash transfers high- to low- and middle-income countries for development projects
Orthogonality condition	A prerequisite condition for choosing good instrumental variables that are not correlated with the dependent variable

Optimism bias	A psychological phenomenon by which humans tend to be systematically optimistic about expected outcomes when faced with uncertainty
Production technical efficiency score	A measure of the relative effectiveness with which a given set of inputs is used to produce an output by various producers
Propensity-score matching	Random sampling of households into treatment and control participant and non-participant groups, holding all other covariates equal based on observed values
Reference class forecasting	A process of identifying a “reference class” of past, similar projects and establishes probability distributions for the selected reference class for uncertain parameters
Rural development programs	Interventions to develop rural areas in development countries run by aid agencies and governments
Selection bias	When a household’s decision is correlated with unobserved time-invariant household characteristics causing the household to self-select into the treatment or control groups leading to non-random selection
Self-selection	Non-random selection of households into treatment and control groups
Social welfare outcomes	Various social, environmental and economic indicators of the wellbeing of a society
Stochastic frontier analysis	A technique for predicting the production technical efficiency score among various producers explaining differences in production given the same level of inputs
Systematic sensitivity analysis	A comprehensive and exhaustive process of testing how model results change in response to variability in parameter value ranges
Upazilas	Sub-district administrative boundaries in Bangladesh that function as counties
Utilization rate	The rate of operation of an infrastructural investment in proportion to the equivalent level of operation at full capacity
Variance Inflation Factor	A measure of existence of multicollinearity between covariates in a multiple regression model

Abstract

United Nations Sustainable Development Goals recognise rural development in low and middle income countries as critical for reducing global poverty because most of the world's poorest and marginalised people are largely concentrated in rural areas of South Asia and Africa. Several meta-analyses of evaluations of rural development strategies, investments and policies have concluded that the actual impact of rural development initiatives on the poorest subpopulations remains poorly understood. Further, development economists bemoan the lack of comprehensive and rigorous quantitative evaluations that can adequately inform the process of designing effective rural development policies.

This thesis contributes to the literature on quantitative evaluation of various initiatives for improving social welfare outcomes in low and middle income countries in the world's poorest rural regions. Specifically, this thesis describes four studies evaluating four distinct ex-post and ex-ante past and prospective rural development initiatives and considers a broad set of social welfare outcomes to contribute to effective investments and policies for improving the livelihood of the poorest subpopulation. A unique feature of this thesis is that it enables a comparison between two spatially and socio-culturally disparate contexts in South Asia and Africa, across a broad set of rural social welfare outcomes.

The thesis utilised quantitative economic estimation approaches to evaluate various initiatives for improving social welfare outcomes, and was designed to address four key issues emerging from a review of evaluation literature. Specifically, this thesis: 1) compared the performance of large- and small-scale infrastructure investments; 2) assessed the importance of considering potential adverse effects of rural development programs; 3) compared complementary multi-objective program designs with single-objective programs; and 4) compared targeted interventions that consider family structures and gender dynamics with universal rural development initiatives.

The first analytical chapter utilised a stochastic benefit cost analysis to estimate the net benefit of a 100 million-dollar (2017 USD) prospective irrigation-expansion investment to support irrigated agriculture in the Nam Ngum River Basin, a tributary of the Mekong, in Lao PDR between 2009 and 2030. The second analytical chapter evaluated the causal influence of microcredit loans on primary school enrolment using quasi-experimental treatment-effects methods based on 2010 Bangladesh census data. The third analytical chapter employed a survey-informed stochastic benefit-cost analysis to estimate the net benefit of incorporating climate-smart technologies to existing livestock donation programs in Rwanda's Western and Eastern provinces. The fourth analytical chapter mixed-effects generalised linear panel regression models to evaluate the influence of mobile phone use on agricultural outcomes based on 2012 and 2015 surveys of rural households in Bangladesh's seven major administrative divisions.

The thesis study found that: 1) community-scale rural development programs may perform better than large-scale regional rural development schemes; 2) rural development investments and policies should consider impacts on a broad set of cross-sectoral rural social welfare outcomes; 3) complementary multi-objective policy packages that make provisions for foreseeable inadvertent adverse impacts of rural development interventions may perform better than single-objective intervention; and 4) targeted and tailored policy interventions that

take into account heterogeneous household characteristics and gender dynamics may perform better than universal interventions.

Declaration Statement

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Publications and Presentations

Journal Articles (peer-reviewed)

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Kandulu, J., Wheeler, S., Zuo, A., and Sim, N. (2019). The impact of microcredit loans on school enrolment in Bangladesh. *The Journal of Development Studies*, *56*(9), pp. 1-20. doi: 10.1080/00220388.2019.1703954

Conference Papers (peer-reviewed)

Kandulu, J., Wheeler, S., Sim, N., and Zuo, A. (2017). Understanding determinants of child-education investment decisions in poor households: an econometric analysis. Paper presented at the 2017 International Conference on Global Issues and Development of Social Sciences Research, Johannesburg, South Africa. 25-26 December, 2017.

Current Working Papers

Kandulu, J., Zuo, A., Wheeler, S., and Chagunda, M. (2020). Improving the effectiveness of livestock donation programs by incorporating climate-smart technologies.

Kandulu, J.M., Wheeler, S., Zuo, A., and Connor, J.D. (2020). Improving rural agricultural production and income in low and middle income countries using mobile phones.

Conference Papers and Seminars

Kandulu, J., Lazarow, N., Meharg, S., Butler, J., Connor, J., Duggan, K., and Roth, C. (2017). Impact evaluation of Australian aid: How successful was the DFAT-CSIRO Research for Development Alliance? Paper presented at the 2017 Australasian aid conference, Canberra ACT. 15-16 February, 2017.

Kandulu, J.M., Wheeler, S., Zuo, A., and Connor, J.D. (2020). The impact of mobile phones on agricultural production. Australasian Agricultural & Resource Economics Society's 64th annual conference. The University of Western Australia, Perth, WA. 12-14 February, 2017.

Chapter 1 Introduction

Chapter 1 provides background, including the broader research context and key study motivation based on reviewed literature. Chapter 1 also describes research objectives, questions, design, and methodology, and outlines the structure of the thesis.

1.1 Background and statement of the research problem

United Nations Sustainable Development Goals recognise rural development in low and middle income countries as critical for reducing global poverty because most of the world's poorest and marginalised people are largely concentrated in rural areas of South Asia and Africa (FAO, 2018a; WB, 2016, 2018). Accordingly, the last two decades have witnessed a consistent increase in the amount of foreign aid directed at funding rural development to improve social welfare outcomes among the poorest subpopulations with total annual disbursements averaging USD9B(2013 USD) between 2000 and 2018 (OECD, 2015, 2018).

The two poorest regions of South Asia and Africa have received the largest amount of rural development funding with 50% of rural development aid disbursements directed to infrastructure investments in the education, health and agriculture sectors between 2000 and 2017 (OECD, 2018). Increasingly, rural development investments and policies have focused on rural financial and digital inclusion initiatives with the World Bank and UNDP spending over 164 million dollars (2006 USD) per year on rural digital and financial inclusion programs over the last two decades (CGAP, 2006).

Several meta-analyses of evaluations of rural development programs have found that the actual impact of rural development initiatives on social welfare outcomes of the world's poorest subpopulations remains poorly understood (Baker, 2000; Conn, 2017; Rola-Rubzen et al., 2001). Further, rural development agencies have lamented the lack of comprehensive and rigorous quantitative evaluations that can adequately inform the process of designing effective rural development investment programs and policies (Banerjee and Duflo, 2011; IFAD, 2019; Masset et al., 2012).

Development economists have identified two main areas for improvement in the evaluation of rural development programs for improving social welfare outcomes. The first area is the use of evaluation findings to recommend supporting policies to increase the effectiveness of rural development investments (Qaim, 2010; Qaim and Kouser, 2013). The second area is using evaluations to identify targeted investments tailored to consider household characteristics and gender dynamics to optimise social welfare outcomes of the poorest households (Curry et al., 2016; Ryan et al., 2017).

1.2 Research objectives

This thesis contributes to the literature on quantitative evaluation of the impact of rural development initiatives on rural social welfare outcomes in the world's poorest regions. Specifically, this thesis describes four distinct household-level quantitative evaluations of ex-post and ex-ante past and prospective rural development initiatives that utilise rigorous quantitative evaluation methods to better inform the process of designing effective investments and policies for improving social welfare outcomes among the world's poorest subpopulations. A unique feature of this evaluation study is that it enables a comparison between two spatially and socio-culturally disparate contexts in South Asia and Sub Saharan Africa in evaluations that considered a broad set of rural social welfare outcomes. Further, the four household-level evaluations of rural development initiatives identified targeted and tailored support policies to enhance the effectiveness of rural development investments taking household characteristics and overall household gender dynamics into account.

In subsequent sections, this chapter presents a detailed literature review describing the broader research context, the theoretical context of the thesis, and the empirical context, in particular, a description of key issues emerging from reviewed empirical evaluation literature that motivated key hypotheses tested. Thesis design, including a description of the quantitative evaluation methods applied, key social welfare outcomes considered, and a detailed description of the structure of the thesis, follow.

1.3 Literature review

The following sub-section outlines the broader research context and motivation for this study, including providing a summary of the theoretical and empirical context, and key issues emerging from the reviewed literature.

1.3.1 The broader research context

Since World War II, over four trillion dollars (2020 USD) in Official Development Assistance (ODA) has been transferred from developed to low and middle income countries to increase economic growth and improve the welfare of the world's poorest population (Qian, 2015). The two regions of South Asia and Africa receive the highest amount of bilateral foreign aid equal to 41M (2018 USD) in 2018 representing a 41% share of gross bilateral ODA funds (OECD, 2019). Thus, the study design enables a comparison between two spatially and culturally disparate contexts.

To date, foreign aid remains one of the most important policy vehicles for transferring financial resources from developed countries to low and middle income countries (OECD, 2018). Bilateral concession loans and grants between governments make up over 70% of ODA accounting for up to 64% of the annual budgets in recipient countries (OECD, 2018; Qian, 2015). Aid in the form of program assistance, humanitarian, and debt relief typically make up the smallest share of gross bilateral aid at 15% in 2018.

Policy debate over the effectiveness of aid raged in the 2000s amidst increased calls from international policymakers for developed countries to increase foreign aid budget allocations. Growing expressions of scepticism about the effectiveness of development aid cited the dearth of substantive empirical evidence linking development aid with economic growth and poverty alleviation outcomes (Baker, 2000). Proponents of aid argue that foreign aid can promote economic growth in recipient countries with prudent economic policies (Burnside and Dollar, 2000). Polarised discussions of the net effectiveness of aid can be inconclusive and lacking in depth, largely because rigorous quantitative evaluations applied to several different types of aid on a comprehensive set of welfare outcomes are sparse (Qian, 2015).

In the 2000s, a poor understanding of the actual impact of foreign aid prompted a series of empirical studies evaluating the impact of aid on economic growth, social welfare, and poverty levels in recipient countries. Empirical literature on the impact of foreign aid provides mixed empirical evidence (Baker, 2000). Several studies found that foreign aid can positively influence economic growth (Collier and Dehn, 2001; Collier and Dollar, 2002; Collier and Hoeffler, 2004) whilst several other studies found insignificant impacts (Easterly, 2003; Easterly et al., 2003; Roodman, 2007). A number of studies found that aid can negatively influence recipient countries' economic growth (Djankov et al., 2008; Rajan and Subramanian, 2011; Svensson, 2000).

Philosophically, the aid debate can be organised into two fundamental questions: 1) has foreign aid been effective, and 2) can foreign aid be effective? To use findings from ex-post evaluations that provide empirical evidence supporting the case against foreign aid to answer the first question in the negative, and to extend the logic further to derive the implication that consequently, aid cannot be effective would not benefit policymakers. On the contrary, using findings from ex-post and ex-ante evaluations of past and prospective aid programs to answer the constructive question of how aid policy and administration can be redesigned to improve aid effectiveness would be most useful for policymakers (Qian, 2015).

Growing calls to restructure foreign aid administration from large bilateral flows of foreign aid transfers to modest aid flows targeting rural development programs in the early 2000s cited several adverse effects of bilateral aid including dependence, rent-seeking and market distortion (Djankov et al., 2008; Rajan and Subramanian, 2011; Svensson, 2000). However, development economists have observed a lack of comprehensive and rigorous quantitative evaluations that can adequately inform the process of identifying design attributes that enhance the effectiveness of rural development programs (Banerjee and Duflo, 2011; Qian, 2015).

Increasingly, evaluations of the effectiveness of rural development programs have focused on measuring impacts on social welfare outcomes based on household-level analyses to better inform effective rural development investments and policies (Gibson et al., 2011; Qian, 2015; Ryan et al., 2017). Evaluating social welfare outcomes of rural development programs at the household level enables consideration of how program impacts may vary due to differences in household characteristics such as gender of household head, number and gender of children, and household dependency ratio.

1.3.2 Theoretical context

Neoclassical household utility theory provides a strong premise for basing evaluation of impacts of rural development programs on households' current and future social welfare outcomes, including production, technical efficiency of production, consumption, and investment in education and technology (Becker, 1965). The microeconomic model underpinning household utility theory assumes that the objective of a rational household is to formulate a multi-period resource allocation plan, which will yield the highest utility (Becker, 1994). Specifically, a household's expected utility from its resource allocation choices are considered to be a function of current and future productive and consumptive outcomes (Michael and Becker, 1973; Prochaska and Schrimper, 1973).

Neoclassical household utility theory lends itself to the evaluation of rural development programs because changes in current and future household welfare outcomes can be assessed before and after program implementation whilst treating households as both producing and consuming units, and taking into account income constraints, and the opportunity cost of resource allocation choices. Specifically, rural development programs that improve households' technical efficiency of production, for example, water and energy infrastructure, technological innovations, and loan and education facilities increase households' current and future consumptive and productive outcomes and reduce the opportunity cost of alternative means of production which is time intensive.

Based on household utility theory, the rational household will thus maximise the discounted present value of utility in its decision to allocated resources between consumptive and productive outcomes by trading off some proportion of current consumptive utility for current and future productive utility. Therefore, the impact of rural development intervention for improving social welfare outcomes can be evaluated by quantifying changes in households' social welfare outcomes reflecting utility maximizing decisions.

1.3.3 Empirical context and key issues emerging from the evaluation literature

Observations emerging from a review of empirical literature reveal that development economists typically favour complementary packages of rural development investments and supporting policies over intervention that consists solely of technological or infrastructure investment (Lenz et al., 2017; Qaim, 2010; Qaim and Kouser, 2013). Additionally, rural development interventions targeted and tailored to address the influence of differences in household characteristics and overall gender dynamics on desired social welfare outcomes are favoured over universal programs (Paris and Rola-Rubzen, 2019; Ryan et al., 2017). These observations are consistent with findings from an extensive review of 23 empirical peer-reviewed evaluation studies of rural development programs in South Asia and Africa published between 2016 and 2020 (Table 1.1).

Further, the extensive literature review process revealed the four main issues and themes emerging from the evaluation literature that motivated the four main hypotheses tested in this thesis. First, small community or household-scale infrastructure investments may perform better than large-scale regional infrastructure investments in part, because large infrastructure investments incur high operations and maintenance costs recovered through prohibitive connection fees and user-tariffs and thus experience low utilization rates among the poorest households. Additionally, rural communities do not take full ownership of maintaining large-scale investments, which can result in stranded and underutilised investments (Bos and Gupta, 2019; Lenz et al., 2017).

Second, considering potential adverse program effects in designing investments and supporting policies can mitigate incidental adverse outcomes of rural development programs. For example, Gibson (2015) found that use of poorly-targeted conditional cash transfers to improve human capital outcomes can have perverse incentives that could distort households' work choices thereby doing more harm than good. Rural development programs that evaluate broad social welfare outcomes across multiple sectors in addition to primary program objectives are favoured over programs with a narrow focus.

Third, complementary intervention packages often perform better than single issue or themed programs. Consequently, evaluations of rural development initiatives should consider potential benefits from implementing alternative program designs that incorporate other complementary secondary investments to inform the efficient allocation of scarce rural development financial resources sourced from the public purse.

Fourth, rural development programs targeted to benefit the poorest households are often more effective than universal interventions. Specifically, targeted investments tailored to consider social welfare impacts of rural development initiatives taking into account the structure of the household, including the gender of the household head, number of dependents, and the distribution of gender and age of children achieve better outcomes than universal programs.

1.3.4 Data and methodological challenges with studying community-level interventions

Studies on the impact of community-level interventions in rural areas of low and medium income countries rely on community-level survey data. Poor infrastructure and remoteness make data collection in regional, rural and remote areas of low and medium income countries prohibitively expensive. To address this impediment, statistics agencies typically employ multi-stage clustered sampling procedures involving selection of Primary Sampling Units (PSUs) and stratification. Households within the same PSU are typically correlated because households in nearby locations (e.g. villages) in most low and medium income countries share similar unobserved factors. As such observations within a cluster (e.g. PSU) are usually similar and observations from different clusters are typically different (Gibson, 2019). There is a challenge with addressing spatial correlations between sampled households because few surveys collect high spatial resolution spatial data on household locations with the exception of Gibson (2011). As such, complex survey design features, including sample weights, clustering and stratification, should be taken into account to control for the effects of unobserved correlated neighbourhood variables. Specifying survey design characteristics also enables drawing inferences about both the sample and the population.

Table 1.1 Summary of key issues emerging from reviewed empirical evaluation literature identifying the main attributes of effective rural development programs

Key issues emerging from evaluation literature	Summary of findings that motivated the four thesis hypotheses
Large- vs. small-scale infrastructure investments	Small community level participatory climate resilience assessments generate more tailored and more effective measures for agricultural systems than large regional scale generalised measures (Choptiany et al., 2017). Regional scale studies on barriers to the adoption of agricultural technologies and their impact on rural agricultural productivity should be used to identify more targeted community-scale solutions to more effectively enhance adoption (Warinda et al., 2020). Rural development strategies tailored at the village level are more effective than generalised national programs (Thanh et al., 2018). Regional scale land use and water resource assessments should be utilised to inform effective farm-scale production strategies in response to changes in the availability of inputs to production (Chapman and Darby, 2016; Meaza et al., 2017; Rhebergen et al., 2016). Large-scale electricity investments are less adaptable to changing agricultural, ecological and economic contexts compared to small-scale investments (Lenz et al., 2017).
Considering inadvertent program outcomes	Programs for enhancing adoption of information communication technology in agricultural production incidentally contribute to women's empowerment and impact other sectors such as health and community development (Hudson et al., 2017). The introduction of commercial cultivars to improve agricultural incomes can unintentionally introduce hosts for disease-carrying vectors (Nachilima et al., 2020) and should consider disease resistance among new commercial varieties (Beyene et al., 2017). Multi-sectoral programs for enhancing nutrition security should consider spillover effects in other sectors including agriculture, nutrition, and health sectors to be effective (Cole et al., 2016).
Complementary multi-objective vs. single-objective programs	Schemes for breeding orange sweet potato varieties to enhance nutrition security were more effective when aligned with complementary nutrition-education programs (Low, 2017). Effective programs for achieving sustainable food security were designed and delivered in ways that simultaneously enhanced social justice (Devereux, 2016). Optimal livestock development programs for improving food and nutritional security were jointly designed to consider social capital benefits (Ngarava et al., 2020). Without complementary rural education programs, microloan initiatives can be ineffective (Greyling and Rossouw, 2019). Effective food security improvement programs ought to concurrently consider broader economic, social, and environmental outcomes (Graef et al., 2017; Kim et al., 2019).
Targeted vs. universal rural development interventions	Targeted agricultural subsidy schemes were more effective than universal programs (Macours et al., 2018). Effective programs for promoting desirable rural environmental outcomes should be targeted considering social, economic, and cultural classifications (Dawson et al., 2016). Rural agricultural development programs targeting females yielded higher productivity returns and closed the gender gap in agricultural productivity than programs with no gender targeting (Uduji and Okolo-Obasi, 2018; Warinda et al., 2020). Rural agricultural development programs that were unique for each crop type were more effective than universal programs (Herzberg et al., 2019). Rural households’ contributions to framing targeted climate adaptation policies resulted in designing effective rural development programs (Tran and James, 2017)

1.4 Research design

The design of this thesis is motivated by the OECD’s principle of designing evaluation research studies to facilitate the process to draw knowledge from experience using past investments as well as carry out ex-ante evaluations that strategically anticipate prospective aid programs to inform systematic improvements in aid effectiveness (Joly et al., 2016). Accordingly, this thesis describes four case study evaluations of four distinct ex-post and ex-ante past and prospective rural development initiatives. The four case study evaluations considered four rural development programs across various sectors in the world’s poorest regions of South Asia and Africa.

Further, these case studies were designed to address the four key issues and themes emerging from empirical literature on the evaluation of rural development programs as summarised in Table 1.1. Specifically, the thesis was designed to: 1) compare the performance of regional and community-scale rural development programs; 2) assess the importance of considering inadvertent outcomes of rural development aid programs; 3) compare complementary multi-objective program designs with single-objective programs; and 4) compare targeted and universal rural development interventions.

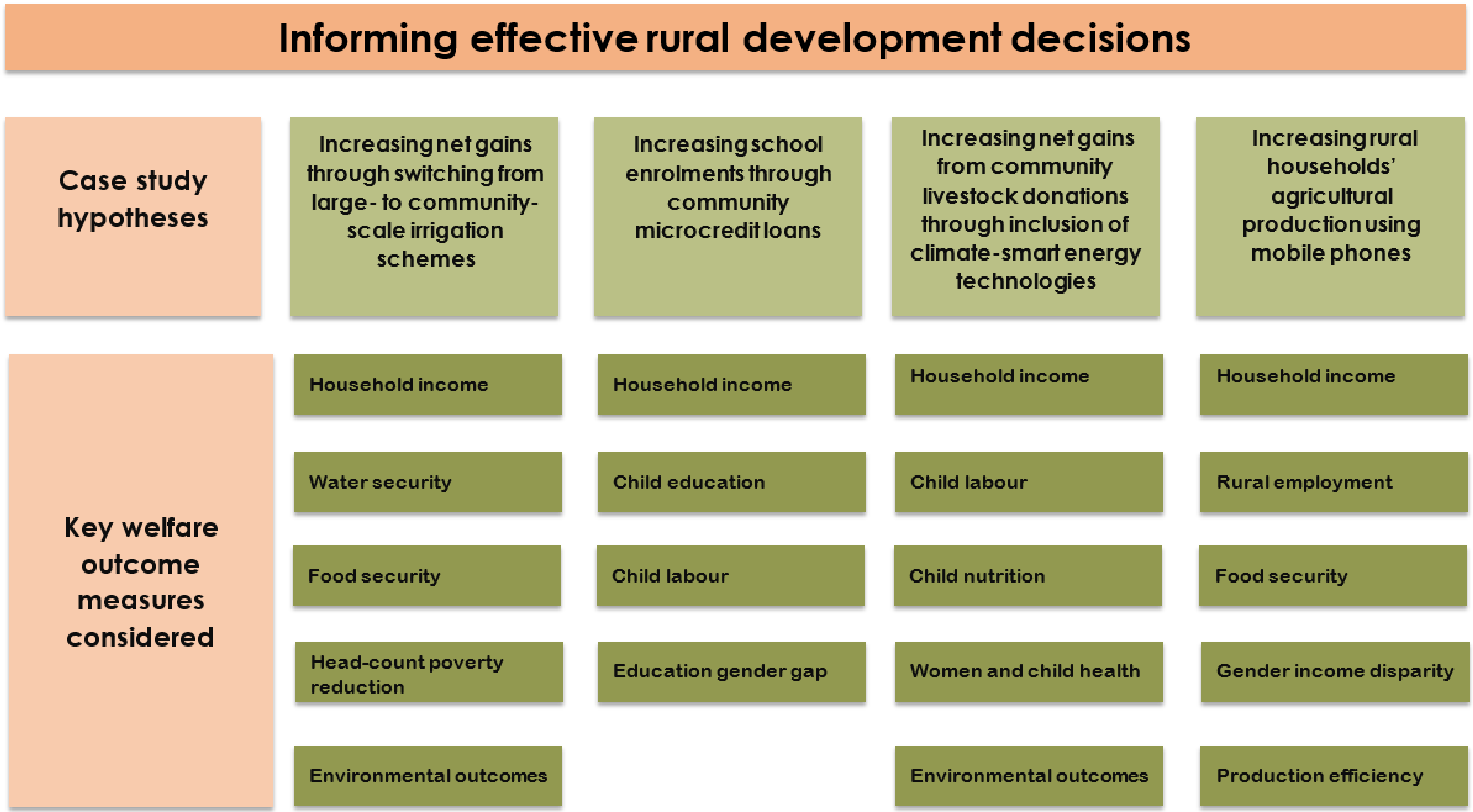
By adopting a case study based quantitative evaluation approach, this thesis assessed the effectiveness of aid programs accounting for complexity due to disparate contexts that affected the pathways from program intervention to social welfare outcomes, thereby providing a set of four detailed stories, each representing a unique program under a unique set of circumstances. Thus, thesis design enabled the process of drawing on reflections and insights, in particular, identifying key program design attributes that can have a significant bearing on the effectiveness of rural development programs at achieving desired social welfare outcomes.

1.5 Methodology

Methodologically, economic estimation approaches were applied, in particular, benefit-cost analysis and empirical econometric analysis consistent with OECD-sanctioned quantitative evaluation methodologies (Joly et al., 2016; Ruegg and Feller, 2003; Ruegg and Jordan, 2007). Figure 1.1 illustrates the conceptual analytical framework for the four evaluations carried out in this thesis including key hypotheses tested and the broad set of social welfare outcomes based on literature review findings in Table 1.1. In total, four rural development programs were evaluated: 1) large-scale versus farm-scale irrigation schemes in Lao, PDR; 2) microcredit finance programs targeting rural women in Bangladesh; 3) livestock donation programs targeting the poorest rural communities in Rwanda; and 4) rural digital inclusion programs in Bangladesh.

The second analytical chapter evaluated the causal influence of microcredit loans on primary school enrolment using quasi-experimental treatment-effects methods based on a 2010 Bangladesh Census dataset that surveyed 60,903 people in 12,240 households. Child-level observational data for 16,712 children aged 5–17 (8,669 boys and 8,030 girls) was used in the analysis.

Figure 1.1 Conceptual analytical-framework



<u>Source:</u> Authors' design

The third analytical chapter employed a survey-informed stochastic benefit-cost analysis to estimate the net benefit of incorporating climate-smart technologies to existing livestock donation programs using a 2018 survey of 1,577 households in Rwanda's Western and Eastern provinces. The fourth analytical chapter used mixed-effects generalised linear panel regression models to evaluate the causal influence of the adoption of mobile phone technology on rural economic welfare outcomes based on repeat national surveys in 2012 and 2015 of 6,500 rural households covering 325 sampling units across each of Bangladesh's seven major administrative divisions.

1.6 Thesis structure

The following chapters provide a detailed description of each of the four case study evaluations, including a review of background literature, case study description, methods, discussion of results, limitations and recommendations for future research direction, and key conclusions. Two out of four studies have been published in peer-reviewed scientific journals and two have been submitted for review and publication in peer-reviewed scientific journals.

Chapter 2 provides an extended description of a published journal article:

> **Kandulu, J.M**., and Connor, J.D. (2017). Improving the effectiveness of aid: An evaluation of prospective Mekong irrigation investments. *International Journal of Water Resources Development*, *33*(2), pp. 270-291. doi: 10.1080/07900627.2016.1188060

This chapter describes a quantitative evaluation of a proposed rural development program to augment hydropower investments with large-scale irrigation infrastructure investments in the Mekong Delta using a case study in Lao PDR. Specifically, large-scale irrigation infrastructure investments were compared with farm-scale irrigation infrastructure investments and investments in other sectors including roads, education, and agricultural research, and development in terms of expected net benefit and head-count poverty reduction.

Chapter 3 presents an expanded description of another published journal article:

> **Kandulu, J**., Wheeler, S., Zuo, A., and Sim, N. (2019). The impact of microcredit loans on school enrolment in Bangladesh. *The Journal of Development Studies*, *56*(9), pp. 1-20. doi: 10.1080/00220388.2019.1703954

This chapter provides a detailed description of an evaluation of inadvertent impacts of microcredit participation and income on households' education outcomes taking into account household characteristics, including the distribution of gender and age of children using a case study in Bangladesh. The motivation for the study is that microcredit initiatives are typically implemented with the primary objective of reducing poverty and improving gender inequality, but there is a growing interesting to understand the causal impact of microcredit on households' education investment decisions.

Chapter 4 describes a working paper that has been submitted for review and publication in a peer-reviewed scientific journal:

Kandulu, J., Zuo, A., Wheeler, S., and Chagunda, M. (2020). Improving the effectiveness of livestock donation programs by incorporating climate-smart technologies.

This chapter describes a quantitative evaluation of integrating climate change adaptation and mitigation technologies to livestock donation programs in rural areas of low and middle income countries by estimating the net benefit of augmenting distribution of climate-smart technological innovations into existing livestock donation programs in Rwanda, Africa. Specifically, an ex-ante evaluation of the net benefit of incorporating distribution of biogas production plants to beneficiary households in addition to distribution of heifers was carried out.

Chapter 5 presents a working paper that has been submitted for review and publication in peer-reviewed scientific journal:

Kandulu, J.M., Wheeler, S., Zuo, A., and Connor, J.D. (2020). Improving rural agricultural production and income in low and middle income countries using mobile phones.

This chapter describes an evaluation of the causal influence of mobile phone ownership on households' economic welfare outcomes in rural areas of Bangladesh to evaluate the impact of addressing the rural-urban and gender digital gap. Particularly, the interaction between mobile phone ownership and household characteristics, in particular, the gender of head of household were quantified to evaluate the impact of addressing gender digital exclusion on social welfare outcomes of rural households in low and middle income countries.

Chapter 6 provides a summary of overall thesis findings, contributions to the body of literature on evaluation of rural development programs, thesis limitations and recommendations for future work. Further, policy recommendations and implications are also discussed in the context of key thesis findings. Finally, appendices and supplementary material, including results from additional analyses, are provided.

Chapter 2 Improving the effectiveness of aid: An evaluation of prospective Mekong irrigation investments

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This chapter describes a quantitative evaluation of a proposed large-scale irrigation infrastructure investment in Lao PDR based on a paper published in the *International Journal of Water Resources Development* (2017). The paper is included here in its published form, with only minor formatting changes consistent with the overall thesis format. There is some repetition with other chapters in this thesis, in particular, the background and conclusion sections.

Abstract

Large irrigation systems seem to be the logical add-on investment to hydropower projects, which are being planned in the Mekong basin. Economic evaluations of irrigation schemes to date have not considered environmental costs and uncertainties about utilisation. Comparisons between economic returns and poverty alleviation benefits from irrigation and from investments in other sectors are also sparse. Our benefit-cost analysis of prospective irrigation investments in Lao PDR considering all these factors found that farm-scale irrigation investments performed better than large-scale investments. The benefit-cost ratio and head-count poverty reduction from large-scale irrigation investment were also substantially lower than for education, road construction, and agricultural research and development.

Keywords: foreign aid investment; benefit-cost analysis; poverty reduction; Monte Carlo simulation; systematic sensitivity analysis; Mekong

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Overall percentage (%)	70%		
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i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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2.1 Introduction

Expansion of irrigated agricultural production was one major driver behind rural economic growth, food self-sufficiency and poverty alleviation in the 1970s and ‘80s, especially in Asia and Africa (CA, 2007). The idea of expanding irrigation is still intuitively appealing as a way to address growing food security concerns in these regions. In addition, irrigation is widely seen as an effective poverty alleviation strategy because agriculture is a large employer of relatively poor people in many low- and middle-income countries (de Fraiture and Giordano, 2014; Xie et al., 2014). Consequently, governments in many low and middle income countries continue to outline plans to expand investments in irrigation to increase their chances of meeting United Nations Development Goals around food security and poverty alleviation (Turral et al., 2010). However, recent evaluations suggest that investments in irrigation are not always economically viable, especially when funded by user charges to recover high operation and maintenance costs leading to low infrastructure utilisation (Cao et al., 2014; Chen et al., 2014; de Walle and Gunewardena, 2001; Molle, 2008). Additionally, negative environmental impacts downstream of irrigated catchments such as reduced fisheries productivity can make irrigation investments less attractive (Costanza et al., 2011; MRC, 2009; Orr et al., 2012). Further, while expansion of irrigation can reduce poverty by increasing income from farm employment; investments in alternative sectors including education, road construction and electricity, can reduce poverty more effectively through improved opportunities for higher-paying off-farm employment (Fan et al., 2007; Smith, 2004; Turral et al., 2010). There are also questions about scale with an increasing perception that large-scale irrigation investments are less adaptable to changing agricultural, ecological and economic contexts compared to farm-scale investments (Mukherji et al., 2009b).

While irrigation development has mostly focussed on arid regions and evaluated in such regions (Al-Ghobari and El Marazky, 2014; Wang et al., 2013a; Wang et al., 2013b; Xie et al., 2012), it is also applicable in monsoonal climates and high rainfall areas because it allows dry season irrigated production in addition to traditional wet season cultivation albeit across disparate cropping and livestock production enterprises (Dhawan, 1992; Xue et al., 2011). This article evaluates the costs and benefits of irrigation infrastructure investments in monsoonal climatic settings for a case study in Lao People’s Democratic Republic (PDR). The study addresses the relative dearth of economics assessments of irrigation projects for supporting dry season irrigated agricultural production in tropical settings. The focus is on the Mekong Basin because recent hydropower dam developments to meet growing energy demands in the region are expected to effectively reduce the cost of setting up irrigation schemes. The logic is that the cost of augmenting irrigation infrastructure to existing hydropower infrastructure should be much lower than the cost of setting up new irrigation schemes (Bartlett et al., 2012; Lacombe et al., 2014). A recent survey of regional government and decision makers in various aid agencies operating in the Mekong Basin reinforced this view with a finding that expected benefits of irrigation would likely exceed costs and lead to significant poverty reduction (Ward and Smajgl, 2014). By contrast, surveys of regional households revealed greater cynicism about expected economic benefits and poverty alleviation impacts of irrigation relative to investments in other sectors including education and road construction (Ward and Smajgl, 2014).

This article challenges the view that augmenting hydropower projects with large-scale irrigation projects is likely to represent good use of scarce development funds using a case study in Lao PDR. The benefit-cost analysis presented expands on previous evaluations (Bartlett et al., 2012; Lacombe et al., 2014) with more comprehensive assessment including: financial as well as environmental costs; consideration of possibly lower than expected utilisation rates, and other cost and return uncertainties. Additionally, the assessment puts benefits from proposed large-scale irrigation investment into perspective in two ways: by providing a comparison between the effectiveness of investment in irrigation and other sectors, including education, road construction and agricultural research and development, to reduce poverty; and by providing assessment of returns relative to investments in smaller farm-scale small pump-based irrigation investment.

We also focus on a lack of transparent treatment of uncertainty in previous irrigation benefit-cost analyses. One fundamental criticism of benefit-cost analysis (BCA) application in general is poor transparency with the process of choosing which costs and benefits to include in evaluation, and determining which parameters and parameter values to use in estimating costs and benefits (McClintock and Griffith, 2010). Part of the problem is that there can be scope for intentional choices to favour predetermined or expected outcomes (Farrow, 2013; Molle, 2008). Another challenge with BCA is the potential for 'optimism bias' – a psychological phenomenon by which humans tend to be systematically optimistic about expected outcomes when faced with uncertainty (Kahneman and Tsversky, 1979a, b). Optimism bias can be observed in laypersons as well as experts including statisticians, engineers, and economists (Ansar et al., 2014; Kahneman and Tsversky, 1979a, b). The resulting potential for bias in BCA can affect credibility if the BCA process is not documented transparently. Optimism bias can be addressed by making use of all relevant information that is available from previous studies in similar contexts to the case study context (termed reference class forecasting). Specifically, reference class forecasting involves identifying a "reference class" of past, similar projects and establishes probability distributions for the selected reference class for uncertain parameters used in BCA (Kahneman and Tsversky, 1979a, b).

A further challenge with evaluation of prospective aid investments in infrastructure such as irrigation, road construction and schools is that these investments are inherently characterised by uncertainty because they involve long economic lives and imperfect information about complex future system dynamics (Hurley et al., 2014; WB, 2010). The most common BCA treatment for uncertainty in practice is superficial sensitivity analyses through adjustments to a select few parameter values based on subjective (expert) judgement about some plausible future scenarios (Almansa and Martínez-Paz, 2011). One problem with this approach is failure to represent the sensitivity of BCA outcomes to various combinations of potentially correlated uncertainties. Adequate treatment of uncertainty can help with producing robust results and decisive conclusions from BCA evaluations (Gentilello et al., 2005; Nichol et al., 2003; Salling and Leleur, 2011).

We demonstrate and discuss an approach for transparent BCA that is unbiased in the sense that it is anchored in past performance of similar projects through probabilistic treatment of multiple uncertainties. The process involved: 1) developing understanding of reference class costs and benefits for inclusion in a BCA, 2) specifying value ranges for uncertain parameters based on review of previous experience with similar projects to minimise optimism bias, 3) using uncertain parameter value ranges for BCA with systematic sensitivity analysis involving Monte Carlo simulation and probabilistic treatment of uncertainties.

In what follows, we outline the Lao irrigation investment case study context (section 2.2) and describe the implementation data and methods (section 2.3). In the case study results (section 2.4), we demonstrate how the approach enabled understanding of ranges of probable net benefits, benefit-cost ratios, the probability of benefits exceeding costs, and the relative contribution of each uncertain parameter to variability in the estimated value of net benefit. We also discuss findings regarding likely economic return and poverty alleviation performance of large-scale irrigation in comparison to small-scale irrigation and other forms of development investment (education, roads, and agricultural research and development). The discussion section provides an interpretation of our results and outlines the potential for and outstanding challenges to broader application of our method. In the conclusion section, we provide an overview of implications of evaluation outcomes, compare the performance of investment options based on our evaluation results, and make recommendations on how to prioritise development investment in Lao PDR.

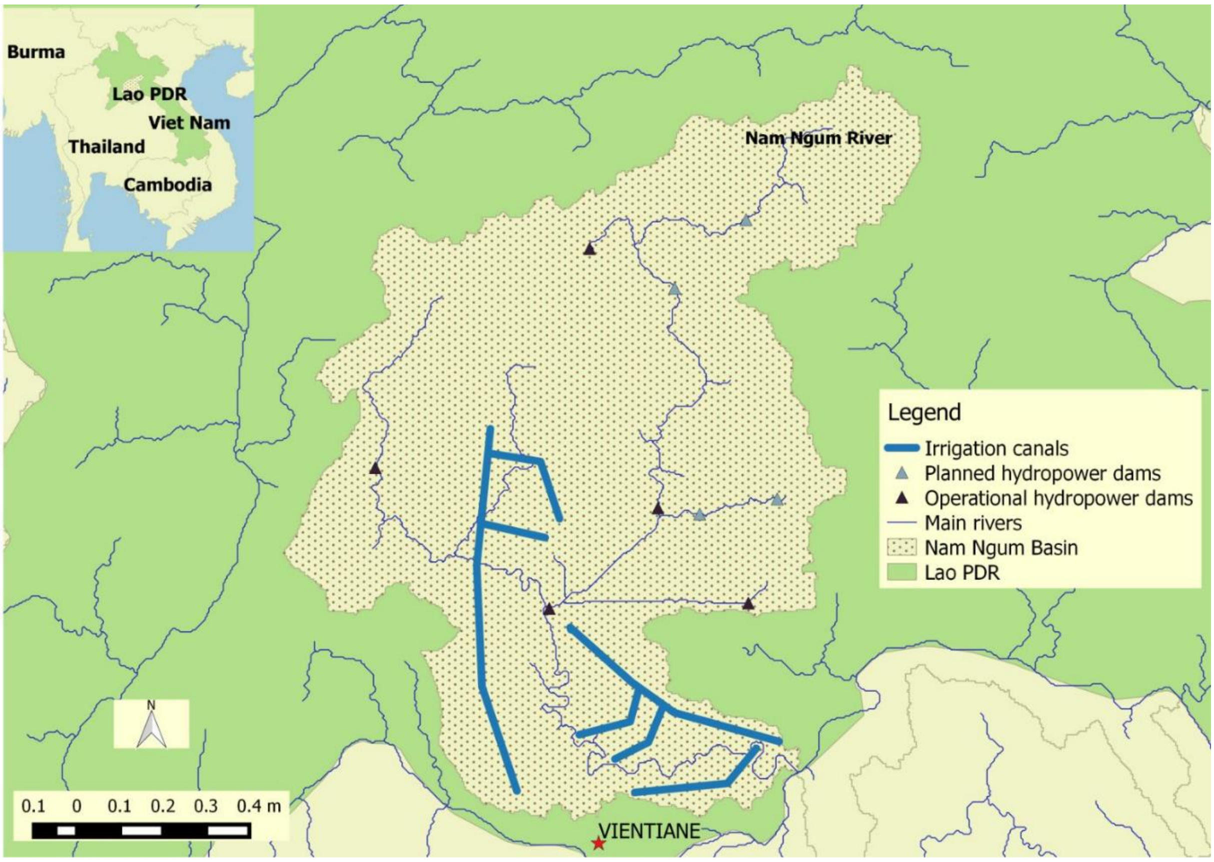
2.2 Case study area

Our case study area is the Nam Ngum River Basin, a tributary to the Mekong, in Lao PDR where additional irrigation investment is under consideration (Figure 2.1). The total irrigation area in Lao PDR was estimated at 166,000 hectares in most recent available reporting and some aspirational plans foresee an increase in area to as much as 548, 916 hectares by 2030 (MRC, 2009). Bartlett et al. (2012) evaluated a scenario involving expanding irrigated areas in the Nam Ngum Basin by more than 100,000 hectares. In the past, Lao government and foreign aid irrigation investments were motivated by the desire to increase glutinous rice production (MRC, 2009). An additional driver was the view that irrigation could provide an ancillary benefit to the growing number of hydropower dams under development in Laos (Menon and Warr, 2013). Further, the Greater Mekong subregion signed an intergovernmental agreement to invest USD10B in transport, energy and agriculture in Lao PDR, Cambodia, Thailand and Vietnam by 2018 and irrigation infrastructure is one form this investment could take (GMS, 2014).

Our case study analysis addresses a growing interest by policy makers and international aid organisations to better understand the economic benefits and costs of irrigation investment in Lao PDR and the Mekong Region in general. We demonstrate a process for robust BCA applied to three related irrigation investment scenarios. The first scenario considered a proposed USD100Minvestment in the Nam Ngum Basin to set up, operate and maintain additional irrigation capacity over a 9049 hectare irrigation command area for a period of 30 years (MRC, 2009). A command area is defined as the total area, which can be irrigated from a scheme given distribution and infrastructure capacity. Irrigation schemes are principally designed under the assumption that every farmer in the command area will utilise the water conveyance infrastructure. The business framework of irrigation schemes is increasingly structured such that operational and maintenance costs of irrigation infrastructure are at least partially recovered by charging a standard fee to irrigators within a command area. In practice, however, only some farmers pay the fee, utilise the infrastructure and have irrigation water delivered to their farms thereby rendering some conveyance infrastructure inoperative. Consequently, amongst other sensitivities assessed, we test the implications of varying command area utilisation rates with a default assumption of 60%, consistent with typical observations of past command area utilisation rates.

In the second scenario, we evaluated whether larger benefit-cost ratios can be expected from farm-scale pump irrigation schemes as opposed to large-scale irrigation schemes evaluated in the first scenario.

Figure 2.1 Nam Ngum Basin. a: operational and planned hydropower dams, b: irrigation canals, and c: main rivers



Sources: Created from MRC (2009) and Bartlett et al. (2012)

Farm-scale pump irrigation generally incurs much lower capital and operating costs than traditional large-scale irrigation schemes (de Fraiture and Giordano, 2014). There has been a recent trend of rapidly spreading farm-scale pump irrigation development across the developing world to convey groundwater for irrigation following the advent of cheap pumps from China (Xie et al., 2014). While only 200 hectares were known to be groundwater irrigated in Lao PDR in 2006, use of autonomous small petrol and electric pumps for irrigation is rapidly expanding in neighbouring Thailand, Cambodia, Vietnam, but also in Indonesia, and in Africa (de Fraiture and Giordano, 2014). In this scenario, we evaluated the investment in farm-scale pump irrigation required to irrigate an equivalent of the 5500 hectares effective irrigated area considered under the large-scale irrigation scenario.

We assessed the probability of benefits exceeding costs, including environmental costs, and how the probability of breaking even was influenced by uncertainty in parameter values used in our BCA. Irrigation expansion in the Mekong Basin can reduce flows into downstream wetlands as well as increase the amount of flows, salt, acid sulphate soils, suspended solids, nutrients and pesticides discharged at the Mekong Delta (MRC, 2009). In this analysis, we only quantified costs associated with reduced flows to wetlands, in particular, decreases in fisheries production. We were unable to analyse broader environmental costs associated with changes in the quality of water discharged at the Mekong Delta because biophysical processes linking water quality with the ecological health of the Mekong Delta have yet to be modelled (Lacombe et al., 2014).

In the third scenario, we evaluated returns from reallocating investment from irrigation agriculture to other sectors including education, road construction, and agricultural research and development. For this scenario, we compared our estimates of returns to irrigation with estimates of returns actually realised in other sectors from past foreign aid investments using data from past evaluations in the Mekong River Basin. This scenario also provided an opportunity to explore treatment of inherently valuable social benefits. This was carried out by comparing not just benefit-cost ratio across sectors but also poverty head-count reduction.

2.3 Methods and data

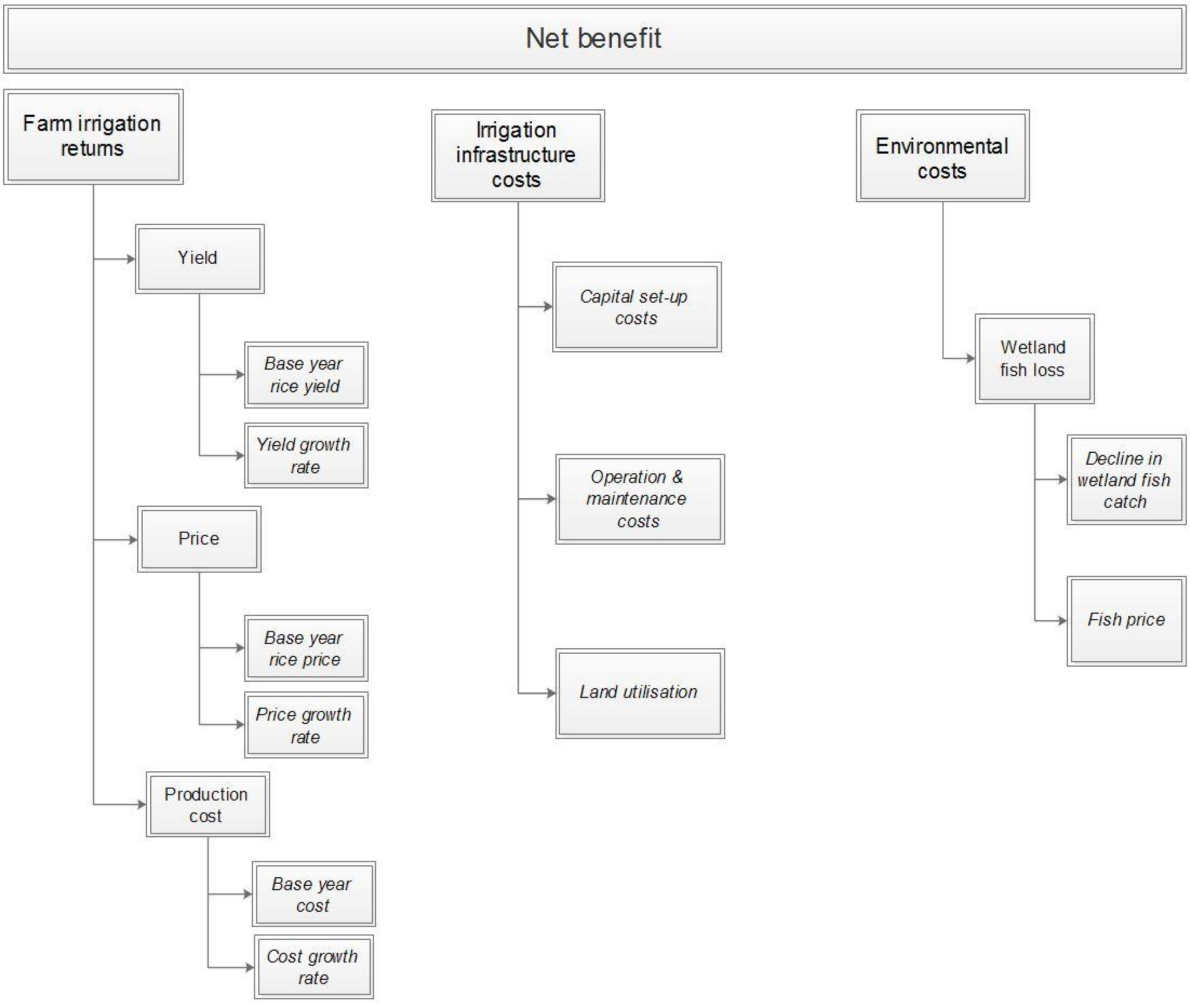
Our methodology involved seven distinct steps: 1) developing a conceptual BCA model by reviewing and synthesising information about key factors determining reference class benefits and costs of irrigation; 2) systematically reviewing published studies that provide a range of probable values for uncertain benefit and cost parameters; 3) calculating net benefits and benefit-cost ratios; 4) carrying out systematic sensitivity analysis with Monte Carlo simulation; 5) testing the sensitivity of BCA results to assumptions about potentially correlated parameters; 6) estimating the net returns from reallocating investments from large-scale irrigation to other sectors including education, road construction, and agriculture research and development; and 7) comparing benefit-cost ratios and head-count poverty reductions from investments in irrigation to other sectors including education, agricultural research and development, and road construction. Further description of the methods is provided in the remainder of this section and a detailed description of data for uncertain parameter range specification is provided in Appendix A.

2.3.1 Developing a conceptual BCA model for estimating the net benefit of irrigation investments

Figure 2.2 shows the BCA conceptual model we developed for the Lao irrigation investment based on a review of ex-post irrigation investments in the Mekong River Basin.

Our efforts to review and synthesise information on key factors determining benefits and costs of irrigation investments in similar contexts to our case study led us to develop a conceptual BCA with three distinct components: 1) farm irrigation returns consisting of yield, price, and production cost and annual growth rates of these three factors (Bartlett et al., 2012; MRC, 2009; SiliPhouthone et al., 2012; Yu and Fan, 2009); 2) an irrigation infrastructure cost model dependent on capital set-up costs, operations and maintenance (O&M) costs, and land utilisation estimates (ADB, 2005; de Walle and Gunewardena, 2001; ISMR, 2002); and 3) environmental costs from the impact of irrigation on wetland based fisheries downstream of the Nam Ngum Basin, the value of which depends on the expected decline in catch and fish price (Costanza et al., 2011; ICL, 2002; Kyophilavong, 2008; MRC, 2002; Sumaila et al., 2007).

Figure 2.2 Organisational structure for estimating costs and benefits of irrigation investments in Lao PDR



<u>Source:</u> Authors' design

Further, our review of the literature revealed that outcomes of assessments of irrigation projects typically vary with the scale of irrigation development. In general, the economics of larger projects involving dams and/or extensive conveyance infrastructure have been shown to be more challenging than the economics of individual farm irrigation with small pumps drawing from local groundwater sources or ponds (de Fraiture and Giordano, 2014; Xie et al., 2014; Zahid et al., 2005). Accordingly, we compared benefit-cost ratios between farm- and large-scale irrigation schemes.

2.3.2 Obtaining parameter value ranges

We carried out a systematic literature review to obtain value ranges for key uncertain parameters for estimating relevant costs and benefits (Figure 2.2). The objective was to consider quantitative estimates of values of key uncertain determinants of costs and benefits from diverse sources including published peer-reviewed and "grey" consulting report literature. Table 2.1 provides: 1) ranges of values for each uncertain parameter used in each of the three component models of our overall conceptual BCA model (Figure 2.2); and 2) relevant sources of data for each parameter value from the reviewed literature. Further detail of the systematic review process and the data is provided in Appendix A.

In most cases, multiple data sources were considered and parameter values were defined by a range. Point estimates were used where only one estimate was available.

2.3.3 Benefit-cost analysis calculation

We provide a description of calculation of key BCA components including irrigation net returns, infrastructure costs and environmental costs using mathematical equations in this section (Figure 2.2). Parameter definitions, values, units, and sources are summarised in Table 2.1 and discussed in detail in Appendix A.

We calculated the net present value benefit of irrigation investments over a period of 30 years between 2014 and 2034. The range of social discount rates considered for this analysis was 3-11% (Table 2.1). The time horizon of analysis was estimated at 30 years, which is the expected economic life of pumping and conveyance infrastructure (ADB, 2005). All costs and prices were reported in 2014 USD and adjusted for inflation using the latest US government Consumer Price Index (CPI) data published on April 15, 2014 (http://www.usinflationcalculator.com/). Where costs were reported in a currency other than USD they were converted to USD at the exchange that prevailed in the reporting year and then adjusted for inflation to obtain equivalent values of USD in 2014.

The net benefit of irrigation investments was calculated as the difference between farm irrigation returns, and the sum of irrigation infrastructure capital and O&M and wetland fish loss value:

$$Net\_benefit(y) = \sum_{y=1}^{Y} \frac{Farm\_irrigation\_returns(y) - (Irrigation\_infrastructure\_costs(y) + Wetland\_fish\_loss(y))}{(1 + Discount\_rate)^{y}} \quad (1)$$

Farm irrigation returns were calculated as:

$$Farm\_irrigation\_returns(y) = \sum_{y=1}^{Y} Yield(y) \times Price(y) - Production\_costs(y) \quad (2)$$

Equations 3, 4, and 5 describe how rice yield, price and cost are inflated over time by an annual growth rate factor:

$$Yield(y) = Yield(y=1) \times (1 + Yield\_growth\_rate)^{y}$$
(3)

$$Price(y) = Price(y=1) \times (1 + Price\_growth\_rate)^{y} \quad (4)$$

$$Production\_costs(y) = Production\_cost(y=1) \times (1 + Cost\_growth\_rate)^{y} \quad (5)$$

Table 2.1 Parameter descriptions, value ranges and sources

Parameter description	Parameter name	Unit	Value (range)	Source(s)
1. Irrigation net return				
Base year rice yield (irrigated second crop)	*Yield*	t/ha	2.6 – 4.0	(MRC, 2009) Pp 6 and 12; (ADBI, 2008) Pp 12; (SiliPhouthone et al., 2012) Pp 9; (NIS, 2008) Pp 14-15: http://www.slideshare.net/RuurdKuiper/081119-national-irrigation-strategy-discussion-parts-a-and-b
Irrigate rice yield annual growth rate	*Yield_growth_rate*	%	2 - 3 linear; 1.6 - 2.4 compound	(MRC, 2009) Pp 11; (Yu and Fan, 2009) Pp 23
Base year price of rice	*Price*	USD/kg	0.15 – 0.62	(MRC, 2009) Pp 7; (Siliphouthone et al., 2012) Pp 882 (ADBI, 2013; FAO, 2013) http://www.adbi.org/files/2013.02.18.cpp.day1.ses3.1.bouahom.douangsavanh.rice.supply.chain.lao.pdr.pdf
Rice price annual growth rate	*Price_growth_rate*	%	-3	(IFPRI, 2001) Pp 106 http://www.ifpri.org/sites/default/files/publications/gfp.pdf
Base year production cost	*Production_cost*	USD/ha	608 - 650	(MRC, 2009) Pp 6; (Siliphouthone et al., 2012) Pp 9
Cost annual growth rate	*Cost_growth_rate*	%	0.0 - 2.0	(MRC, 2009)
2. Irrigation scheme capital, O&M expenditures				
Capital set-up costs per hectare for large- and farm-scale irrigation infrastructure	*Capital costs*	USD/ha	4707-9345 large; 242-538 farm	(ADB, 2005)Pp 53; (UN, 2001)Pp 46; (Zahid et al., 2005) Pp 38 http://publications.iwmi.org/pdf/H039306.pdf
Planned irrigation area	*Planned_area*	Ha/year	9,049	(Bartlett et al., 2012) Pp2; (MRC, 2009) Pp 6
Land utilisation	*Land_utilisation*	%	40 - 80	(ADB, 2005; NIS, 2008) Pp 204; Pp 14 – 15: http://www.slideshare.net/RuurdKuiper/081119-national-irrigation-strategy-discussion-parts-a-and-b
Operations and maintenance cost	*O&M costs*	USD/ha/ year	210 – 514	(ISMR, 2002) Pp 20-21: http://www.mekonginfo.org/assets/midocs/0003465-farming-an-irrigation-report-update.pdf
3. Local cost of reduced fisheries yields				
Decline in fish catch from large- scale irrigation	*Decline_in_catch*	Kg/ha/ year	54 - 130	(ICL, 2002; Kyophilavong, 2008) Pp 37 ; Pp 3: http://www.aquaticresources.org/pubs/R7793-FTRR.pdf

Table 2.1 Parameter descriptions, value ranges and sources (continued)

Parameter description	Parameter name	Unit	Value (range)	Source(s)
Fish price	*Fish_price*	USD/kg	0.84 – 4.56	(Costanza et al., 2011; MRC, 2002; Sumaila et al., 2007) pp 21-22; pp vii., 11, 14, 52; http://www.seaaroundus.org/researcher/dpauly/PDF/2007/JournalArticles/AGlobalExVesselPriceDatabase.pdf ;
Discount rate	*Discount_rate*	%	3 - 11	(PC, 2010) Pp v. http://pc.gov.au/__data/assets/pdf_file/0012/96699/cost-benefit-discount.pdf
Time period of investment	*Y*	Years	30	(ADB, 2005) pp 170

Irrigation infrastructure costs under the large-scale irrigation scenario were calculated as:

$$Irrigation\_infrastructure\_costs = (Capital\_costs + O\&M\_costs) \times (Land\_utilisation \times Planned\_area) \quad (6)$$

The present value of wetland fish loss was calculated as:

$$Wetland\_fish\_loss(y) = \sum_{T} \left(\left(\frac{Decline\_in\_catch \times Fish\_price}{\left(1 + Discount\_rate^{y}\right)} \right) \right) \quad (7)$$

We also calculated benefit-cost ratios by dividing net benefits by total costs, and the probability of net discounted benefits exceeding discounted costs, termed the break-even probability for each of the two investment scenarios.

2.3.4 Systematic sensitivity analysis

We ran a stochastic BCA model using Monte Carlo simulation as a basis for systematic sensitivity analysis. Specifically, we calculated probable values for net benefit and benefit-cost ratio over 1000 random selections of values from probability distributions of each of the uncertain parameters given as a range in Table 2.1. Uncertainties in BCA parameter values were represented by specifying probability distributions. All uncertain parameters were assumed to have Beta distribution, a continuous probability distribution function typically used for uncertain parameters with known median and range. This choice of functional form was somewhat arbitrary, given we only had knowledge that parameter values lie within a known interval but no adequate data or expert opinion to assume or statistically test for functional form (Balcombe and Smith, 1999b; Pouliquen, 1970). Still, Pouliquen (1970) found that the exact choice of distributions for uncertain parameters is not as critical as accurate representation of parameter value ranges. Our Beta distribution resembled a truncated normal distribution with a symmetrical bell-shaped density curve about the median value and bounded intervals. This specification was sufficient in its ability to determine the way in which uncertain parameters may contribute to variations in BCA results individually and in combination holding all other parameters at their median values.

2.3.5 Testing implications of correlated uncertainties

We used a simplified categorisation of correlations and arbitrary benchmarks to test the sensitivity of BCA results to assumptions about various degrees of correlations following Balcombe and Smith (1999a). Specifically, we specified pair-wise linear correlation coefficients between: *Yield* and *Price*, *Price* and *Production costs*, and *Decline in Catch* and *Fish Price* under three correlation assumptions: 0.0 for *non-existent*; ±0.5 for *weak*, and ±0.9 for *strong* correlations. Assumptions about the direction of correlations were based on economics of farm management, empirical evidence, and basic supply and demand theory. Specifically, *Yield* and *Price* were assumed to be positively correlated based on economic theory and empirical evidence supporting positive price elasticity of supply. Expectations about growing product prices are typically reflected in increased acreage (land utilisation) allocated to rice production as well as farm input intensity levels, and consequently, yields (Bakhshi and Gray, 2012; Haile and Kalkuhl, 2013; Roberts and Schlenker, 2010). *Price* and *Cost* would also be expected to be positively correlated because in general inflation scenarios commodity prices would be expected to rise with production costs. *Decline in Catch* in local fisheries was assumed to be negatively correlated with *Fish Price* at local markets because most local fisheries supply local fish markets therefore fish scarcity would typically be reflected in higher fish prices. We ran three simulation models to obtain three sets of model results in order to test whether or not the variance of net returns and benefit-cost ratios were significantly different under the three correlation assumptions.

2.3.6 Estimating the net return from reallocating investments from large-scale irrigation to other sectors

We estimated net benefit change for a scenario where a quarter of the total investment value, USD25M, was reallocated from large-scale irrigation towards other sectors including education, road construction and agricultural research and development. This involved multiplying the difference between the benefit-cost ratio from large-scale irrigation and from past investments in the other sectors by the total amount of investment value reallocated, USD25M. Estimates for benefit-cost ratios of investments in these sectors in countries neighbouring Lao PDR were obtained from Fan et al. (2007) and can be found in Appendix A.

2.3.7 Assessing head-count poverty reduction impacts

We used a published dataset to carry out a superficial analysis of the nature of the relationship between benefit-cost ratios and head-count poverty reduction impacts of investments and variation across sectors (Fan et al., 2007). Fan et al. (2007) collated data on benefit-cost ratios and poverty head-count reduction impacts of several public investment projects in various sectors including irrigation, road construction, education, agricultural research and development, electricity, power, soil and water conservation, health, and anti-poverty programs in four Asian countries including India, China, Vietnam, and Thailand. We used this dataset to calculate and compare benefit-cost ratios and head-count poverty reductions that would be expected from a USD1M investment in each of these sectors. Appendix A provides the dataset used in this analysis.

2.4 Results

We present results in four subsections: (1) net returns to large and farm-scale irrigation infrastructure investments, (2) the benefits of reallocating investments from large-scale irrigation to alternative sectors, (3) systematic sensitivity analysis, (4) assessment of head-count poverty reduction impacts of investments across various sectors of the economy. Our model results were not sensitive to correlations. (We refer the reader to Appendix A for detailed results of a comparative analysis showing no significant differences under the three correlation assumptions).

2.4.1 Net returns to large and farm-scale irrigation investments

Table 2.2 shows estimated net returns, benefit-cost ratios and break-even probabilities for large- and farm-scale irrigation infrastructure investments evaluated at median values for all uncertain parameters. Overall, large-scale irrigation investments in the Nam Ngum Basin would be expected to incur a loss with a break-even probability of less than 16% and a benefit-cost ratio of less than one. By contrast, farm-scale irrigation expansion would likely yield a positive net return and benefit-cost ratio greater than one with a break-even probability of at least 69% overall. Including wetland fisheries costs increased the estimated benefit-cost ratio by 0.1 and the break-even probability by 7% for large scale irrigation investments. For farm-scale irrigation investments, including wetland fisheries costs increased the estimated benefit-cost ratio by 0.9 and the break-even probability by 15%.

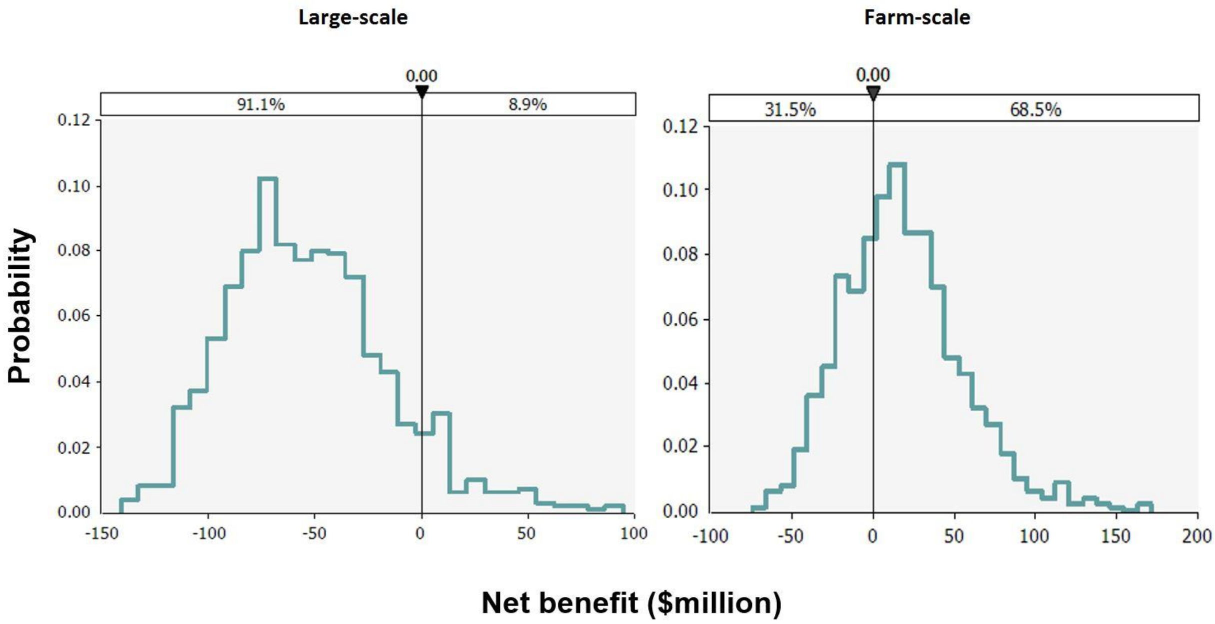
Table 2.2 Net returns, benefit-cost ratio, and break-even probability (or better) under large- and farm-scale irrigation investment scenarios in the Nam Ngum Basin

	Large-scale		Farm-scale	
	With wetland loss cost	**Without wetland loss cost**	**With wetland loss cost**	**Without wetland loss cost**
Net present value (USDM)	-53.5	-36.3	18.0	35.3
Benefit-cost ratio	0.5	0.6	1.4	2.3
Break-even probability	8.9%	15.6%	68.5%	83.0%

Figure 2.3 shows probability distributions of net returns (x-axis) under large- and farm-scale irrigation investment scenarios accounting for the value of wetland fisheries loss.

Probable net returns between USD141.2 and USD94.7M were estimated for the large-scale investment scenario and ranged between USD74.3 and USD171.5 M under the farm-scale investment scenario.

Figure 2.3 Comparing net returns to irrigation under large- and farm-scale investment scenarios

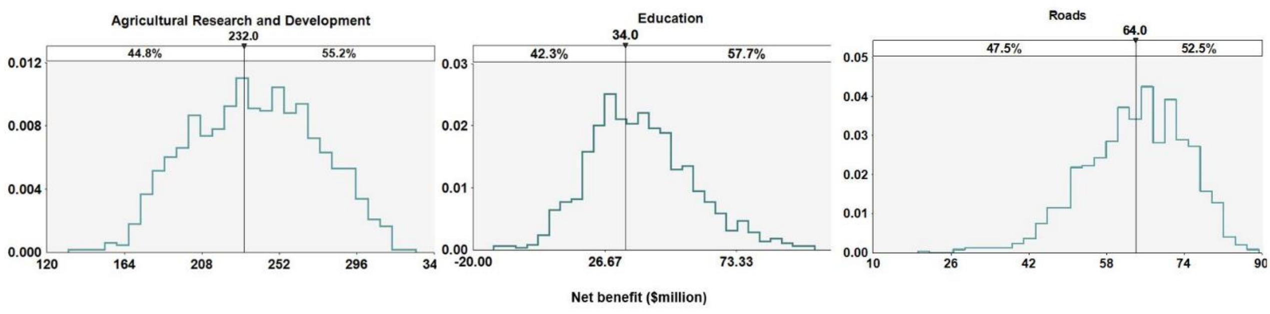


Source: Authors' design

2.4.2 Benefits of reallocating funds from large-scale irrigation to other sectors

Figure 2.4 shows probability distributions of net benefit of reallocating USD25Mfrom large irrigation infrastructure to agricultural research and development, education and road construction. Overall, positive net returns would be expected from reallocating to any one of the three alternative sectors with agriculture research and development delivering the highest return estimated at USD232M on average. Negative returns would be highly unlikely from these reallocations with a probability of less than 1% of incurring negative net returns from reallocating to education. This assumes that returns from future investments in these sectors in Lao PDR would yield similar returns to past investments in Vietnam, Thailand, and China (Fan et al., 2007).

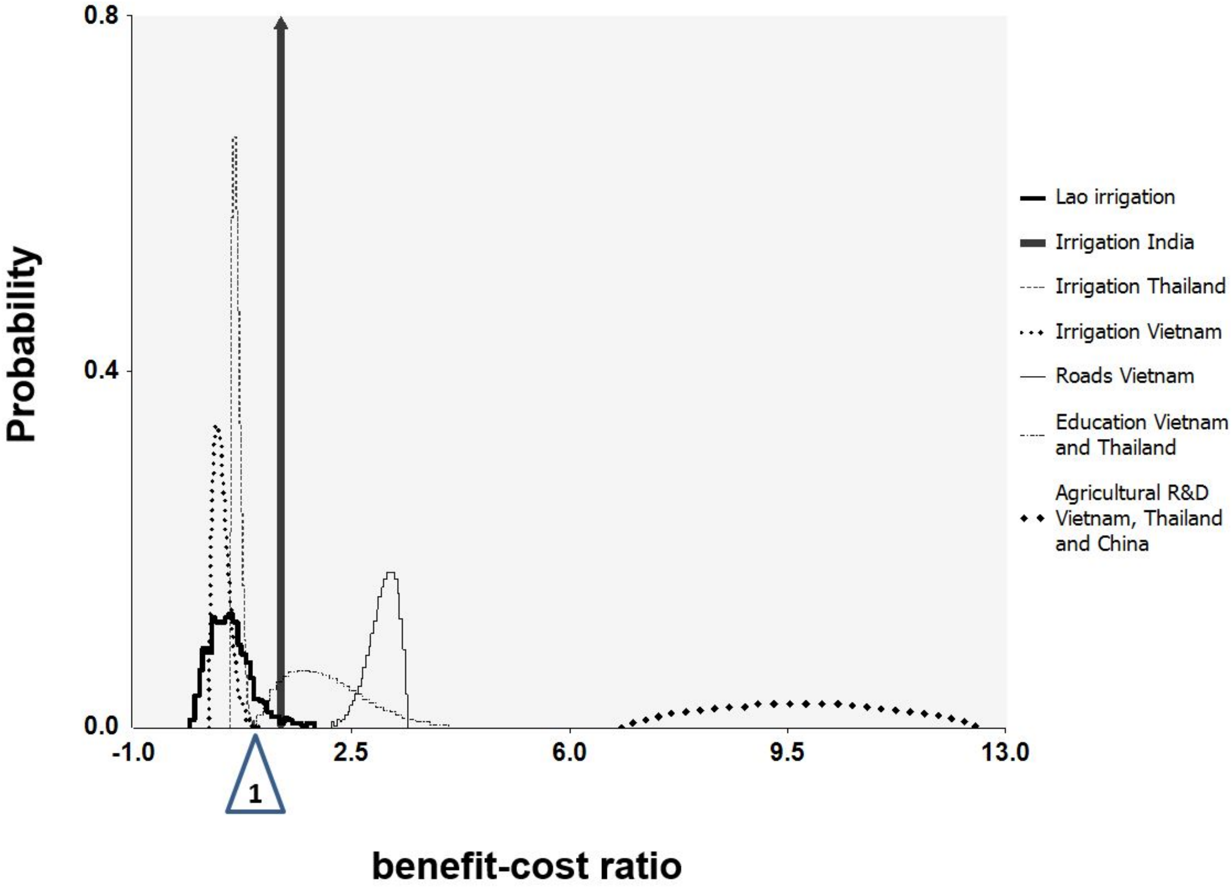
Figure 2.4 Expected benefits of reallocating USD25M from large-scale irrigation to other sectors (USDM)



Source: Authors' design

Figure 2.5 compares expected benefit-cost ratios of large-scale irrigation investments in Lao with benefit-cost ratios of alternative investments in neighbouring countries from past BCA studies, including: 1) irrigation investments in India, Thailand, and Vietnam; 2) road construction in Vietnam; 3) education in Vietnam; and 4) agricultural research and development in Vietnam.

Figure 2.5 Comparing benefit-cost ratio estimates of investing in large-scale irrigation with investing in other sectors



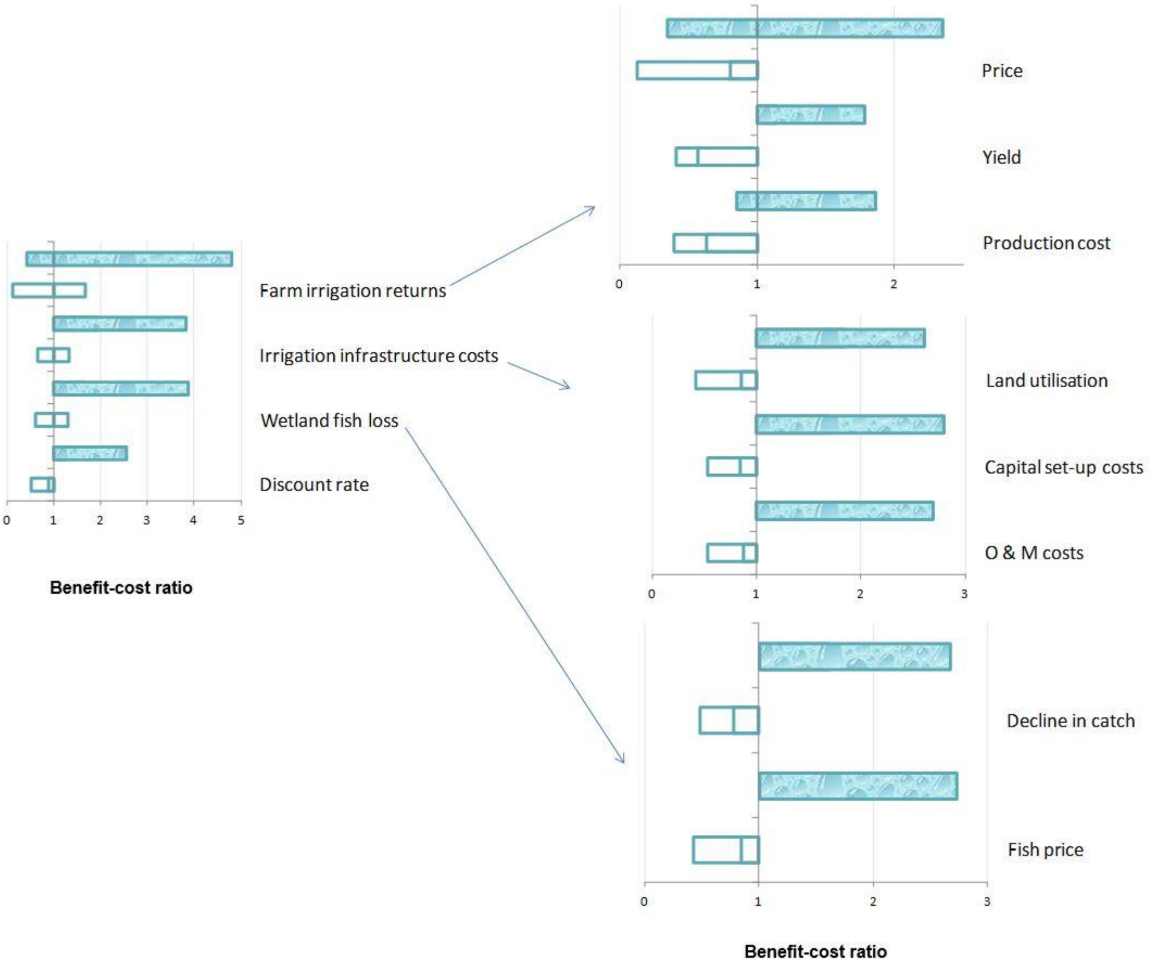
Source: Authors' design

Figure 2.5 indicates that benefit-cost ratios of foreign aid investments in road construction, agricultural research and development, and education would be expected to be greater than benefit-cost ratios of investments in large-scale irrigation investments.

2.4.3 Systematic sensitivity analysis

Figure 2.6 shows the sensitivity of our benefit-cost ratio estimates to uncertainties in parameter values individually, and in combination for large- and farm-scale irrigation investment scenarios. This gives an indication of the relative contribution of uncertain parameters to variability in benefit-cost ratio estimates. Uncertainties in price, yield and production cost values used to estimate farm irrigation net returns collectively contributed the most to variation in estimates of benefit-cost ratios and they are important enough to influence overall BCA conclusions. Specifically, we can estimate a benefit-cost ratio of less than one or greater than one under both farm- and large-scale irrigation investment scenarios, depending on our assumptions about the most likely values of these three parameters within the specified probable range of values in Table 2.1 holding all other parameters at their median values.

Figure 2.6 Sensitivity of benefit-cost ratio estimates to uncertain parameter values under farm- (shaded) and large-scale irrigation investments



<u>Source:</u> Authors' design

Variations in farm irrigation returns were influenced the most by uncertainties in price followed by production cost. Uncertainties in price and in cost were each found to be important enough to change BCA conclusions under the farm-scale irrigation investment scenario. Assumptions about yield and yield growth rates were not important enough to influence BCA conclusions under both farm- and large-scale irrigation investment scenarios.

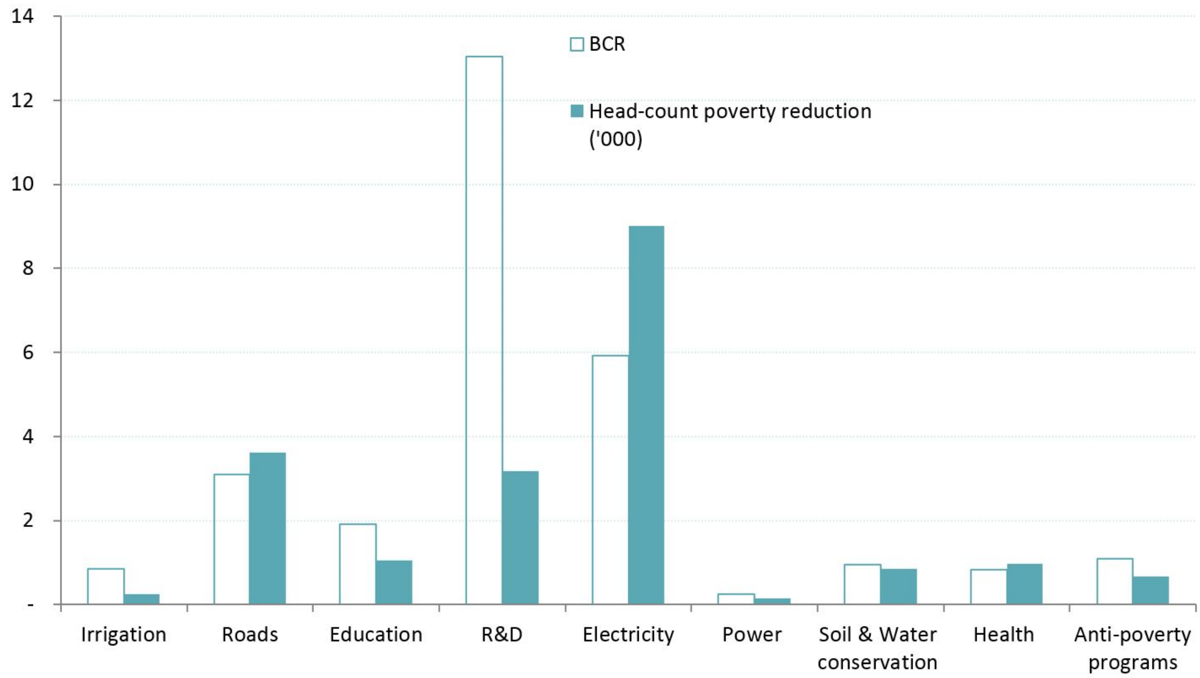
Collectively, uncertainty in parameter values used to estimate the cost of irrigation infrastructure and wetland fish loss were important enough to influence BCA conclusions under the large-scale irrigation investment scenario. Benefit-cost ratios of less than or greater than one can be estimated with almost equal likelihood for large-scale irrigation investments, depending on assumptions on the most likely values from the ranges of values of parameters used to estimate the cost of irrigation infrastructure and wetland fish loss. BCA results were not sensitive to assumptions about the social discount rate in both large- and farm-scale irrigation investment scenarios.

Variations in irrigation infrastructure costs were almost equally influenced by uncertainties in irrigation scheme utilisation, capital set-up costs, and O&M costs. None of these parameters was individually important enough to influence BCA conclusions but in combination, these uncertainties were important enough to influence BCA conclusions under the large-scale irrigation investment scenario. Variations in wetland fish loss values were approximately equally influenced by uncertainties in decline in catch and fish price.

2.4.4 Assessing head-count poverty reduction impacts

We observed that benefit-cost ratios and head-count poverty reduction impacts for investments across various sectors were not perfectly correlated, however some positive correlations can be detected (Figure 2.7). In general, sectors with high benefit-cost ratios also have relatively high reductions in head-count poverty and vice versa.

Figure 2.7 Comparing benefit-cost ratio estimates and poverty head-count reductions of USD1.0M investment in various sectors



Source: Authors' design

Road construction, education, agricultural research and development, and electricity score higher than irrigation in terms of both benefit-cost ratio and head-count poverty reduction.

2.5 Discussion

The discussion section is structured into three distinct components: 1) discussion and interpretation of results of our study, 2) Comparison between findings of our study with findings of other similar studies, and 3) discussion of limitations of our study and scope for further research.

2.5.1 Interpretation of results

Our results suggest that increasing large-scale irrigation investments is not always an effective strategy for achieving economic growth and poverty reduction. Using cost and benefit parameter values consistent with values used in similar past reference class investments, we estimated the probability of negative net returns to new large-scale irrigation investments at between 84% and 91% for the Nam Ngum Basin case study in Lao PDR. Positive net returns were only estimated to be likely under very optimistic assumptions, including high rice prices and yields, low production costs, high utilisation, low capital set-up and O&M costs, and little resulting fish catch decline. We also found that investments in other sectors such as education, road construction, and agricultural research and development can be more effective at achieving economic growth and reducing poverty than large-scale irrigation investments. Reference-class investment experience suggests that all three alternative sectors could generate both greater return on investment and higher poverty head-count reductions. Given there are likely to be alternative foreign aid investments with higher returns, investing in irrigation may actually perform worse than investments in other sectors. It is worth noting that investments in education, road construction, agricultural research and development and other sectors of the economy can complement irrigation investments. For example, when complimented with new road development, irrigation schemes can be particularly beneficial (Fan et al., 2007). Evaluations of impacts of investing in alternative sectors of the economy should therefore not consider different sectors in isolation. This finding bears significant relevance as countries in Asia and other parts of the world shape new develop plans to better align with United Nations Sustainable Development Goals.

Overall, economics of farm-scale pump irrigation investments appear to be more favourable than large-scale irrigation investment with a higher probability of positive net return. Still, there are some risks and significant uncertainties considering a probability of negative net return of up to 31% under farm-scale irrigation investments. Additionally, there is no existing inventory of the scope of potential sites that may be biophysically suited to operation of farm-scale pump irrigation in Lao PDR. An assessment of the scope for feasible adoption of farm-scale pump irrigation in Lao PDR is required to understand the extent to which this irrigation investment scenario is plausible. Based on these results, Lao PDR, and other countries with similar contexts, may benefit more substantially from policies that encourage investments in farm-scale pump irrigation than large-scale irrigation.

Prioritising investments across various sectors based on benefit-cost ratios alone may not adequately reflect poverty reduction impacts that can be expected from equal investments in each of the sectors. We found ranking of poverty reduction benefits to be only partially correlated with benefit-cost ratios. Even if increases in farm economic returns as a result of additional irrigation investments suggest potential for high benefit-cost ratios, evidence suggests such investment could favour wealthy farm owners at the expense of farm employees (Ward and Smajgl, 2014). On the other hand, investments in road construction, electricity, and education could improve opportunities for higher-paying off-farm employment thereby more effectively reducing poverty than irrigation investments (Fan et al., 2007). Targeted investments based on understanding of complex pathways from economic benefits of investments to social welfare benefits would be better than investments prioritised based on benefit-cost ratios alone, if key objective is to reduce poverty.

Costs associated with environmental impacts in the form of wetland fish production losses were found to be significant. Inclusion of this cost was important enough to influence BCA conclusions under large-scale irrigation investment scenario. Inclusion of environmental costs in evaluation of small farm-scale pump irrigation reduced the benefit-cost ratio from 2.3 to 1.4. Further, there are additional known negative impacts that were not monetised including sedimentation, salinity, nutrient, and agrochemical pollution impacts from irrigation. A more complete inclusion of these costs would only reinforce the conclusion that large-scale irrigation is likely to provide negative net benefit. However, it could also reverse the conclusion about positive net return from farm-scale pump irrigation investments.

2.5.2 Comparison of our findings with other studies

Our findings are consistent with previous research including Inocencio et al. (2007) who found that small-scale irrigation schemes generally perform better than large-scale schemes. A number of studies have observed that government and foreign aid sponsored large-scale irrigation development projects are in decline in Asia while community and private funded small-scale irrigation investments in groundwater are growing in popularity in India, Bangladesh, and China (Akteruzzaman et al., 1998; Mukherji et al., 2009a; Turral et al., 2010). Projections by Turral et al. (2010) show a shift away from large- to small-scale irrigation infrastructure investments in future. This shift will likely be influenced by increasing demand for adaptable irrigation systems that can be more precisely targeted to specific agricultural, ecological and economic contexts at the farm level (Ward, 2010). Further, competing demands for water for municipal and industrial uses, energy generation and the need to mitigate negative environmental impacts of irrigation will likely influence the shift towards more economically efficient small-scale irrigation systems (Mukherji et al., 2009a; Turral et al., 2010).

We found that variability in farm irrigation return was the largest single factor influencing variability in our BCA model results. Baseline price, cost and yield values contributed to variability in BCA outcomes more than assumptions on growth rates. Given that in-country inspections should yield good information to narrow this uncertainty, gathering such information may be cost-effective in reducing uncertainty about net benefit estimates. Another uncertainty that may be reduced at relatively low cost would be a review of how utilisation rates relate to irrigation charges to help in designing irrigation schemes and charges. In contrast, it may be quite expensive to reduce ranges around some other uncertain parameters such as fishery decline impacts where better assessments could require extensive fieldwork and process modelling. Better resolution of the range of parameter values for fisheries impacts would not likely influence BCA conclusions to the same extent as previously outlined factors.

We contend that our treatment of uncertainty in BCA provided robust results and a basis for informed conclusions with reduced bias and enhanced credibility. Methods applied in this study are transferrable to broader BCA application under uncertainty. One remaining challenge is more sophisticated treatment of correlation to resolve contradictory evidence suggesting that BCA results from simulations may not be sensitive to correlation assumptions in some cases (Bock and Trück, 2011), but quite sensitive in other cases (Reutlinger, 1970).

2.5.3 Limitations and scope for further research

Other potential ancillary economic benefits of irrigation investments not quantified in this study include benefits from increased dairy production and inland farm fisheries (Kumar et al., 2014). Increased dairy and inland farm fisheries production could lead to increasing agricultural labour demand and rising agricultural wage rates. These ancillary benefits may be greater under large-scale schemes compared to small farm-scale irrigation schemes. It is worth noting that quantification of benefits of additional dairy production and aquaculture investments as an "add-on" to large-scale irrigation would require defining future scenarios involving new capital investments. This was beyond the scope of the analysis provided in this study.

Our study only considered the net return from irrigated crops. Ideally, with a more comprehensive data basis, we would have assessed the incremental return from irrigation, factoring out income from rainfed production. Accounting for this foregone opportunity cost of irrigation investments could slightly reduce the net benefit from all forms of irrigation including large- and small-scale irrigation schemes. We note that this cost is likely to be small because the dry season in Laos is drought prone, leading to poor yield potential and consequently, most households leave fields fallow in this season (Adamson and Bird, 2010). Additionally, this opportunity cost would have to be included for both large- and small-scale investments, and thus including it would not change relative net returns from small- and large-scale irrigation investments.

Irrigation return flows from large gravity irrigation schemes can increase availability and quality of groundwater water resources. In turn, augmented additional investments in hand and pump wells for extracting additional groundwater resources can increase water supply for drinking and other domestic uses in villages and municipal areas (Kumar et al., 2014). This benefit was not quantified in this study due to data limitations. Future studies should investigate the significance of this benefit.

Multiplier effects of irrigation induced growth on indirectly affected sectors and regions of the economy were not considered as these were outside the scope of this study. This omission may lead to some understatement of the impact on regional economies increasing demand for outputs from related complementary inputs to production such as fertilisers, fuel, machinery and locally produced goods, or through indirect effects from income and wage rises for irrigation farmers and in linked sectors (Malik, 2007).

Another limitation of this study is that a number of potential environmental impacts of the large irrigation infrastructure investment were not quantified to data limitations, including waterlogging and soil salinization, possible rise in groundwater table, water pollution, and savings in cost of energy used for pumping groundwater for irrigation. Social impacts were also not quantified because they were outside the scope of the analysis. Future research can quantify the omitted impacts, conduct socio-economic implications assessments and employing non-market valuation techniques to quantify non-market costs and benefits.

2.6 Conclusion

Increasing large-scale irrigation investments is not always the most effective strategy for achieving economic growth and reducing poverty. Farm-scale pump irrigation investments could be more effective than large-scale investments. Use of benefit-cost ratio estimates alone can be misleading as a means of prioritising investments across various sectors to most-effectively reduce poverty. Costs associated with environmental impacts could be significant and need to be included in evaluations of aid investments. Uncertainty in farm returns and the sensitivity of utilisation rates to irrigation charges may be important in determining economic viability of irrigation schemes. Despite inherent uncertainties in prospective BCA evaluation, adequate treatment of uncertainty in parameter values can provide robust results, decisive conclusions, reduce bias, and enhance credibility of BCA outcomes.

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Chapter 3 Impact of microcredit loans on school enrolment in Bangladesh

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This chapter describes an econometric evaluation of the causal influence of microcredit loans on primary school enrolment in Bangladesh based on a paper published in *The Journal of Development Studies* (2019). The paper is included in its published form, with some minor formatting changes consistent with the overall thesis format. There is some repetition with other chapters in this thesis, in particular, the background and conclusion sections.

Abstract

Human capital investment, especially in education, is a well-known precursor of economic growth in developing countries. In recent years, there has been a proliferation of microfinance programs, yet evidence as to whether microfinance leads to increased educational investment is tenuous at best. We utilise a large-scale cross-sectional household dataset from Bangladesh and geospatial data to study how microcredit participation and increasing microcredit incomes – that is, the extensive and intensive margins of microcredit – affects the probability of children's school enrolment. The causal influence of microcredit participation on enrolments was estimated by utilising the propensity score matching (PSM) technique – a quasi-experimental treatment effects model. Whilst microcredit participation, the extensive margin, did not significantly influence the likelihood of school enrolment for boys, it increased girls' enrolment. Further, microcredit income, the intensive margin, had a stronger influence on girls' and younger siblings' enrolment than on boys' and older siblings' enrolment. Omission of spatial influences can overstate microcredit influence on enrolment, while not utilising PSM can underestimate the influence of microcredit participation on enrolment. Results suggest policies that focus solely on increasing microcredit participation, without increasing the amount of microcredit income accessed by households, may be less effective at improving children's education outcomes.

Keywords: microfinance; econometric analysis; gender equality; women's empowerment; poverty alleviation

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Name of Principal Author (Candidate)	John Kandulu		
Contribution to the Paper	Undertook the literature review. Collected all of the data. Prepared data for analysis and performed econometric analysis in Stata. Interpreted data and wrote the manuscript. Acted as the corresponding author.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	12/07/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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3.1 Introduction

Since the 1960s, development economists have cited human capital investment, particularly in education, as one of the main driving forces behind sustainable economic growth, development and poverty alleviation (Frank, 1960; Pelinescu, 2015; Sabot, 1992). Because household investment in children's education often precedes development (Deng et al., 2014; Hu, 2012; Rosati and Rossi, 2003; Smits and Hosgor, 2006), there has been a growing interest in understanding whether microfinance, and in particular microcredit, can lead to increased educational investment, besides reducing poverty, gender inequality and increasing overall quality of life (Copestake, 2007; Garikipati et al., 2017).

Microcredit initiatives have been credited for increasing household educational investment and reducing gender disparity in education (Garikipati et al., 2017; Holvoet, 2001; Owusu-Danso, 2014; Posso and Zhang, 2017). The rationale behind this association is that financial empowerment of women through microcredit increases women's bargaining power in the household and enables mothers to make better family decisions regarding their children's education (Hill and King, 1995; Kaur and Lecit, 2012; Klasen, 2003; Matthews and Nee, 2000; Seguino, 2000).

The conceptual link between microcredit and educational investment can be analysed using the nexus between household microcredit income, children's education demand and child labour demand. School enrolment and child labour participation are not mutually exclusive; although a number of studies have found that children who participate in the labour force are less likely to be enrolled in school (Beegle et al., 2009; Putnick and Bornstein, 2015). The major cause of household child labour demand is the need for households to generate additional income in mitigating vulnerability to income shocks, for example due to undesirable and unforeseen health or climatic incidences (Boutin, 2014; Frölich and Landmann, 2018; Islam and Choe, 2010). Thus, credit constrained households are vulnerable to income shocks and may have an urgent need to transfer expected future income earnings in order to support current consumption, by moving children from school to work. Several empirical studies have reported that microcredit can enable households to borrow against future earnings to reduce vulnerability to income shocks and unexpected expenses, thus negating the need for children's participation in the labour force and increasing school enrolments (Copestake, 2007; Corrie, 2011; Garikipati et al., 2017; Khandker, 2005; Landman and Frolich, 2015; Sivachithappa, 2013; Swain and Floro, 2012).

Whilst the positive link between microcredit and education has intuitive appeal, empirical evidence on how microcredit affects household education outcomes has been tenuous at best. For example, there is no consensus in the literature on whether or not microcredit leads to more education investment. On the one hand, researchers have found: 1) microcredit initiatives targeting women have a positive effect on education in poor households (Chakrabarty, 2015; Holvoet, 2004; Swain and Floro, 2012); 2) women's financial empowerment leads to improvements in children's education (Allendorf, 2007; Duncanson et al., 2014; Gulland, 2014; Lokshin and Fong, 2006; Pandey and Lee, 2012; Parashar, 2005; Patel et al., 2015; Pikalkova, 2003; Sethuraman et al., 2006); and 3) an increase in a mother's nonwage income has a larger beneficial effect on household educational investment, compared with a similar increase in a father's nonwage income (Brown and Park, 2002; Liu, 2008). Conversely, other studies have found that microcredit is statistically insignificant in its influence on household educational investment (Stark et al., 2015) or even significantly negative (Cida, 2007; Maldonado and Gonzalez-Vega, 2008).

Whilst these contrasting findings could reflect differences in geographical contexts or econometric methods used, a common observation is that most studies do not distinguish between the influence of microcredit participation (the extensive margin) and the influence of increasing the amount of microcredit income received (the intensive margin) on participating households' education investment. Further, most studies consider a limited number of control variables due to data limitations, and spatial and locational characteristics of households are largely omitted. The ability to control for a large set of socioeconomic and spatial characteristics is important because it is extremely difficult to find an exogenous instrument for microcredit – therefore the next best solution is to reduce omitted variable bias as much as possible by employing a large set of controls (Hannum, 2005; Smits and Hosgor, 2006; Yamauchi and Tiongco, 2013).

In addition, cross-sectional econometric studies estimating the causal influence of microcredit on enrolment face empirical endogeneity challenges arising from non-random selection of households between participating and nonparticipating groups. Specifically, households can self-select for microcredit participation due to observed and unobserved program placement artefacts and design attributes favouring households with certain characteristics that would have not otherwise participated (Coleman, 2006). Households that own land, but would otherwise be unlikely to participate in microcredit can self-select into a microcredit program designed in such a way that eligibility for participation is determined based on the amount of land-holding status. Studies that do not comprehensively address the self-selection challenge fail to isolate the pure effect of microcredit participation from the effects of other observed and unobserved characteristics, and may likely over- or under-attribute the influence of microcredit participation on enrolments. Results from such studies are thus not informative of the likely effect of policies that promote microcredit participation in an effort to increase enrolments.

We address these issues by constructing a dataset that combines large-scale census data from Bangladesh and spatial datasets, to study the effect of microcredit on school enrolment. Our rich dataset enabled us to make three contributions. Firstly, we explored the effect of microcredit participation and the amount of microcredit income received to assess the difference in the influence of increasing participation – as distinct from increasing the amount of microcredit incomes received by participating households – on household education investment. Receiving large microcredit incomes increases the scope and profitability of household enterprises thereby increasing both household child labour demand and education's opportunity cost (Chakrabarty, 2015). Secondly, we controlled for a large set of socioeconomic and geospatial characteristics to reduce omitted variable bias, which to our knowledge is the largest set of controls employed in the relevant literature. Third, our empirical strategy for estimating the causal influence of microcredit participation on enrolments seeks to overcome self-selection, a challenge commonly faced in previous literature, by utilising quasi-experimental treatment effects models and propensity score matching (PSM) techniques.

Bangladesh is an excellent country to study as it is a microfinance leader. For instance, it pioneered the successful operation of microcredit institutions in 1976 for women with the primary objective of contributing to women's empowerment in order to improve quality outcomes for children (Goetz and Gupta, 1996; Hashemi et al., 1996). Thus, it has the largest microcredit market and the longest experience with microfinance in the world (Salim, 2013). Most microcredit programs in Bangladesh intentionally target women as a key design attribute because women have high loan repayment rates compared to men. In addition, women represent a small credit risk group; are more credit constrained; have less access to wage-based employment; have limited bargaining leverage in household decisions; and are more likely than men to share the benefits of microcredit loans with other members of the household – in particular children (Rahman et al., 2017). Bangladesh also has the most comprehensive dataset and oldest records on microcredit projects. The dataset employed in this study has considerable information on microcredit incomes received within the household and on household education investment. The location of surveyed households is also known, enabling construction of spatial regional and location variables. Finally, the study findings regarding the impact of microcredit on household education investment in Bangladesh will also be relevant for many other developing countries.

3.2 Contextual background

We first conducted a comprehensive analysis of peer-reviewed published empirical studies on household educational investments (i.e. number of children in school, total school expenditure, likelihood of a child being enrolled in school, and a child's years of schooling).

3.2.1 *Determinants of a household's educational investment*

From our analysis, we enumerated the span of explanatory variables used in these studies on the relative importance of various factors that influence household education investment. We organised variables into eight distinct categories: Household and child characteristics, Income and expenditure, Employment characteristics, Parents' characteristics, Housing characteristics, Community characteristics, Parents' expectations and School characteristics (Table B.1 in Appendix B).

The most important and commonly found influences on school enrolment in the literature include household wealth (typically measured using income and expenditure variables), along with household and parent characteristics – in particular population and parents' education and employment status. The range of explanatory variables considered as determinants of children's education, and the nature and strength of the relationship between household education investment and explanatory variables varies considerably. Heterogeneity in the explanatory variables included and relevant variables excluded in these studies can, for the most part, be explained by data limitations. However, the issue of potential bias in model results due to omission of relevant variables has been raised by several studies (Brown and Park, 2002; Hannum et al., 2009; Shabaya and Konadu-Agyemang, 2004; Smits and Hosgor, 2006; Yamauchi and Tiongco, 2013).

3.2.2 *Case study context*

In Bangladesh, despite the appreciable increase in enrolment rates over the years, some issues remain. There is considerable inequality in access to basic education between rich and poor households and between boys and girls (Ahmad et al., 2005); with the 20th percentile poorest households registering enrolment rates of 57% for boys, compared with 65% among the next 20th percentile of poorest households.

In addition, poor quality of education services remains an issue in Bangladesh (Ahmed and Arends-Kuenning, 2006). A joint UNICEF and World Bank report recommended policy interventions to address gender disparity in school enrolments in Bangladesh (UCW, 2011).

Subsequently, gender disparities in school enrolments have reversed since the start of various programs for encouraging girls to enrol in school, and the enrolment of girls is now significantly higher than that of boys (BIGD, 2018).

3.3 Methodology

3.3.1 ***Conceptual framework***

Our empirical regression analysis was underpinned by a household utility function for basing human capital investment decisions to optimise competing current and future consumption, taking into account income and wealth constraints (Becker, 1994). A household's expected utility, based on its decision on whether or not to enrol a child in school, *Eu*, was characterised as a function of current and future consumptive and non-consumptive benefits. Examples of consumptive utility from education include: education as a consumptive good in and of itself, and the utility from educated parents enjoying educated children more than uneducated children. Non-consumptive utility from education includes social status and social acceptance benefits. Consumptive utility from non-enrolment results directly from income of children participating in the labour market and/or household enterprises, and indirectly through children relieving parents from running the household to undertake income-generating activities. Examples of non-consumptive utility from non-enrolment include caring for dependents (i.e. elderly parents, younger children). This is premised on the notion that when households invest in education, they trade-off some proportion of current consumptive, c_c, and non-consumptive, nc_c, utility from non-enrolment, for expected current, and future consumptive, c_f, and non-consumptive, nc_f, utility from current enrolment:

$$Eu\left(c_c, nc_c, c_f, nc_f\right) = \left(u_c^e(c_c, nc_c) + \frac{u_f^e(c_f, nc_f)}{1+\delta}\right) - u_c^n(c_c, nc_c) \qquad (1)$$

u_c^e is current utility from current enrolment, u_f^e is future utility from current enrolment and u_c^n is current utility from current non-enrolment. Expected future utility gains from education investments are discounted to consider the time value of money as well as the uncertainty inherent in future returns to current investments, δ.

Our conceptual framework for enumerating and organising explanatory variables that influence a household's decision whether or not to enrol a child in school was underpinned by the household expected utility function, and by findings in the previous literature (Table B.1 in Appendix B). Various demand and supply factors that can influence a households' decision on whether or not to enrol a child in school based on the expected utility function were considered (i.e. household population and structure, income and expenditure, district minimum daily wage, parents' education and employment status and community characteristics). In addition, housing characteristics, for example drinking water supply and electricity, were used as indicators of demand for household labour and by extension school enrolment, because they determine the amount of time spent fetching water and collecting firewood. Supply factors included geographical spatial variables influencing school accessibility (exposure to severe floods), district participation in school feeding programs that reduce the net cost of education, and quality of school infrastructure.

Further, we also modelled girls and boys separately in recognition of the fact that the expected current and future utility from their education is different in developing countries due to: 1) differences in access to employment and earnings between men and women; 2) cultural differences influence variability in expected income remittances from daughters and sons; 3) girls typical share of household chores; and 4) the effect of policy interventions and development initiatives for restoring gender parity in school enrolment.

3.3.2 ***Data***

A summary of all the variables used, household-level descriptive statistics and data sources is provided in Table 3.1. The main data asset for this study was the 2010 Bangladesh Household Income and Expenditure Survey (HIES), a census dataset which surveyed 12,240 households from 612 Primary Sampling Units (PSUs) across Bangladesh and asked questions about income, health, education, assets, and employment. A total of 60,903 people were surveyed, 16,712 of which were children aged 5-17 (Table 3.2). In total, 16,699 child-level observations, including 8,669 boys and 8,030 girls, and 12,237 household-level observations were used for analysis with 13 child-level observations and three households not used due to missing data. Three age groups were also considered for analysis, including children aged 5-9 (6,810 observations), 10-14 (6,748 observations), and 15-17 (3,141 observations).

Income and expenditure values were measured in Bangladesh Taka (BDT). In total, 4,822 households with a total 9,162 children received microcredit income in 2010. Observations for the subsample of households with positive microcredit income in 2010 were used in analysis of the influence of increasing the amount of microcredit income on enrolments. Further, a constant value of 0.1 was added to all observations of the various income and expenditure variables before applying the logarithm transformation. The percentage of observations with zero values for the log-transformed input cost and net revenue variables ranged between 4.12% and 8.37%. Additionally, models with logarithm transformations of income and expenditure covariates were compared to models with inverse hyperbolic sine (IHS) transformations to test the sensitivity of estimates to the scale of transformation of zero-value observations after Bellemare and Wichman (2020).

Spatial information from a number of sources was compiled to characterise various district level geographical features. Specifically, GIS techniques were used to collect geospatial data on flood proneness at the sub-district *thana* level of spatial resolution. Areas prone to floods deeper than 360cm were identified using information from the Centre for Geographic and Information Services (CEGIS) for the year 2009. Areas prone to severe drought events across the three main seasons in Bangladesh (*pre-kharif*, *kharif* and *rabi*) were also identified using spatial data from the 2006 Bangladesh Country Almanac. Our use of the only publicly available GIS information on drought and flood events in Bangladesh for the year 2006, to analyse 2010 enrolments, is validated by findings from a 50-year analysis of Bangladesh’s climate and hydrological data between 1959 and 2009, which showed that the spatial distribution, frequency or severity of rainfall, and droughts did not change between 2006 and 2010 (Brammer, 2016). Further, spatial data on key horticultural districts, districts that participated in school feeding programs, and average aid funds disbursed to support district banking services were also collected.

Table 3.1 Descriptive summary household-level statistics (n= 12,237)

Variable name	*Description*	*Mean*	*SD*	*Min*	*Max*
Dependant variables					
Child enrolment in school[1]	1=child is enrolled in school, 0=otherwise	0.7	0.3	0.0	1.0
Boy enrolment in school[1]	1=boy is enrolled in school, 0=otherwise	0.8	0.2	0.0	1.0
Girl enrolment in school[1]	1=girl is enrolled in school, 0=otherwise	0.7	0.2	0.0	1.0
Child & parent characteristics					
Age [1]	Child age	10.7	3.6	5.0	17.0
Girl (binary) [1]	1=girl; 0=otherwise	0.5	0.5	0.0	1.0
Non-biological child (binary) [1]	1=Non-biological child	0.1	0.2	0.0	1.0
Household Income (Bangladeshi Taka (BDT))					
Microcredit participant (binary) [1]	1=Household eligible and receives microcredit loan income	0.4	0.4	0.0	1.0
Microcredit income received (log) [1]	Amount of loan income received in 2010	9.1	4.7	6.2	10.1
Remittances income (log) [1]	Remittance income from within and outside Bangladesh	4.6	5.2	-2.3	11.3
Wage & salary income (log) [1]	Monthly wage and salary from main employment	8.3	10.0	-2.3	14.8
Revenues from household enterprises	Revenue from non-farm enterprises	7.0	5.1	-2.3	11.1
Mother attended private school (binary) [1]	1=mother attended private school	0.04	0.2	0.0	1.0
Mother's school years[1]	Mother’s years of schooling	3.1	4.0	0.0	19.0
Father attended private (binary) [1]	1=father attended private school	0.1	0.3	0.0	1.0
Father's school years[1]	Father’s schooling years	4.0	4.5	0.0	19.0
Mother's age[1]	Mother age (years)	33.3	15.9	0.0	91.0
Mother ill this year (binary) [1]	1=mother was seriously ill in 2010	0.2	0.4	0.0	1.0
Father's age[1]	Father age (years)	38.7	20.9	0.0	84.0
Father ill this year[1]	1=father was seriously ill in 2010	0.3	0.5	0.0	1.0
Islam (binary) [1]	1=Head of house’s religion is Islam	0.8	0.4	0.0	1.0
Household structure & employment					
Household size[1]	No. of people	4.5	1.9	1.0	17.0
Proportion of females [1]	No. of females divided by household size	0.5	0.2	0.0	1.0
Female head (binary) [1]	1=Household head is female	0.1	0.3	0.0	1.0
Number of under 5 children[1]	No. of children <5	0.4	0.7	0.0	6.0
Proportion of people over 66[1]	Proportion >66 by household size	0.1	0.1	0.0	0.5
Number of non-biological children[1]	No. of non-biological children in a household	0.2	0.5	0.0	3.0
Thana minimum daily wage in Bangladeshi Taka (log) [1]	Log of minimum daily wage in thana	7.3	3.9	-2.3	8.0
Total active months[1]	No. of months parents actively employed	11.0	2.0	1.0	12.0
Employed in agriculture[1]	1=employed in agriculture sector	0.5	0.6	0.0	1.0

Table 3.1 Descriptive summary statistics (n=12,237) (continued)

Variable name	*Description*	*Mean*	*SD*	*Min*	*Max*
Housing characteristics					
Drinking water supplied (binary) [1]	1=drinking water supplied	0.1	0.3	0.0	1.0
Electricity (binary) [1]	1=household has electricity	0.6	0.5	0.0	1.0
Urban (binary)[1]	1=household in a major urban area	0.2	0.41	0.0	1.0
Spatial variables					
Prone to severe flooding (binary)[3]	1=prone to deep floods (>360cm)	0.03	0.04	0.0	1.0
Prone to severe drought (binary)[4]	1=prone to severe drought events	0.04	0.2	0.0	1.0
Horticulture district (binary) [2]	1=located in a horticultural district	0.5	0.5	0.0	1.0
School Feeding Program district (binary)[5]	1=household in district with SFP	0.4	0.5	0.0	1.0
District banking support aid (‘000 USD)[6]	Disbursements to district bank services	281.4	153.7	3.9	6,403

[1]HIES-2010 [2]http://daeext.info/officer_Horticulture_Centers.aspx [3]Bangladesh Country Almanac (BCA, 2006) [4]Centre for Geographic and Information Services (CEGIS, 2009) [5] https://www.wfp.org/content/wfp-bangladesh-annual-report-2010 [6]geo.aiddata.org

Table 3.2 A summary of the total number of observations used in analysis by sub-group

Group	**Number of observations**
Surveyed households	12,240
Number of household-level observations used	12,237
Surveyed individuals	60,903
Surveyed children	16,712
Number of child-level observations used	16,699
Boys	8,669
Girls	8,030
Age 5-9	6,810
Age 10-14	6,748
Age 15-17	3,141
Households that received microcredit income	4,822
Number of children in households that received microcredit income	9,162
Number of boys in households that received microcredit income	4,737
Number of girls in households that received microcredit income	4,425
Number of children aged 5-9 in households that received microcredit income	3,743
Number of children aged 10-14 in households that received microcredit income	3,708
Number of children aged 15-17in households that received microcredit income	1,711

3.3.3 *Regression methods*

Two separate regression models were specified to estimate the influence of microcredit participation on enrolment in the first regression model and the influence of microcredit income on enrolment in the second regression model. A dichotomous dummy variable was generated for each child aged 5-17 indicating whether or not they were enrolled in school based on the HIES survey. Microcredit participation, the extensive margin, was generated as a dichotomous dummy variable based on whether or not a household received loan income in 2010. Microcredit income, the intensive margin, was measured as the log of the amount of microcredit loan income received in 2010. Our income models were estimated for the sample of households with positive microcredit income.

In addition to estimating the effect of participation on the likelihood of enrolment, the objective of the intensive margin model was to investigate differences in enrolment rates between households that received relatively small amounts of microcredit income and households that received relatively large amounts of income.

The dependent variable - child enrolment in school (a dummy that equals one if a child was enrolled in school and zero otherwise) was expressed as a function of the independent variables - microcredit participation, the extensive margin, measured as a dummy variable, M_γ, that equals one if a household participates in microcredit and zero otherwise (in the first model), and other socioeconomic and geospatial variables, X:

$$y_i = f\left(C, \alpha M_\gamma, X\beta\right),$$

$$for\ \gamma = 1{:}\ microcredit\ participation, and\ 2{:}\ microcredit\ income \quad (2)$$

In the second model, microcredit income, the intensive margin, M_γ was measured as a continuous variable using the log of microcredit income received by a household. Further, we carried out separate regressions across three age groups (e.g. 5-9, 10-14, 15-17) to investigate if microcredit led to substitution across siblings.

C is a constant term, α is the coefficient for the effect of microcredit finance on child enrolment, and β is a vector of coefficients for each explanatory variable included in the vector X – a suite of socioeconomic and geographic variables that influence a household's education investment decision, adapted from a list of important determinants of household education investment enumerated from the literature review (Table B.1 in Appendix B). Specifically, variables were broadly categorised into: 1) child characteristics; 2) household income variables (e.g. income, wealth and expenditure); 3) employment characteristics (e.g. employed in agriculture and total number of months of active employment); 4) parent characteristics (e.g. parents' education and religion); 5) household structure (e.g. size, and female head of house); 6) housing characteristics (e.g. access to drinking water supply and electricity); 7) exposure to drought and flood; and 8) district and region characteristics (e.g. households located in high income horticultural districts, and in districts that participated in school feeding programs). Average marginal effects and standard errors were computed using the delta method (Oehlert, 1992).

3.3.4 ***Addressing model uncertainty***

Treatment of model uncertainty typically involves a series of ad hoc robustness testing exercises as a basis for including or dropping some controls from the baseline model. Use of a large set of covariates can introduce high likelihood of multicollinearity due to inclusion of highly correlated confounding covariates that may not necessarily improve the explanatory power of a regression model. We carried out multicollinearity checks by estimating variance inflation factors (VIF) from the microcredit participation model for all children with the full set of controls (Table B.15 in Appendix B). All covariates selected for inclusion in the model with the full set of controls had a VIF score of less than five with an average of 1.65, suggesting no serious multicollinearity.

We used a parsimonious regression model based on a systematic variable selection process using machine learning techniques (Table D.13 in Appendix B). Specifically, least absolute shrinkage and selection operator (LASSO) and Bayesian model averaging (BMA) were utilised to determine which control variables were important in the microcredit participation model for all children with the full set of controls (Table B.16 in Appendix B). LASSO is a comprehensive model selection method, which is useful when dealing with a large set of controls (Dyar et al., 2012) and BMA provides the posterior probability associated with each control, thereby helping to determine which control variables are important (De Luca and Magnus, 2011). In the initial step, the LASSO estimator was utilised to select a subset of controls from a large set of variables. Next, we used BMA to treat model uncertainty by estimating the model with all possible combinations of control variables selected, using LASSO and averaging over all the models using Bayesian model averaging and weighted-average least squares, to calculate the relative importance of each control variable. Our systematic approach to treatment of model uncertainty improves on commonly applied methods that typically involve an ad hoc series of robustness testing exercises as the basis for including or dropping control variables.

We ran multiple models with varying sets of covariates at various stages including: 1) models with the full set of controls with PSM (baseline models); 2) models that omitted spatial variables, but utilised PSM; 3) models with the full set of controls, but without PSM; 4) parsimonious models based on post LASSO and BMA variable selection with PSM; and 5) models that applied IHS transformations of income and expenditure covariates, instead to logarithm transformations, to test the sensitivity of estimates to the scale of transformation of zero-value observations. We also compared parsimonious models with and without specifying the survey design characteristics of the Bangladesh Household Income and Expenditure Survey, including sampling weights and the Primary Sampling Units (PSU), to test robustness of results to the level of clustering (Table 3.8). Regressions with specification of the survey design characteristics were also carried out to inform inferences about both the sample and the population (Gibson, 2019).

3.3.5 *Addressing endogeneity*

Estimating the causal influence of microcredit participation on enrolment is challenging due to non-random selection of households between treatment and control groups from observational data. For example, microcredit loans typically require that household enterprises be established because they provide less opportunity for loan misuse. Poor households that operate their own enterprises, but would otherwise not likely participate, would select themselves into such a microcredit program. Non-random selection of households (or *self-selection*) confounds the process of inferring the causal influence of microcredit participation on enrolments, which essentially requires random sampling of households into treatment, and control participant and non-participant groups, holding all other covariates equal (termed, *matching*). This challenge is technically referred to as ‘lack of common support’ or the ‘common support problem’ - whereby households that are unlikely to be in the treatment group, when estimated based on observed covariates (termed, *off support*), are included in the treatment group in the actual observations.

To correct for non-random selection and lack of common support, we used propensity score matching (PSM), a sample matching method that assigns households into treatment and control groups based on a predicted propensity score of likelihood to participate - which in turn is estimated in a first stage probit regression, based on a selection of observed covariates likely to influence participation status. PSM only utilises observations in the region of common support where we are able to obtain matched observations when comparing predicted and actual likelihood of participation. That is, unmatched observations are excluded from the analysis altogether, meaning we do not estimate potentially confounding treatment effects outside the region of common support. We compared results with and without PSM to estimate the effect of not addressing the self-selection problem adequately.

A key challenge in estimating the causal effect of increasing the amount of loan income received by households is that their qualification to borrow high incomes may reflect other unobserved characteristics that could also influence enrolment (Chakrabarty, 2015). This implies that the influence of microcredit on enrolment, estimated using the amount of loan incomes received, is potentially endogenous and biased because loan incomes received are not randomly assigned to households.

We addressed endogeneity by adopting a two-stage instrument variable (IV) probit regression method. We used two instrumental variables: 1) the interaction between a) household-level eligibility to participate in microcredit programs, a dummy variable, and b) microcredit facility availability in each village, a village-level dummy variable; and 2) the average village-level travel distance to microcredit facilities.

The rationale behind the first instrument is that availability of a microcredit facility in a village and a household's eligibility status are prerequisites for receipt of microcredit income. As such, the interaction between a household's eligibility status and an indicator for the presence of a microcredit facility in a given village can be considered as instruments for the actual receipt of microcredit income (Islam and Choe, 2010).

The intuition behind use of the average village-level travel distance to a microcredit facility was that we can assume that there is likely to be a strong correlation between the average travel distance to microcredit facilities in a village to the amount of microcredit income received by households. Thus the average travel distance to a microcredit facility can influence the likelihood of school enrolments through its influence on the amount of microcredit income received. The Pearson's correlation coefficient between the amount of microcredit income received and the average travel distance to a microcredit facility in a village was calculated as 0.67 whereas the correlation coefficient between the average village-level travel distance to a microcredit facility and the likelihood of school enrolments was calculated as 0.12.

Further, IV models were re-estimated using IHS transformations of all income and expenditure covariates, instead of logarithm transformations, to test the robustness of IV estimates to the scale of transformation of zero-value observations. Results of a two-stage endogenous treatment effect model and instrumental variable estimation for microcredit participation and income for all children show statistically significant *p*-values between treatment variables and the instrument in the first-stage reduced form models (Table 3.3 and Table 3.4). IV estimates were robust to use of either logarithm or IHS transformations of income and expenditure covariates (Table B.11 and Table B.12 in Appendix B).

Table 3.3 Results of a two-stage endogenous treatment effect model for microcredit participation

Variable	Coefficient^^	SE^^	t^^	P>t^^	P>t (adjusted for Type I Error) ^^
First-stage results: dep. variable is microcredit participation					
Interaction between household's eligibility status and the availability of a microcredit facility in a village	**3.65**	**0.32**	**11.35**	**0.00**	**0.00**
The average travel distance to microcredit facilities in a village	**0.03**	**0.01**	**2.73**	**0.01**	**0.01**
Intercept	-0.98	0.11	-8.76	0.00	0.00
Second-stage results: dep variable is likelihood of school enrolment					
Microcredit participation	***0.031***	***0.015***	***1.980***	***0.048***	***0.064***
Non-biological child	-0.11	0.02	-4.57	0.00	0.00
Mother's school years	0.01	0.00	3.24	0.00	0.00
Father's school years	0.01	0.00	5.86	0.00	0.00
Household size	0.00	0.00	1.03	0.30	0.40
Proportion of females	0.18	0.03	6.76	0.00	0.00
Proportion of people over 66	-0.31	0.04	-7.33	0.00	0.00
Number of non-biological children	0.02	0.01	1.85	0.07	0.09
Thana minimum daily wage	0.00	0.00	-7.04	0.00	0.00
Father's age	0.00	0.00	-0.93	0.35	0.47
Father ill this year	0.02	0.01	2.46	0.01	0.02
Prone to severe flooding	-0.39	0.14	-2.79	0.01	0.01
Intercept	0.60	0.03	23.34	0.00	0.00
Observations	16,699				
Number of clusters (degrees of freedom) (PSUs)	612				
F statistic	38.94				
Prob > *F*	0.00				

^^ With survey design specification

Table 3.4 Results of the instrumental variable estimation for microcredit income

Variable	Coefficient^^	SE^^	t^^	P>t^^	P>t (adjusted for Type I Error) ^^
First-stage results: dep. var is log of microcredit income					
Interaction between household's eligibility status and the availability of a microcredit facility in a village	**0.01**	**0.02**	**0.42**	**0.03**	**0.04**
The average travel distance to microcredit facilities in a village	**0.13**	**0.01**	**20.01**	**0.00**	**0.00**
Non-biological child	0.00	0.04	0.07	0.74	0.99
Mother's school years	0.00	0.01	-0.42	0.68	0.90
Father's school years	0.01	0.00	2.09	0.04	0.05
Household size	0.02	0.01	2.31	0.02	0.03
Proportion of females	0.09	0.09	1.09	0.28	0.37
Proportion of people over 66	-0.21	0.10	-2.03	0.04	0.06
Number of non-biological children	-0.03	0.03	-0.78	0.44	0.59
Thana minimum daily wage	-0.01	0.00	-5.72	0.00	0.00
Father's age	0.00	0.00	-1.05	0.29	0.39
Father ill this year	-0.01	0.02	-0.25	0.71	0.94
Prone to severe flooding	0.42	0.18	2.32	0.02	0.03
Intercept	7.86	0.09	88.68	0.00	0.00
Second-stage results: dep variable is likelihood of school enrolment					
Microcredit income received	***0.053***	***0.102***	***0.520***	***0.002***	***0.003***
Non-biological child	-0.43	0.11	-4.03	0.00	0.00
Mother's school years	0.03	0.01	1.85	0.06	0.09
Father's school years	0.03	0.01	2.73	0.01	0.01
Household size	0.00	0.02	-0.27	0.71	0.94
Proportion of females	0.88	0.13	6.63	0.00	0.00
Proportion of people over 66	-0.77	0.20	-3.90	0.00	0.00
Number of non-biological children	0.02	0.05	0.45	0.65	0.87
Thana minimum daily wage	-0.01	0.00	-3.22	0.00	0.00
Father's age	0.00	0.00	-1.09	0.28	0.37
Father ill this year	0.07	0.05	1.40	0.16	0.22
Prone to severe flooding	-1.00	0.57	-1.75	0.08	0.11
Intercept	-0.21	0.92	-0.23	0.62	0.83
Number of observations	9,162				
Number of clusters (PSUs)	612				
F statistic	15.20				
Prob > *F*	0.00				

^^ With survey design specification

Over-identification tests to test the exogeneity of the instruments suggested that we cannot reject the null hypothesis that the instruments are uncorrelated with the error term at $p<0.05$ with values estimated at 0.20 and 0.28 for microcredit participation and microcredit income models. The instruments are thus correctly excluded from the estimated equation. A rejection of null would cast doubt on the validity of the instruments (Table 3.5).

Table 3.5 Results of the instrumental variables tests, including test statistics, *p*-values and critical values for weak identification tests (in parentheses)

Variables	Microcredit participation	Log of microcredit income received
Regression results		
Regression method	OLS	OLS
Control variables	Yes	Yes
Number of observations	16,699	9,162
R-squared	0.050	0.047
Endogeneity and model test with IV		
Over-identification test (Hansen J statistic)[a]	1.674	1.170
	(0.196)	(0.280)
Weak identification test (K-P Wald F statistic)[b]	8479.35	49.41
	(26.87)	(29.18)
Endogeneity test (Chi-squared statistic)[c]	1.082	0.927
	(0.298)	(0.336)

[a] The joint null hypothesis is that the instruments are valid instruments, or uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.
[b] Weak identification refers to the excluded instruments being correlated with the endogenous regressors, but only weakly. If the test statistic exceeds the 10% critical value (e.g. 26.87 for the microcredit participation model), we can reject the null hypothesis that the instruments are weak.
[c] The null hypothesis is that the specified endogenous regressors can be treated as exogenous. Failing to reject the null hypothesis suggests that the specified endogenous regressors were exogenous to the dependent variables.

In addition, we can reject the null hypothesis that the instruments are weak because the minimum eigenvalue test statistic values, estimated at 8,479 and 49 for microcredit participation and microcredit income models exceed critical values (27 and 29). On the basis of this test, we do not have a weak-instrument problem.

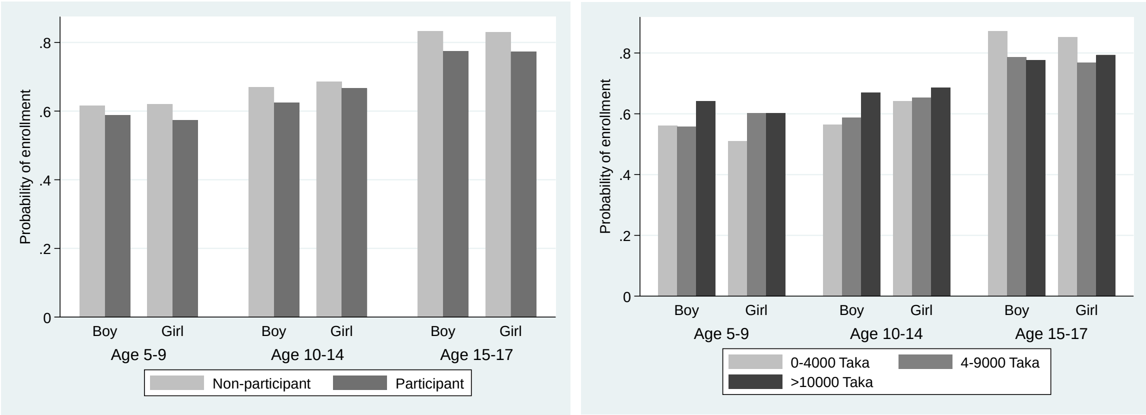
Overall, endogeneity test results show that we cannot reject the null hypothesis that our treatment variables are exogenous at p=0.05 with p-values at 0.30 and 0.34 for microcredit participation and microcredit income models, respectively, hence use of IVs is not necessary.

3.4 Results and discussion

3.4.1 *Influence of microcredit participation on school enrolments*

The objective of this study was to analyse the intensive and extensive marginal effects of microcredit, in particular microcredit participation and income, on children's school enrolment – controlling for a wide range of socioeconomic and geospatial variables. Figure 3.1 shows a plot of enrolment rates, distinguished by children's age and gender, along with microcredit participation status and the amount of microcredit income received based on Bangladesh's 2010 HIES survey data, which is comparable to reported statistics from Ahmad et al. (2005).

Figure 3.1 Rate of school enrolment by microcredit participation status (left) and by amount of microcredit income received by age and gender in Bangladesh



Source: Created from HIES 2010 survey data

Table 3.7 shows Beta coefficient values for the influence of microcredit participation on the probability of enrolment across 24 treatment effects regression models including: 1) models with the full set of controls with PSM (baseline models); 2) models that omitted spatial variables, but utilised PSM; 3) models with the full set of controls, but without PSM; and 4) parsimonious models based on post LASSO and BMA variable selection with PSM.

Table 3.6 provides a summary of sample sizes, including treated, untreated, the number of observations used for matching, the number of observations dropped, or unmatched in the PSM process for estimating the influence of microcredit participation on enrolments.

Table 3.6 Sample sizes, including treated, untreated, the number of observations used for matching and the number of observations dropped

	Off support			On support			
	Untreated	**Treated**	**N (not used)**	**Untreated**	**Treated**	**N (used)**	**N (total)**
Child	37	3	39	10,308	6,352	16,660	16,699
Boys	21	0	21	5,341	3,307	8,648	8,669
Girls	0	4	4	4,982	3,044	8,026	8,030
Age 5-9	17	2	19	4,110	2,682	6,791	6,810
Age 10-14	5	0	5	4,179	2,564	6,743	6,748
Age 15-17	24	0	24	2010	1107	3117	3,141

Table 3.7 Estimates of the average marginal effects (AME) of microcredit participation on school enrolment under different models

Model description	AME	SE	z	P>t	P>t (adjusted for Type I Error)	Total number of observations
1) Full controls, PSM (baseline)						
Child	**0.0162 ****	**0.008**	**2.02**	**0.044**	**0.044**	16,699
Boy	0.0016	0.011	0.14	0.886	0.87	8,669
Girl	**0.018***	**0.011**	**1.65**	**0.099**	**0.099**	8,030
Age 5-9	0.0119	0.020	0.60	0.552	0.552	6,810
Age 10-14	0.0003	0.016	0.02	0.984	0.984	6,748
Age 15-17	**0.054***	**0.030**	**1.78**	**0.075**	**0.075**	3,141
2) No spatial controls, PSM						
Child	0.008	0.006	1.29	0.198	0.241	16,699
Boy	0.011	0.008	1.40	0.161	0.196	8,669
Girl	**0.024***	**0.008**	**2.88**	**0.047**	**0.057**	8,030
Age 5-9	0.006	0.014	0.38	0.701	0.853	6,810
Age 10-14	-0.003	0.013	-0.25	0.805	0.980	6,748
Age 15-17	-0.012	0.023	-0.52	0.602	0.733	3,141
3) Full controls, No PSM						
Child	0.002	0.006	0.27	0.783	0.783	16,699
Boy	0.003	0.008	0.34	0.734	0.734	8,669
Girl	**0.005***	0.001	**1.56**	**0.061**	**0.061**	8,030
Age 5-9	**0.029***	**0.002**	**1.77**	**0.060**	**0.060**	6,810
Age 10-14	0.014	0.022	0.65	0.518	0.518	6,748
Age 15-17	0.017	0.021	0.8	0.426	0.426	3,141
4) Parsimonious model, PSM						
Child	0.003	0.004	0.71	0.476	0.635	16,699
Boy	0.003	0.006	0.45	0.654	0.872	8,669
Girl	**0.009***	**0.002**	**0.42**	**0.074**	**0.090**	8,030
Age 5-9	**0.019***	**0.001**	**1.73**	**0.056**	**0.075**	6,810
Age 10-14	**0.017***	**0.001**	**1.64**	**0.067**	**0.089**	6,748
Age 15-17	0.028	0.023	1.22	0.221	0.295	3,141

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

Whilst microcredit participation did not significantly influence the likelihood of school enrolment for boys; overall, girls from participating households were positively and significantly more likely to be enrolled in school than girls from nonparticipating households. Girls from participating households were between 0.5% and 2.4% more likely to be enrolled than girls from nonparticipating households. Our overall findings are different from the results by Stark et al. (2015) who found microcredit participation to be statistically insignificant at influencing children's school enrolment in Indonesia.

We further used Beta coefficient results for the girls' model, under the baseline model with the full set of controls (estimated at 1.8%) as a reference point for comparing across the parsimonious model with a selection of controls (estimated at 0.9%), as well as the model without spatial dummies (estimated at 2.4%), and a treatment effects model without PSM (estimated at 0.5%) (Table 3.7). When compared to the baseline model with the full set of controls: 1) the influence of microcredit participation on girls' enrolment was overestimated by 0.9% under the parsimonious model; 2) omitting spatial controls overstated the influence of microcredit participation on the likelihood of girls' enrolment by 0.6%; and 3) a treatment effects model that did not utilise PSM underestimated the influence of microcredit participation on girls' enrolment by 1.3%. Additionally, there is no consistent finding on the influence of microcredit participation on the likelihood of enrolment across different age groups. Table 3.8 shows marginal effects of microcredit participation on the probability of school enrolment with and without survey specification (from Table 3.7).

Table 3.8 Comparing average marginal effects (AME) of microcredit participation on the probability of school enrolment with and without specification of survey design characteristics

	AME ^	AME ^^	SE^^	t^^	P>t^^	P>t (adjusted for Type I Error) ^^	Number of observations^^	Number of PSUs^^
Child	0.003	0.011	0.010	1.04	0.30	0.40	16,999	609
Boys	0.003	-0.005	0.014	-0.39	0.70	0.93	8,669	608
Girls	**0.009***	**0.028*****	**0.013**	**2.14**	**0.03**	**0.04**	8,030	606
Age 5-9	**0.019***	**0.054*****	**0.017**	**3.17**	**0.00**	**0.00**	6,810	604
Age 10-14	**0.017***	0.007	0.013	0.50	0.62	0.82	6,748	606
Age 15-17	0.028	-0.0181	0.023	-0.78	0.44	0.58	3,141	576

^Without specification of survey design characteristics (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
^^With specification of survey design characteristics.

Overall, the results were robust to the level of clustering with the exception of a few cases. The average marginal effects of microcredit participation on school enrolment was statistically significant at p=0.1 for the models (Girls and Age 5-9) without survey design specification. The average marginal effect was statistically significant at p=0.05 and p=0.01, respectively for the Girls model and Age 5-9 model, with specification of survey design after correcting for Type I error (Table 3.8). However, the average marginal effect of microcredit participation on school enrolment was statistically significant for children aged 10-14 for the model without specification of survey design characteristics at p=0.10, whereas it was statistically insignificant for the model with specification of survey design characteristics.

Further, model estimates were robust to use of either logarithm or IHS transformations of income and expenditure covariates instead of logarithm transformations with the exception of the model for children aged 5-17 (Table B.13 in Appendix B). Specifically, the average marginal effect of microcredit participation on school enrolment was statistically insignificant for children aged 15-17 for the model with logarithm transformations, whereas it was statistically significant for the model with IHS transformations at p=0.05.

The overall significant finding that microcredit participation influenced girls' enrolments positively, but not boys', is relevant in the context of growing calls for policy intervention to address gender disparity in Bangladesh school enrolments in favour of girls - with a higher percentage of boys than girls employed in the informal labour market (UCW, 2011). Microcredit could have led to substitution across siblings in favour of girls at the household level of enrolment decision-making. Therefore, microcredit programs alone may not effectively address gender disparity in education and may need to be accompanied by tailored, more targeted incentive packages.

A limitation is that data for the gender of the recipient of the microcredit loan were not available thus were not to test if the influence of microcredit participation on enrolments between male- and female recipients were statistically significantly different. A number of studies have showed that financial empowerment of women through microcredit increases women's bargaining power in the household and enables mothers to make better family decisions regarding their children's welfare (Hill and King, 1995; Kaur and Lecit, 2012; Klasen, 2003; Matthews and Nee, 2000; Seguino, 2000). Specifically, women's financial empowerment can contribute to improvements in children's education (Allendorf, 2007; Duncanson et al., 2014; Gulland, 2014; Lokshin and Fong, 2006; Pandey and Lee, 2012; Parashar, 2005; Patel et al., 2015; Pikalkova, 2003; Sethuraman et al., 2006). This is a potential area for future research.

3.4.2 *Influence of microcredit income on school enrolments*

Table 3.9 provides shows coefficient values for the influence of microcredit income amounts received by a household on enrolment across 18 probit regression models including: 1) models with the full set of controls (baseline models); 2) models that omitted spatial variables; and 3) parsimonious models based on post LASSO and BMA variable selection.

Summary results of estimates of the average marginal effect of microcredit participation on enrolments are provided in Table 3.9, Table 3.10 and Table 3.11. Full regression results are provided in Table B.2, Table B.3, Table B.4, Table B.5, Table B.6, Table B.7, Table B.8, Table B.9 and Table B.10 in Appendix B, including standard errors, *t*-statistics and *p*-values.

Table 3.9 Comparing estimates of the average marginal effects of microcredit income on school enrolment under three different models

Model description	Child (n=9,162)	Boy (n=4,737)	Girl (n=4,425)	Age 5-9 (n=3,743)	Age 10-14 (n=3,708)	Age 15-17 (n=1,711)
Full controls (baseline)	***0.002******	***0.002*****	***0.003*****	***.0769******	*-0.0058*	*-0.0102*
No spatial controls	***0.022******	***0.017******	***0.026*****	***0.0755******	*0.0063*	*0.0144*
Parsimonious model	***0.026*****	***0.020****	***0.033****	***0.0850******	*-0.0398*	*-0.0578*

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

Whilst the influence of microcredit participation, the extensive margin, was positive and significant for girls, but not boys, the amount of microcredit income received, the intensive margin, influenced the likelihood of enrolment for both boys and girls positively, and significantly with a stronger influence on girls than boys

Overall, the baseline model for estimating the influence of increasing the amount of microcredit income received by a household on enrolment estimated that increasing microcredit loan income by 1% would be expected to increase the likelihood of enrolment by 0.2% for boys and 0.3% for girls (Table 3.9). Table 3.10 and Table 3.11 present full regression results including coefficients for all the other covariates for nine regression models, including with and without geospatial covariates and for the parsimonious models for all children, boys and girls.

Using the baseline model with the full set of controls, a 5% increase in microcredit loan incomes would be required to achieve a 1% increase in enrolments for boys; whereas a 3% increase in microcredit incomes would be needed to increase girl’s enrolments by the same amount. Significant chi-square values indicate that the influence of microcredit incomes is significantly larger on girls’ enrolments than boys’. For the model that used the full set of variables as in the baseline model, but omitted spatial variables, we estimated that increasing the amount of microcredit loan income by 1% would be expected to increase the likelihood of enrolment by 1.7% for boys and 2.6% for girls.

This is consistent with results from other studies, which found the increasing amount of microcredit income could encourage households to relieve children from income generating activities to enrol them in school (Putnick and Bornstein, 2015; Tansel, 2002; Tzannatos, 2003).

A comparison across the baseline models with full controls, the parsimonious models with a selection of controls, and models without spatial dummies showed that: 1) the influence of microcredit income on enrolment was stronger by between 1.8-3.0% under parsimonious models than under baseline models; and 2) omitting spatial controls can overstate the influence of the amount of microcredit income on enrolment by up to 2.3%. Implementation of policies that focus solely on increasing microcredit participation rates, without increasing the amount of microcredit incomes accessed by households, may thus be ineffective at increasing enrolment rates.

Table 3.12 shows marginal effects of microcredit income on the probability of school enrolment with and without survey specification.

Overall, the results on the average marginal effect of microcredit income on school enrolments were robust to the level of clustering with the exception of a few cases. The AME for the Child model was statistically significant at p=0.05 and p=0.01, respectively before and after survey design specifications and Type I error correction. The AME for the Boys model was statistically significant at p=0.10 and p=0.01, respectively before and after survey design specifications and Type I error correction. The AME for the Girls model was statistically significant at p=0.10 and insignificant, respectively before and after survey design specifications and Type I error correction. In addition, the AME for the Age 5-9 model was statistically significant at p=0.01 and p=0.10, respectively before and after survey design specifications and Type I error correction. (Table 3.12).

Further, AME estimates of microcredit income on school enrolments were robust to use of either logarithm or IHS transformations of income and expenditure covariates with the exception of the model for children aged 5-9 (Table B.14 in Appendix B). Specifically, the AME of microcredit income on school enrolment was statistically significant for children aged 5-9 for the model with logarithm transformations at p=0.01, whereas it was statistically significant for the model with IHS transformations of income and expenditure covariates at p=0.10.

The influence of microcredit income on enrolment was positive and statistically significant for children aged 5-9 and statistically insignificant for children aged 10-17. Microcredit can thus lead to substitution across siblings in favour of younger siblings, as evidenced in studies of conditional cash transfers (CCT) (Bauchet et al., 2018; Ferreira et al., 2009; Filmer and Schady, 2011). Microcredit would likely not influence all age groups to the same extent and may need to be accompanied by additional CCT policies targeting incentivising enrolment of older siblings. In all models, the percentage of cases for which the dependent variables were correctly predicted was greater than 80% and *p*-values for the null hypothesis tests that all of the regression coefficients are simultaneously equal to zero were rejected with $Prob > chi^2$ values found to be less than 0.01 (Table 3.10).

Table 3.10 Estimates of the influence of microcredit income on enrolment (with and without geospatial variables)

Variable	Child (baseline model)	Boy (baseline model)	Girl (baseline model)	Equal coefficient Chi^2 test	Child (no spatial variables)	Boy (no spatial variables)	Girl (no spatial variables)
Age	-0.08***	-0.07***	-0.08***	47.87***	-0.08***	-0.06***	-0.07***
Girl	0.03*				0.03*		
Non-biological child	0.9***	1.1***	0.8***	11.52***	0.93***	0.87***	0.83***
Microcredit income received	***0.002****	***0.002***	***0.003***	***0.06****	***0.022****	***0.017****	***0.026***
Remittances income	0.001	0.003*	-0.0003	1.83	0.001	0.003*	-0.0007
Wage and salary income	-0.01***	-0.01***	-0.007***	1.76	-0.001***	-0.07	-0.003+
Revenues from own enterprises	-0.005***	-0.008***	-0.002	13.22***	-0.003***	-0.007***	-0.001
Mother attended private school	-0.08+	-0.01	-0.1+	0.78	-0.16	-0.01	-0.1
Mother's school years	0.02***	0.03***	0.006	7.03***	0.02***	0.03***	0.006
Father attended private school	0.1***	0.1**	0.1***	0.14	0.16***	0.1*	0.1**
Father's school years	0.02***	0.02***	0.02***	0.22	0.02***	0.02***	0.02***
Mother's age[1]	0.0004	-0.0008	0.002	1.08	0.0004	-0.0006	0.002
Mother ill this year	0.03	0.09**	-0.05	5.75**	0.03	0.09*	-0.05
Father's age	-0.001+	-0.001	-0.002	0.06	-0.001	-0.001	-0.002
Father ill this year	0.05*	0.03	0.07**	0.87	0.05*	0.03	0.07*
Islam	0.04**	0.05+	0.04+	0.05	0.04*	0.03	0.04
Household size	0.06***	0.06***	0.07***	0.66	0.06***	0.06***	0.07***
Proportion of females	0.2***	-0.4***	0.8***	121.24***	0.2***	-0.4***	0.8***
Female head	-0.1***	-0.1*	-0.2**	0.21	-0.1***	-0.1*	-0.2**
Children under 5	-0.02+	-0.002	-0.05*	1.71	-0.02+	-0.002	-0.06
Proportion of people over 66	-4.8***	-4.6***	-4.9***	1.86	-4.8***	-4.6***	-4.8***
Number of non-biological children	-0.3***	-0.3***	-0.3***	0	-0.3***	-0.3***	-0.3***
Thana minimum daily wage	-0.02***	-0.02***	-0.01***	25.23***	-0.02***	-0.02***	-0.01*
Total active months	-0.006+	-0.005	-0.006	0.03	-0.006+	-0.004	-0.006
Employed in agriculture	-0.04***	-0.05***	-0.02	0.9	-0.04***	-0.05*	-0.02
Drinking water supplied	-0.03	-0.02	-0.05	0.12	-0.01	-0.03	-0.08
Electricity	0.05***	0.06**	0.03+	0.61	0.05**	0.06*	0.04
Urban	0.0009	-0.03	0.03	2.43*	0.001	-0.03	0.07
Prone to severe flooding	-0.7***	-0.6**	-0.8***	0.33			
Prone to severe drought	0.08**	0.03	0.1**	1.72			

Table 3.10 Estimates of the influence of microcredit income on enrolment (with and without geospatial variables) (continued)

Variable	Child (baseline model)	Boy (baseline model)	Girl (baseline model)	Equal coefficient Chi^2 test	Child (no spatial variables)	Boy (no spatial variables)	Girl (no spatial variables)
Horticulture district	-0.02^{+}	-0.02	-0.02	0.04			
School Feeding Program district	0.02	0.02	0.02	0.03			
Constant	0.7^{***}	0.8^{***}	0.5^{***}				
N	*9,162*	*4,737*	*4,425*		*9,162*	*4,737*	*4,425*
% correctly classified	*81.78*	*81.79*	*82.21*		*90.70*	*84.09*	*89.33*
Pseudo R^2	*0.32*	*0.42*	*0.37*		*0.43*	*0.33*	*0.31*
Wald chi^2 (p-value)	*0.25*	*0.99*	*0.12*		*0.37*	*0.77*	*0.73*

$^{+}$ $p < 0.2$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Under the parsimonious model, it was estimated that increasing the amount of microcredit loan income by 1% would be expected to increase the likelihood of enrolment by 2.0% for boys and 3.3% for girls (Table 3.11).

Table 3.11 Estimates of the influence of microcredit income on enrolment (with parsimonious model covariates)

	Child	Boy	Girl
Microcredit income received	***0.0262****	***0.0204***	***0.0331***
Non-biological child	0.925^{***}	1.094^{***}	0.762^{***}
Age	-0.0788^{***}	-0.0726^{***}	-0.0812^{***}
Mother's school years	0.0108^{*}	0.0240^{***}	-0.00357
Father's school years	0.0230^{***}	0.0229^{***}	0.0242^{***}
Household size	0.0406^{***}	0.0443^{***}	0.0469^{***}
Proportion of females	0.410^{***}	-0.337^{***}	0.992^{***}
Proportion of people over 66	-4.733^{***}	-4.409^{***}	-5.022^{***}
Number of non-biological children	-0.276^{***}	-0.277^{***}	-0.269^{***}
Log of district minimum daily wage	-0.0149^{***}	-0.0178^{***}	-0.0112^{***}
Father's age	-0.000254	-0.00125	0.000678
Father ill this year	0.0205	0.0445	0.000248
Prone to severe floods	0.0942^{*}	0.0841^{*}	0.133^{**}
Constant	0.802^{***}	0.917^{***}	0.566^{***}
N	9,162	4,737	4,425

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

Table 3.12 Estimates of the average marginal effects (AME) of microcredit income on the probability of school enrolment (with specification of survey design characteristics)

	AME^	AME^^	SE^^	t^^	P>t^^	P>t (adjusted for Type I Error) ^^	Number of observations^^	Number of PSUs ^^
Child	**0.026****	**0.003*****	**0.001**	**3.92**	**0.00**	**0.00**	9,162	557
Boys	**0.020***	**0.003*****	**0.001**	**2.98**	**0.00**	**0.00**	4,737	524
Girls	**0.033***	0.002	0.001	1.72	0.09	0.11	4,425	528
Age 5-9	**0.085*****	**0.002*****	**0.001**	**1.96**	**0.05**	**0.07**	3,743	520
Age 10-14	0.040	0.007	0.015	0.46	0.65	0.86	3,708	503
Age 15-17	0.058	0.000	0.028	0.00	0.75	1.00	1,711	392

^Without survey design specification (*p < 0.10, ** p < 0.05, *** p < 0.01).
^^ With survey design specification.

Geospatial variables were found to be important, in particular exposure to severe flooding significantly and negatively influenced enrolment. Further, as noted above, omitting geospatial variables (drought and flood exposure, horticultural districts, and districts that participated in school feeding programs) led to an overestimation of the impacts of microcredit participation and income on enrolment.

Overall, household income variables, in particular wage and salary incomes, along with revenues from household operated enterprises, had a statistically significant negative influence on enrolments, consistent with other study findings (Ahiakpor and Swaray, 2015; Hu, 2012).

Parent characteristics influenced child enrolment statistically significantly and positively, with no difference found across genders. One exception was a mother's school years, which had a statistically significant positive influence on boys' enrolment, but a statistically insignificant influence on girls' enrolment. Mother's education is typically strongly linked with mothers' financial empowerment and bargaining power in the household (Duncanson et al., 2014; Gulland, 2014). The positive statistically significant influence of mothers' education on boys' enrolments could reflect historical gender disparity in education favouring boys, prior to recent subsidy programs (Ahmad et al., 2005).

The likelihood of child enrolment was statistically significantly less among female-headed households, households with a high proportion of dependents, and households with a high number of non-biological children. This could reflect the high opportunity cost of enrolling children in school in households with high labour demand for looking after dependent members of the family (Chakrabarty, 2015; Liu, 2008). Similarly, households with no access to electricity had a lower likelihood of enrolling children in school, reflecting higher labour demand for carrying out time-intensive household chores, such as preparing meals.

Agricultural households with high family farm-labour demand; thanas with high minimum daily wages; and households with a high proportion of girls - were less likely to enrol boys than girls. Heavily incentivising girls' education may have resulted in households preferring to employ boys in the informal labour sector and to carry-out farm activities and household chores (UCW, 2011).

3.5 Conclusion

This study assessed the intensive and extensive marginal effects of microcredit on boys' and girls' enrolments in Bangladesh, whilst controlling for a wide range of socioeconomic and geospatial variables. Whilst microcredit participation, the extensive margin, did not influence boys' enrolments significantly, girls from households that participated in microcredit were positively and significantly more likely to be enrolled in school than girls from nonparticipating households. In addition, the amount of microcredit income received, the intensive margin, influenced the likelihood of enrolment for both boys and girls positively and significantly, with a stronger influence on girls than boys. Policies that focus solely on increasing microcredit participation rates, without increasing the amount of microcredit incomes accessed by households, may be ineffective at improving children's education outcomes. Further, microcredit incomes did not influence enrolments to the same extent across different age groups and may lead to substitution across siblings in favour of younger siblings. Conditional cash transfer programs may be a more effective alternative integrated strategy for increasing enrolments across different ages, because they can be tailored in favour of older siblings whose enrolment is not strongly influenced by microcredit incomes. Further, Conditional cash transfer programs may also be targeted at households with girls as girls from households that participated in microcredit were positively and statistically significantly more likely to be enrolled in school than girls from nonparticipating households. Omission of geospatial variables in evaluating microcredit influences on enrolments can overstate the influence of microcredit on enrolment. Additionally, inadequate treatment of the self-selection challenge in evaluating microcredit participation influences, the extensive margin, on the probability of enrolment can underestimate the influence of microcredit participation enrolment.

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Chapter 4 Improving the effectiveness of livestock donation programs by incorporating climate-smart technologies

This chapter presents an unpublished manuscript that has been prepared for submission to a journal for publication. Accordingly, the formatting follows the standard journal article format. As such, there is some repetition with other chapters in this thesis, in particular the background and conclusion sections.

Abstract

Frequent droughts induced by climate change threaten food security and pose a risk to the viability of smallholder crop and livestock production systems, which play a vital role in sustaining livelihoods of rural communities in Africa (SSA). There is thus an urgent requirement to prioritise effective adaptation and mitigation efforts of rural poverty reduction programs in smallholder SSA's agricultural production systems to moderate climate change impacts. This study applies a survey-informed stochastic benefit-cost analysis to estimate the net benefit of incorporating climate-smart technological innovations to existing livestock donation programs from the beneficiary households' perspective. In particular, we estimated the net benefit of incorporating climate-smart cowsheds and biogas production plants to livestock donation programs in Rwanda's East and West provinces. Our findings show that incorporating a complementary package that includes climate-smart cowsheds and biogas production plants can achieve a higher benefit-cost ratio of five to one. In addition, use of biogas in rural households, a cleaner source of energy than traditional fuelwood, can reduce deforestation, GHG emissions and the risk of respiratory infections. Harnessing broader economic, environmental, social and health benefits from livestock donation programs through installation of climate-smart technologies can thus generate positive economic, environmental and health benefits, thereby enhancing long-term economic viability of smallholder production systems and the overall welfare of poor rural communities.

Keywords: biodigester; aid effectiveness; sustainable economic development; Africa; poverty reduction; stochastic benefit-cost analysis; Girinka

Statement of Authorship

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Name of Principal Author (Candidate)	John Kandulu		
Contribution to the Paper	Undertook the literature review. Collected some of the data. Prepared data for analysis and carried out benefit-cost analysis in @Risk. Interpreted data and wrote the manuscript. Acted as the corresponding author.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	12/07/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Sarah Ann Wheeler		
Contribution to the Paper	Supervised the benefit-cost analysis, edited and wrote parts of the manuscript.		
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Contribution to the Paper	Supervised the benefit-cost analysis and wrote parts of the manuscript.		
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Contribution to the Paper	Collected some of the data, contextualised results and wrote parts of the manuscript.		
Signature		Date	12/02/2020

4.1 Introduction

Sustainable development goals (UN General Assembly, 2015) recognise agricultural development as critical for reducing poverty and improving food security because most of the world's poorest and marginalised people, largely concentrated in rural areas of South Asia and Africa (SSA), depend directly or indirectly on agriculture (Christiaensen et al., 2011; FAO, 2018a; WB, 2016, 2018). Agriculture drives most rural economies thus agricultural development is an inclusive and pro-poor poverty reduction strategy because it allows for greater involvement of poor and marginalised subpopulations in economic growth processes than less targeted development strategies (Corral et al., 2017; DFID, 2005; Ellis and Freeman, 2004).

Frequent droughts induced by climate change threaten food security and pose a risk to the viability of smallholder crop and livestock production systems which play a vital role in sustaining livelihoods of rural communities in SSA (Battisti and Naylor, 2009; Thornton et al., 2009; Tubiello et al., 2007; UNDP, 2010). Increasing rates of greenhouse gas (GHG) emissions from agricultural production are projected to further exacerbate the frequency and severity of extreme drought events (IPCC, 2007). There is thus an urgent requirement to prioritise adoption of effective adaptation and mitigation efforts in smallholder SSA's agricultural production systems to moderate impacts of climate change in rural poverty reduction efforts (Hansen et al., 2019; Shikuku et al., 2017; UNDP, 2010; Vermeulen et al., 2013).

Livestock production is increasingly being recognised as an effective climate adaptation option for sustaining SSA's smallholder agricultural systems and rural livelihoods, and livestock donation programs have been credited for improving incomes, nutrition and food security thus reducing poverty across SSA (Argent et al., 2014; Baidoo et al., 2016; Inoni, 2010; Kafle, 2014; Ntanyoma, 2010). Livestock contributes to increased incomes directly through milk and meat sales and indirectly by enabling purchase of inorganic fertilisers and providing organic fertiliser thus improving soil fertility, increasing crop productivity and farm size in SSA's mixed smallholder farming systems (Ndambi and Hemme, 2008; Powell et al., 2004; Thornton and Herrero, 2001). Livestock donation programs thus complement cropping systems and provide diversified sources of food and income thereby mitigating the magnitude of seasonal variation in food availability (IFAD, 2016; Randolph et al., 2007; Salazar et al., 2018).

The rapid and steady increase in the number of livestock donation programs being trialled globally, as a poverty reduction strategy targeting smallholder farmers, can be harnessed as an opportunity to mitigate climate change effects through installation of biogas plants that utilise livestock waste to generate clean energy for domestic use (Bedi et al., 2013; Ezeanya and Kennedy, 2016). Most poor households in rural SSA rely on fuelwood as the primary source of energy, but sustained growth in population and increasing rates of deforestation continue to place enormous pressure on fuelwood as a reliable and inexpensive source of energy (FAO, 2011; GTZ, 2009; WB, 2012). Supporting beneficiaries of livestock donation programs to produce biogas as a cleaner and cheaper alternative energy source for domestic use yields not only economic, health and environmental benefits, but also social benefits because women and children are traditionally responsible for fetching firewood and cooking in most of rural SSA (Calvin and Venkataramanan, 2015; FAO, 2018a). Additionally, increased adoption of biogas production as a key component of livestock donation programs can offset GHG emissions from livestock production, thereby reducing the overall environmental footprint of livestock donation programs (SDSN, 2013).

Numerous empirical assessments of economic and social impacts of livestock donation programs have been carried out in SSA and elsewhere across the world (Argent et al., 2014; Baidoo et al., 2016; Hansen et al., 2019; Inoni, 2010; Kafle, 2014; Ntanyoma, 2010; Rawlins et al., 2014; Salazar et al., 2018; Shikuku et al., 2017). Most evaluations have focused primarily on specific outcomes of interest, for example, changes in income and nutrition (Kafle, 2014; Kayigema, 2013; Rawlins et al., 2014) and enhanced crop productivity (Christian, 2014; Kayigema, 2013; Kim et al., 2013). Whilst economic benefits of integrating climate change adaptation and mitigation technologies in poverty reduction strategies, including livestock donation programs, are widely discussed (Bucagu et al., 2014; Ezeanya and Kennedy, 2016; Kayigema, 2013; Kayigema and Rugege, 2014; Klapwijk et al., 2014), quantitative evaluations of benefits of adopting climate-smart technologies into poverty reduction programs are sparse (Hansen et al., 2019; Shikuku et al., 2017). Shikuku et al. (2017) carried out an ex-post evaluation of impacts of climate-smart livestock technologies using regression analysis, and Hansen et al. (2019) assessed the impact of climate-smart technologies on agricultural production and income using evidence from ex-post econometric studies.

This study contributes to the fledging literature on quantitative assessment of the benefit of climate-smart technological innovations by carrying out an ex-ante evaluation of the net benefit of distributing biogas production plants and heifers to rural households using a case study of the *One Cow per Poor Family Program* in Rwanda's East and West provinces. A unique feature of this study is that it considers a broad range of fixed capital and variable costs and benefits from the perspective of beneficiary households and adequately addressed variability due to heterogeneity across beneficiary households. Specifically, our evaluation framework consisted of a stochastic household benefit-cost analysis (BCA) that explicitly quantified inherent variability in parameter values that influence costs and benefits at the household level. Comprehensive quantification of variable household costs and benefits thus took into account heterogeneity across households, in particular, with regard to the cost of animal feed, water, and access to artificial insemination (AI) and veterinary services (Bebe et al., 2002; Kayigema and Rugege, 2014; Mutimura and Everson, 2011) and enabled adequate testing of robustness of net benefit estimates.

Omitting assessment of the potential benefits from implementing alternative program designs that incorporate donation of livestock with distribution of biogas plants to harness use of livestock waste for biogas production presents a lost opportunity to influence more efficient allocation of development aid resources. The advent of new, affordable small-scale biogas production technologies and their reported success in Latin America (Garfi et al., 2016) presents a great opportunity to consider distribution of biogas plants as a component of the Girinka program and other livestock donation programs in SSA (Mwirigi et al., 2014).

4.2 Contextual background

4.2.1 Case study area context description

Our case study area is Rwanda's Eastern and Western provinces in SSA, considered among the world's most food insecure regions (FAO, 2018a) (Figure 4.1).

Figure 4.1 Map of Rwanda showing the Eastern and Western provinces (shaded)

Source: Locator map adapted from eMapsWorld

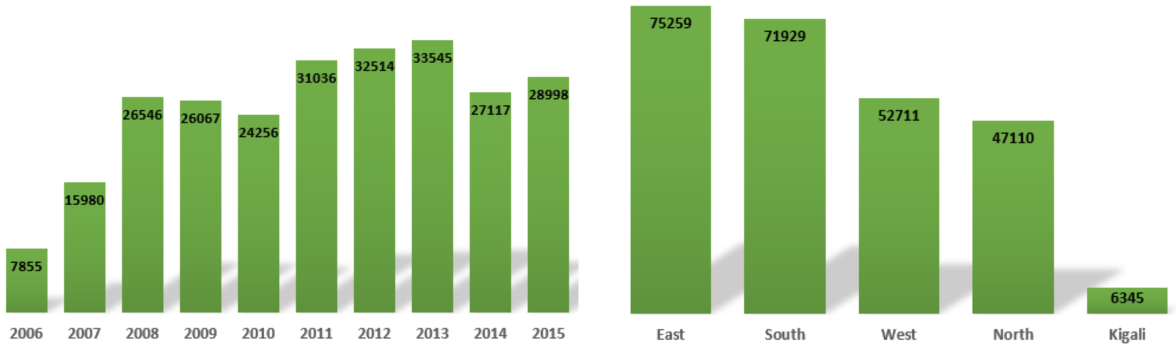
Located between east and central Africa, Rwanda is the most densely populated country in SSA with a population of 11.6 million and a total area of 26,338km2, 33% of which is arable land (Ezeanya and Kennedy, 2016; IFAD, 2016). Agriculture drives Rwanda's rural economy contributing substantially to food production, rural employment and incomes. In 2015, 81% of Rwanda's population lived in rural areas, with 68% of the rural population living below the poverty line (WB, 2018). With 67% of Rwanda's poor people located in rural areas and depending on agriculture, sustained growth in productivity in the agricultural sector is considered as key to attaining food security and poverty reduction (19% of households are food insecure and 38% of children under the age of five suffer from stunted growth induced by chronic undernutrition (WB, 2018). Land use typically involves mixed crops (main crops include beans, cassava, wheat, maize and rice) and livestock smallholder farming systems covering land areas between 0.2 and 1 hectare (ha) per farm, with an average land holding of 0.76 ha for the majority of farmers (MINAGRI, 2006). Livestock farming plays an important role in agricultural production, and is integral to the economic and cultural life of Rwanda's rural areas as a source of nutrition, income and employment, with over 70% of agricultural households involved in livestock husbandry (UNUWIDER, 2016). The average household in Rwanda has seven to eight members (Kamanzi and Mapiye, 2012) and one to three cows (Bishop and Pfeiffer, 2008).

Fuelwood consumption for household energy use has led to desertification with the average consumption of fuelwood and charcoal in Rwanda estimated at two kilograms per person per day, placing enormous pressure on the 16% of Rwanda's rural land that is forested (GTZ, 2009; WB, 2012). Fuelwood is also becoming increasingly expensive, with rural households spending up to 15% of their monthly incomes on fuelwood for cooking and lighting (FAO, 2011). Further, exposure to indoor pollution from use of fuelwood stoves in SSA has been strongly linked to respiratory diseases, in particular among women and children who are traditionally charged with cooking duties (WHO, 2006). Introduction of alternative clean energy sources for rural household energy use is widely considered as the logical option, with an emphasis on biogas generated from cow dung due to steady increases in the availability of cow dung across rural areas of Rwanda.

The rise in cattle ownership in rural areas of Rwanda is a result of a government poverty reduction livestock donation program initiated in 2006 known as the '*One Cow Per Poor Family*' program (locally termed, *Girinka*). Under the Girinka program, crossbred heifers are distributed to economically vulnerable households who pass on the first female calf to a poor neighbour (MINAGRI, 2006). Beneficiary households are identified by the village community based on eligibility criteria including no prior cow ownership, ownership of land with an area between 0.25 and 0.75 hectares, prior construction of a traditional cowshed and regarded as 'poor'. The primary objectives of the program are to increase rural milk consumption so as to reduce malnutrition, increase household food security by increasing crop productivity through use of organic manure to improve soil fertility and generate alternative income through integrated crop farming and dairy cattle rearing. Smallholder dairy production thus provides a pathway out of poverty for most rural households (FAO, 2018b). Secondary objectives include introducing environmentally friendly agricultural production systems through emphasising zero-grazing and harnessing organic fertiliser and domestic energy from manure through generation of biogas as an alternative source of energy to fuelwood.

The Girinka program is funded by the Rwandan government in partnership with the private sector, civil society organisations, local non-government institutions and international organisations. Between 2006 and 2015, the Girinka program distributed 297,060 heifers to 297,060 rural households impacting over 1.2 million individuals representing around 16% of Rwanda's total rural population (RGB, 2018). Figure 4.2 shows how cows were distributed between 2006 and 2015 across Rwanda's five provinces under the Girinka program. The Rwandan government intends to reach more than 700,000 poor households by 2035 under the Girinka program. Challenges faced by the program include inadequate veterinary services and water supply which can impose high costs on beneficiary households and reduce the expected net benefit of the program for beneficiary households (Kayigema, 2013).

Figure 4.2 Distribution of cows between 2006 and 2015 (left) and across Rwanda's five provinces (right)



Source: Adapted from RGB, (2018, p. 13)

However, despite wide discussion of the opportunity presented by Girinka to benefit poor rural households through harnessing biogas production as a cheaper source of energy than fuelwood in addition to provision of other social and environmental benefits, adoption of biogas plants has been remarkably low, largely due to prohibitive capital set-up costs (Mwirigi et al., 2014; Roopnarain and Adeleke, 2017; Rupf et al., 2015). The Rwandan government put in place energy policies to prioritise biogas energy production and use in recognition of the opportunity presented by the Girinka program to reduce deforestation and GHG emissions (Ezeanya and Kennedy, 2016). A government subsidy program aimed at providing materials and technical support to rural households in Rwanda's Eastern Province to incentivise biogas generation at the household level has not yet proven to be effective (Roopnarain and Adeleke, 2017; UNUWIDER, 2016). Communal biogas plants provided by government to clusters of households (five households per biogas plant) at no cost to households in Southern and Northern provinces have caused social issues, with households in Eastern Provinces that paid for biogas plant installation expressing feelings of being marginalised (Mwirigi et al., 2014; UNUWIDER, 2016).

The potential for realising positive economic, health, social and environmental externalities from the Girinka program through adopting biogas production for domestic energy use to replace traditional fuelwood is widely discussed in the literature (Bucagu et al., 2014; Kayigema, 2013; Kayigema and Rugege, 2014; Klapwijk et al., 2014), but the net benefit at the household level is rarely quantified. This study estimates the net benefit to households under a program that involves joint distribution of biogas production plants and heifers to enable biogas generation by rural households.

4.2.2 Costs and benefits of livestock and biogas production to households

We carried out a literature review to highlight the various cost and benefit components and basic assumptions that are considered both qualitatively and quantitatively in studies that evaluate heifer husbandry and biogas production at the household level. A summary of key findings is outlined in Table 4.1.

Costs were broadly categorised into fixed capital set-up costs (*cowshed construction costs*), and variable operations and maintenance (O&M) costs (*feed, watering, AI, veterinary* *services and labour*). Benefits included direct benefits of owning a heifer (*manure, calves, milk and meat consumption and revenue*) and benefits of owning a biogas plant (*health benefits and GHG emission and reduced deforestation*). Health, social, cultural and environmental benefits are the most rarely quantified.

4.3 Methodology

The methodology for estimating households' net economic benefits of current and alternative Girinka program design scenarios involved three key steps. The first step involved providing a description of a 'without project scenario', or circumstances that would prevail absent the Girinka program. The 'without project scenario' serves as the baseline scenario - a reference point for enumerating and quantifying additional household costs and benefits that can be expected under the current program and three alternative counter-factual program designs (Zerbe and Farrow, 2013).

Next, a description of proposed program design adjustments under three alternative counterfactual scenarios will be outlined. This facilitated systematic assessment of marginal changes can be expected to occur under alternative program designs (Robinson and Hammitt, 2017). The second step involved development of a conceptual framework for enumerating and organising costs and benefits under the current program and under three alternative program design scenarios (Boardman et al., 2018). Specifically, this involved identifying relevant cost and benefit components and parameters required to: 1) calculate net benefits with versus without the Girinka program under the current program design; and 2) compare incremental costs with additional benefits of switching from the current program design to three alternative program design scenarios. The third step was to carry out a sensitivity analysis to test the robustness of household net benefit estimates in recognition of the fact that households are typically heterogeneous in particular with regard to reported sources and costs of labour, animal feed, water, artificial insemination (AI) and veterinary services (Bebe et al., 2002; Kayigema and Rugege, 2014; Mutimura et al., 2015). Specifically, we applied probabilistic treatment of specified value ranges for uncertain parameters used to calculate costs and benefits at the household level using Monte Carlo simulation. Further, we tested the robustness of net benefit estimates by varying key assumptions under the baseline scenario to assess the sensitivity of net benefit estimates to alternative baseline scenario descriptions (Boardman et al., 2018).

Cost and price values were converted to USD based on the prevailing exchange rate in the reporting year, adjusted for inflation using US government CPI data (http://www.usinflationcalculator.com/) and reported in 2020 USD equivalent values to standardise cost and benefits used in net benefit calculations. The net present value benefit to households was calculated over a period of 25 years between 2018 and 2043 to be consistent with infrastructure asset investments lifetimes (Boardman et al., 2018) and discount rates between four and seven percent were used (Garfi et al., 2016; IFAD, 2016; IFRC, 2016).

Table 4.1 Summary of benefits and costs of owning a heifer and a biogas production plant to households and basic assumptions based on a review of literature

Costs and benefits	Finding
Household costs	
Capital set-up costs	
Cowshed construction costs	Households spend between USD31 and USD62 per cow on cowshed installation per year depending on the quality of materials used (Kayigema, 2013). Top end climate-smart cattle shelter can cost up to USD165 per cow (Miklyaev et al., 2017). A climate-smart cowshed includes a rainwater harvesting system, good quality flooring and a waste management system for efficient removal and storage of dung and urine and improved feed and watering points (IFAD, 2016)
Operation and maintenance costs	
Feed	The cost of feeding a heifer varies significantly depending on the type of feed used and can range between USD119 and USD2,837 per cow (IFRC, 2016; Miklyaev et al., 2017)
Watering	Households spend between USD15 and USD730 per cow per year on watering (IFAD, 2016; Kayigema, 2013; Miklyaev et al., 2017)
Artificial insemination	The Rwandan government provides AI services at a heavily subsidised cost to smallholder dairy farmers (Lukuyu et al., 2009; MFEP, 2012). Use of AI services is low, with 58% of farmers having access AI services (USAID, 2015)
Veterinary services	Treating against risk of mastitis can incur a cost of up to USD26 per cow in veterinary services, and USD12 per cow for treatment (Mwabonimana et al., 2015). Annual veterinary costs can total between USD61 and USD70 per cow (Miklyaev et al., 2017)
Labour	The cost of labour to care for animals can range between USD47 and USD79 per cow per year depending on the quality of care provided (Miklyaev et al., 2017). Family labour is usually sufficient, with average household population of eight people per household (Christian, 2014)
Household benefits	
Benefits of owning a heifer	
Manure	Over 90% of Girinka beneficiaries use manure, and report increased yields and improved soil fertility due to manure use (Kim et al., 2013; Kim et al., 2011).
Calves	Girinka beneficiaries reported selling the second calf for up to USD329 per calf (IFRC, 2016). The average calving interval is typically between 15 and 18 months (Miklyaev et al., 2017)
Milk consumption and revenue	Provision of heifers with training increased milk production for household consumption and for sale (Argent et al., 2014). Girinka contributed 89% increase in milk production between 201and 2015 (RGB, 2018)
Meat consumption and revenue	Meat sales from post-lactation cows that have been culled can generate significant income for households (Salazar et al., 2018). Rawlins et al. (2014) found substantial impacts of cow transfers on household meat consumption and children’s nutrition outcomes. The average calving interval was assumed as ranging between 15 and 18 months and after four intervals, a heifer is culled and slaughtered to be consumed or sold for meat (Miklyaev et al., 2017).

Table 4.1 Summary of benefits and costs of owning a heifer and a biogas production plant to households and basic assumptions based on a review of literature (continued)

Costs and benefits	Finding
Benefits of owning a biogas plant	
Household energy cost savings	Biogas use for household energy needs can save households from incurring monthly energy expenditures of up to USD15 per household (Mwakaje, 2008; Surendra et al., 2014). Integrating biogas to Girinka program can yield significant energy cost savings for rural households (UNUWIDER, 2016)
Health benefit from reduced pollution	Fuelwood powered stoves used for cooking emits toxic gases linked with high prevalence of respiratory diseases (Smith et al., 2000; WHO, 2006)
Reducing GHG emissions and deforestation	Widespread adoption of biogascan reduce GHG emissions and deforestation (Garfí et al., 2012; Katuwal and Bohara, 2009; Paul et al., 2017)

4.3.1 Scenario description

Table 4.2 provides a summary description and assumptions considered under the baseline ‘without project’ scenario, the current program scenario and three alternative program design scenarios. In addition, program costs, household costs, household benefits, and basic assumptions are outlined under each scenario.

The baseline scenario is the ‘without project’ scenario describing what would occur in the absence of the Girinka program (Boardman et al., 2018). The baseline scenario is thus the reference scenario against which each of the four scenarios considered were evaluated, and served as our benchmark scenario for enumerating and quantifying additional household costs and benefits that can be expected under the current Girinka program and under three alternative counter-factual program designs (Zerbe and Farrow, 2013). Our baseline scenario is a counter-factual scenario characterised by very few households owning heifers and traditional cowsheds, and a negligible number of households owning climate-smart cowsheds and biogas production plants with most households practising subsistence rainfed cropping systems. Climate-smart cowsheds consist of effective rainwater harvesting, flooring and waste management systems to ensure efficient removal and storage of manure and disease management. Thus, climate-smart cowsheds experience less manure production loss and milk loss due to mastitis than traditional cowsheds made from locally found materials, with basic flooring and no storm and waste water management system (IFAD, 2016). Mastitis infections in dairy cows are largely caused by poor hygiene practices, including ineffective cowshed waste management, which can lead to udder infections and reduction in milk yield and quality (Iraguha et al., 2015). In additional sensitivity analyses, we quantified the net benefit value under various baseline scenarios to account for various initial adoptions of different plausible combinations of heifers, climate-smart cowsheds and biogas plants prior to program intervention to adequately account for heterogeneity in asset ownership across beneficiary households (Robinson and Hammitt, 2017).

Table 4.2 Description of benefits and costs considered and basic assumptions under each scenario

Scenario	Scenario description	Program costs	Household costs	Household benefits
Without project	A counterfactual scenario absent the Girinka program characterised by very few households that can afford to own a heifer with most households practicing subsistence rainfed cropping systems. Very low adoption rates for climate-smart cowsheds and biogas production plants would also be expected	No program costs incurred	Includes the cost of buying heifers, cowshed construction and maintenance, food, water AI and veterinary services and biogas plant construction and O&M costs	Revenues from milk, calves, post-lactation cow sales.
Current Girinka program	This scenario reflects the status quo where one lactating heifer is distributed to each eligible household with the minimum requirement that beneficiaries construct a traditional cowshed. Very few households with climate-smart cowsheds and biogas production plants	Includes the cost of buying and distributing heifers including transactions costs of identifying eligible beneficiary households	Construction and maintenance of a traditional low-cost cowshed, food, water and AI and veterinary services	Revenues from milk, calves, post-lactation cow sales and relatively small energy cost savings expected due to low biogas production
Girinka + climate-smart cowsheds	A counterfactual scenario that builds on the current Girinka program by providing beneficiary households with materials and labour to augment effective rainwater harvesting, flooring and waste management systems to traditional cowsheds thereby increasing manure production	Includes program costs under the current Girinka program plus additional costs of augmenting traditional cowsheds with effective rainwater harvesting, flooring and waste management systems	Construction and maintenance of a traditional cowshed, food, water and AI and veterinary services	Revenues from milk, calves, post-lactation cow sales
Girinka + biogas plants	A counterfactual scenario that builds on the current Girinka program by providing each beneficiary households with a biogas production plant in addition to lactating heifers under traditional cowshed systems	Includes program costs under the current Girinka program plus the additional costs of constructing biogas production plants for each beneficiary household	Construction and maintenance of a traditional cowshed, food, water and AI and veterinary services and biogas plant O&M costs	Revenues from milk, calves, post-lactation cow sales and energy cost savings
Girinka + climate-smart cowsheds + biogas	A counterfactual scenario that builds on the current Girinka program by providing each beneficiary households with a climate-smart cowshed and a biogas production plant	Includes program costs under the current Girinka program plus additional climate-smart cowshed augmentation costs and construction costs for biogas production plants	Construction and maintenance of a traditional cowshed, food, water and AI and veterinary services and biogas plant O&M costs	Revenues from milk, calves, post-lactation cow sales and energy cost savings

In the first analysis, the baseline scenario was used as a benchmark to estimate the net benefit to households under the current Girinka program design focused primarily on distributing one lactating heifer per poor rural household with the minimum requirement that beneficiaries construct a traditional cowshed. Secondly, the net benefit of switching from the baseline scenario to a scenario that involved incorporating distribution of climate-smart cowsheds to beneficiary households in addition to lactating heifers was calculated. Thirdly, the net benefit of distributing affordable biogas production plants (tubular polyethylene biodigesters) in addition to lactating heifers under traditional cowshed systems was calculated with reference to the baseline scenario. Energy costs savings from substituting fuelwood, the main source of energy for domestic uses were considered under this scenario. In the fourth analysis, the net benefit of the 'everything scenario' involving distribution of biogas production plants and climate-smart cowsheds in addition to lactating heifers to each beneficiary household relative to the 'without project scenario' was estimated. In further sensitivity analyses, we calculated net benefits under alternative baseline scenario descriptions to assess the sensitivity of net benefit estimates to changes in baseline scenario assumptions.

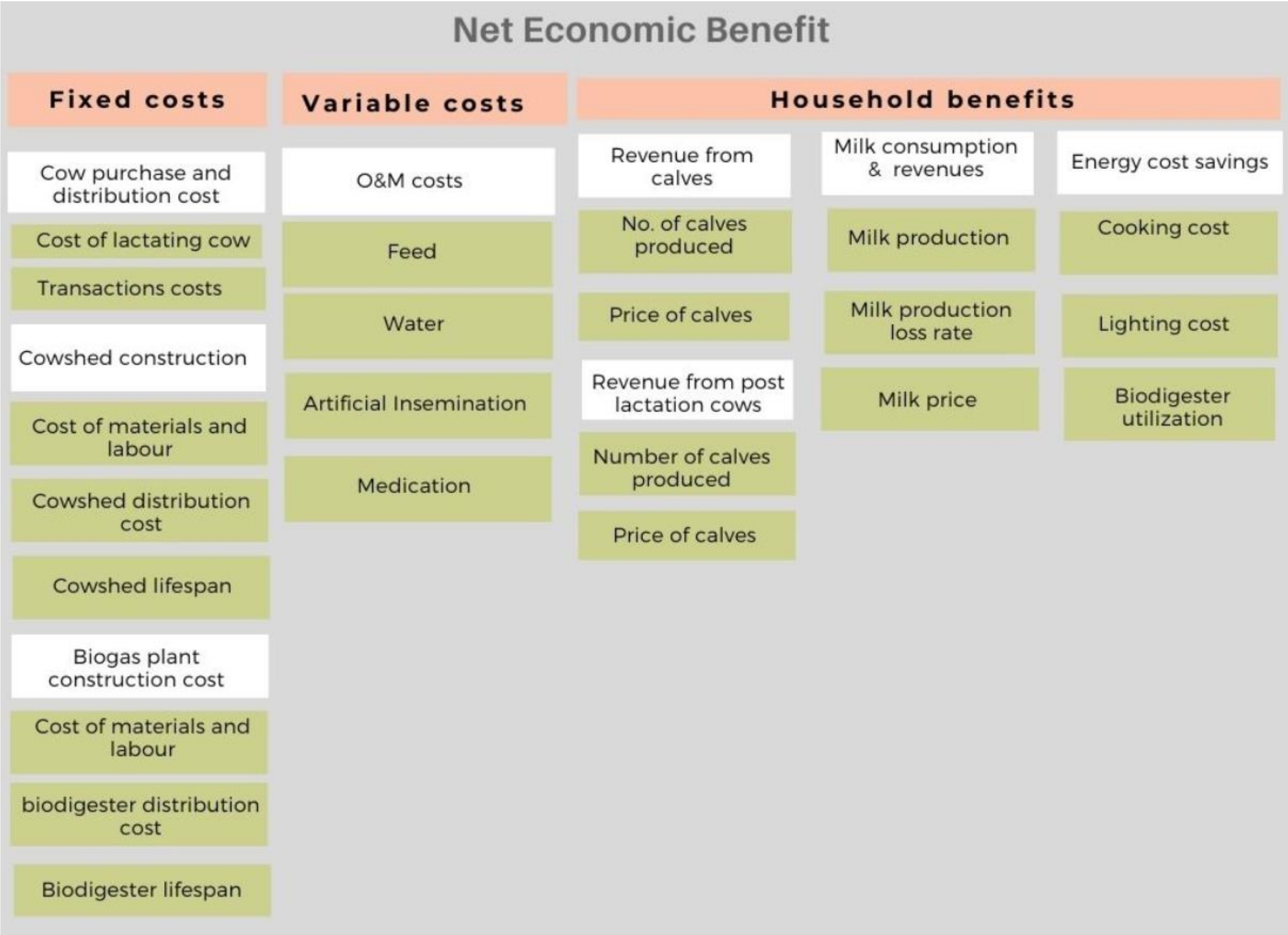
4.3.2 Conceptual BCA framework

We developed a conceptual BCA model framework for evaluating the average net economic benefit to a beneficiary household under the current program design and under three alternative program design scenarios.

Costs and benefits were enumerated following a review of the literature on livestock donation programs and biogas production for household energy use Table 4.1). The BCA framework consists of three main costs and benefits including: 1) fixed capital set-up costs; 2) variable costs; and 3) household benefits (Figure 4.3).

Fixed program costs included: 1) capital set-up costs of purchasing lactating heifers and overhead costs of distributing lactating heifers including transactions costs; 2) the additional cost of augmenting climate-smart features to traditional cowsheds including rainwater harvesting, flooring and waste management systems; and 3) the cost of installing biogas production plants. Fixed capital set-up costs for a household included the cost of installing a traditional cowshed with no storm and waste water management system, consistent with current Girinka program requirements.

Figure 4.3 Organisational structure used to estimate costs and benefits of current and alternative Girinka design programs



Source: Authors' design

Variable costs included various operations and maintenance (O&M) costs including feed, water and artificial insemination (AI) and veterinary services. Household benefits included consumption and revenues from sales of milk, calves and post lactation cows. Benefits from increased crop production, as a result of increased use of manure in subsistence crop production as a substitute for inorganic fertilisers (Kim et al., 2013; Kim et al., 2011), were not quantified. We assumed increases in crop yields from manure application would be offset by decreased yields due to reduction in the amount of labour employed in crop production to meet increased demand for labour for heifer husbandry.

4.3.3 Data

The main data asset used in this study was a 2018 cross-sectional survey of households conducted face-to-face by the University of Rwanda's College of Agriculture, Animal Sciences and Veterinary Medicine in a research project, commissioned by the Bill and Melinda Gates Foundation, to understand the impact of the Girinka program on household food and nutrition security. The survey questionnaire was primarily designed to collect data on economic costs and benefits of owning a heifer at the household level including incomes from milk sales, manure collection and use, crop production, primary sources of energy for domestic use, and cost of animal feed, water, veterinary and artificial insemination (AI) services. A total of 2,000 households were approached to participate in the survey from two of Rwanda's most populous provinces with the longest history with the Girinka program, with 1,577 households agreeing to be surveyed. Specifically, households from diverse demographic and socio-economic backgrounds were chosen from each district in Rwanda's Western and Eastern provinces with the total number surveyed per district reflecting the weighted average of population of smallholder dairy farmers in the district. A survey response rate of 77% was achieved in the Eastern Province and a 66% survey response rate was achieved in the Western Province.

A dataset was created based on observations from survey responses from 1,436 (of 1,577) households for which observational data were available, including milk production costs, milk revenues, primary source of energy and crop production for 1,415 households that received a heifer under the Girinka program and 21 households that did not receive a heifer. Of the surveyed households, 54% resided in Rwanda's Eastern Province and 46% resided in the Western Province. A summary of descriptive statistics from survey responses is provided in Table 4.3.

Of the survey respondents 80% relied on fuelwood as the main source of household energy for cooking and lighting. 2% used biogas, 1% used electricity, and 2% used charcoal and solar energy. In addition, secondary data was collated from peer-reviewed published studies from the case study region and consulting reports in Rwanda. Survey data were reviewed and confirmed by a local scientist with experience working as a field expert and practitioner from the Rwanda Agriculture Board (F. Shumbusho 2019, Personal Communication, 31 October 2019) - in consultation with Girinka program coordinators in the West and East provinces.

Table 4.3 Descriptive summary statistics of a survey of Girinka program participant households in Eastern and Western Rwandan provinces (N=1,436)

Variable name	Description	Mean	Median	SD	Min	Max
Grow crops	1 = household grew crops, 0 = otherwise	0.96	1	0.19	0	1
Crop area	Total crop land area operated by household (hectares/year)	3.00	3.0	1.05	0	1
Crop sale income	1 = household earns income from crop sales, 0 = otherwise	0.01	0.00	0.1	0	1
Livestock sale income	1 = household earns income from sale of livestock, 0 = otherwise	0.00	0.00	0.04	0	1
Cultivate maize	1 = household grows maize, 0 = otherwise	0.70	1	0.47	0	1
Cultivate beans	1 = household grows beans, 0 = otherwise	0.89	1	0.31	0	1
Cultivate sweet potatoes	1 = household grows beans, 0 = otherwise	0.75	1	0.43	0	1
Cultivate cassava	1 = household grows cassava, 0 = otherwise	0.29	0	0.45	0	1
Firewood	1 = household uses firewood as a source of energy, 0 = otherwise	0.80	1	0.23	0	1
Charcoal	1 = household uses charcoal as a source of energy, 0 = otherwise	0.02	0	0.15	0	1
Solar	1 = household uses solar as a source of energy, 0 = otherwise	0.02	0	0.14	0	1
Electricity	1 = household uses electricity as a source of energy, 0 = otherwise	0.01	0	0.1	0	1
Biogas	1 = household uses biogas as a source of energy, 0 = otherwise	0.02	0	0.03	0	1
Pay for AI services	1 = household pays for AI services, 0 = otherwise	0.19	0	0.39	0	1
Cost of AI services (USD/session)	Average cost of AI services per session	3.65	3.59	2.59	0.32	16
Cost of veterinary services (USD/visit)	Average cost of AI services per visit	0.97	1	3.15	0.00	30
Buy feed	1 = household pays for animal feed, 0 = otherwise	0.12	0	0.32	0	1
Cost of feed (USD/day)	Cost of animal feed per day	0.62	1	2.16	0.00	1.35
Cost of water (USD/day)	Cost of watering animals per day	0.1	0.00	.012	0.00	0.87
Milk production (L/day)	Average milk production per household per day	3.32	3.00	3.47	0	26
Milk production loss rate	Average milk production loss rate per household per day	0.15	0.14	0.07	0	0.23
Price of milk (USD/L)	Average price of milk sold by dairy households	0.04	0.03	0.08	0.00	0.32

A summary of parameter descriptions, notations, units, range of values and data sources is provided in Table 4.4. Values in Table 4.4 were converted to per year per household equivalents to enable calculation of present value household costs, benefits and net benefits.

The range of parameter values obtained from the survey (Table 4.3), in particular for input costs and milk production and price, were likely obtained from clustered samples from farmers in the same village, or from nearby villages, and may not be representative of the entire population of Rwanda's East and West provinces. To address this, survey data values presented in Table 4.4 for input costs and milk production and price were compared with average values estimated in peer-reviewed studies to come up with a more representative range of value estimates for each parameter. The range of parameter values used in net benefit calculations encompassed values from both survey responses and reviewed local studies.

Further, the final value ranges used in the benefit cost analysis were reviewed and confirmed by a local scientist with experience working as a field expert and practitioner from the Rwanda Agriculture Board (F. Shumbusho 2019, Personal Communication, 31 October 2019) - in consultation with Girinka program coordinators in the West and East provinces.

Specifically, we carried out an extensive review of several peer-reviewed studies on the Girinka case study including in Rwanda's West and East provinces to identify a 'reference class' of past evaluations of the Girinka program (please refer to Table 4.4 and the list of references below). Next, we established probability distributions for the selected reference class for parameters used in BCA based on ranges of probable parameter value estimates considering both survey data values and findings from the reviewed literature.

Thus, parameter values used in the benefit cost analysis were anchored in values from similar past reference class program evaluations. Survey data values used in the BCA, included input costs and milk production and price (please refer to Table 4.4 and the list of references below). For example, the range of values for the cost of animal feed, water and access to artificial insemination (AI) and veterinary services from survey data were compared with estimates from several other studies (Bebe et al., 2002, IFAD 2016, Mutimura and Everson, 2011, Kayigema and Rugege, 2014).

4.3.4 Calculating costs and benefits for each component

The process of calculating costs and benefits for each component used to estimate net benefits to the household (Figure 4.3) is described using mathematical equations in this section. Parameter descriptions, notations, units, value ranges, assumptions and sources used in the following mathematical equations are provided in Table 4.1 and Table 4.4

4.3.4.1 Fixed capital set-up costs

The cost of purchasing a lactating heifer would be incurred entirely by households under the 'without project' scenario. Under both the current Girinka program and three alternative program design scenarios, fixed costs incurred in the initial year of program implementation were calculated as the sum of the cost of procuring lactating heifers and transactions costs of distributing heifers to eligible households. Transactions costs encompassed delivery and institutional and administration overhead costs of disbursing heifers to beneficiary communities. Delivery costs encompassed maintenance of heifers in transit to destination communities, including hiring and operating facilities and staff to transport, feed, water and clean heifers, as well as removal and disposal of cow dung. Institutional and administrative overheads included hiring program leaders to carry out focus group workshops with local leaders, village administrative groups and community members to identify and validate eligible beneficiary households as well as provision of training on basic animal husbandry and support with cowshed construction (IFAD, 2016; IFRC, 2016).

The present value (PV) of fixed costs of constructing a traditional cowshed was calculated as the sum of the present value of construction costs incurred in the initial year of program implementation, t_0, and the present value of replacing the cowshed in each year that it reaches the end of its lifespan over the course of the 25-year period of analysis. The present value fixed cost of constructing a traditional cowshed was thus calculated as:

$$PV\ Cowshed\ cost_{T_{trad}} = \sum_{t_{trad}} \frac{Construction\ cost_{trad}}{(1 + Discount\ rate)^{t_{trad}}}$$

$$\text{for } t_{trad} = 0, 4, 8, 12, 16, 20$$

Where, t_{trad} is the year that a replacement traditional cowshed is constructed every five years after the initial year of program implementation, t_0 (i.e. t_{trad} = 0 inclusive) with the average lifespan of a traditional cowshed estimated at five years.

The present value of fixed capital costs of distributing and constructing climate-smart cowsheds with a longer lifespan than traditional cowsheds with the average lifespan estimated at 12 years were calculated as:

$$PV\ Cowshed\ cost_{T_{cs}} = \sum_{t_{cs}} \frac{Dist\ cost_{cs} + Construction\ cost_{cs}}{(1 + Discount\ rate)^{t_{cs}}}$$

$$\text{for } t_{cs} = 0, 11, 22$$

Where, t_{cs} is the year that a replacement climate-smart cowshed is constructed 11 years after the initial year of program implementation inclusive with the average lifespan of a climate-smart cowshed estimated at 11 years.

The present value cost of constructing a tubular polyethylene biodigester, the most economically viable biogas production plant (Garfi et al., 2016), was calculated as the sum of the present value of distribution and construction costs incurred in the initial year of program implementation and the present value cost of replacing the biodigester in each year that it reaches the end of its lifespan of five years, t_{biogas}, over the course of the 25-year period of analysis:

$$PV\ Biodigester\ cost_{T_{biogas}} = \sum_{t_{biogas}} \frac{Dist\ cost_{biogas} + Construction\ cost_{biogas}}{(1 + Discount\ rate)^{t_{biogas}}}$$

$$\text{for } t_{biogas} = 0, 4, 8, 12, 16, 20$$

Table 4.4 Parameter value ranges used to calculate program and household annual costs and benefits (unit costs and prices were converted to 2020 USD)*^

BCA Component	Parameter	Unit	Value	Source(s)
Fixed capital set-up costs				
Cost of lactating heifer	*Heifer cost*	USD/cow	583-1211	(IFAD, 2016; IFC, 2007; IFRC, 2016)
Transaction costs	*Transaction costs*	USD/cow	11-15	(IFRC, 2016)
Traditional cowshed	*Construction cost$_{trad}$*	USD/ cowshed	31-62	(Kayigema, 2013)
Lifespan (traditional cowsheds)	t_{trad}	Years	5	(Kayigema, 2013)
Climate-smart cowshed	*Construction cost$_{cs}$*	USD/ cowshed	230-282	(IFAD, 2016)
Distribution cost (climate smart cowsheds)	*Dist cost$_{cs}$*	USD/ cowshed	9-11	(IFAD, 2016)
Lifespan (climate smart cowsheds)	t_{cs}	Years	12	(IFAD, 2016)
Construction cost biogas plant	*Construction cost*	USD/plant	813-993	(Garfi et al., 2016; Kayigema and Rugege, 2014; Mwakaje, 2008)
Distribution cost (biogas plant)	*Dist cost$_{biogas}$*	USD/plant	33-37	(Garfi et al., 2016)
Lifespan of biogas plant	t_{biogas}	Years	5	(Garfi et al., 2016)
Variable costs				
Cost of feeding	*Feed*	USD/cow	119-287	Table 4.3 (IFRC 2016)
Cost of water	*Water*	USD/cow	11-33	Table 4.3 (Kayigema, 2013; IFAD, 2016)
Cost of AI**	*AI*	USD/cow	0-16	Table 4.3
Cost of veterinary services	*Veterinary*	USD/cow	0-85	Table 4.3 (Kayigema 2013; IFAD, 2016)
Household benefits				
Milk production	*Production$_m$*	Litres	680-1220	Table 4.3 (Kim et al., 2011; Klapwijk et al., 2014; Paul et al., 2017))
Milk production loss (traditional cowshed)	*Production loss$_{trad}$*	%	7-23	Table 4.3 (Juozaitienė et al., 2006)
Milk production loss (climate-smart cowshed)	*Production loss$_{cs}$*	%	3-12	Table 4.3 (Kayigema 2013; IFAD, 2016)
Price of milk	*Price$_m$*	USD/Litre	0.12-0.36	Table 4.3 (CIAT, 2016))
Price of one calf^	*Calf price*	USD/calf	112-329	(IFC 2007; IFRC 2016)
Price of post-lactation cow	*Cow price$_p$*	USD/cow	121-307	(IFC 2007; IFRC 2016)
Lifespan of cow^^	t_p	Years	9	(Miklyaev et al., 2017)
Energy cost savings	*Energy cost*	USD/ household	177-297	(Garfi et al., 2016; Mwakaje, 2008)
Utilisation (traditional)	*Utilization$_{trad}$*	%	75-85	(IFAD 2016)
Utilisation rate (climate-smart)	*Utilization$_{cs}$*	%	85-95	(IFAD 2016)

* Transaction costs of distribution were assumed at between 9 and 13% of cost of animal (IFRC, 2016)

** AI is not accepted and practiced by all Girinka beneficiaries with some preferring natural mating (Mwabonimana and Habimana, 2015)

^ We assumed a large range in calf price value because heifers typically cost more than bull calves

^^ Calving age estimated at 2 years, calving interval range (1.25-1.5 years) over a total of 3.3-4.5 lactation cycles (Miklyaev et al., 2017)

*^ Adjusted for inflation using US government CPI data (http://www.usinflationcalculator.com/), reported in 2020 USD equivalent values

Construction costs consisted of the sum total of materials and soliciting technical support to supervise installation of biodigesters (Garfi et al., 2016). The total present value fixed cost (PFC) per household under each scenario, i, was thus calculated as:

$$PFC_i = \alpha(Cost\ of\ lactating\ heifer) + \beta(Transactions\ cost) + \sigma(PV\ Cowshed\ cost) + \gamma(PV\ Biodigester)$$

where α=1 and β=γ=0 under the 'without project' scenario with the household incurring the cost of a lactating heifer. α=β=σ=1 and γ=0 under the current Girinka program and under the scenario that incorporates distribution of climate-smart cowsheds under the current program design with the household incurring the cost of constructing a traditional cowshed. α=β=σ=γ=1 under scenarios that incorporate distribution of biogas plants with the household incurring the cost of constructing a traditional cowshed.

4.3.4.2 Variable costs

The present value of total household operations and maintenance (O&M) costs was calculated as the sum of present value feed, water, AI and veterinary service costs:

$$PVC_I = \sum_i \frac{Annual\ O\&M\ cost_i}{(1 + Discount\ rate)^T}$$

for $i = feed, water, AI, veterinary$

AI costs were assumed at a value of zero in the initial year of program implementation, t_0, because lactating (pregnant) cows are typically distributed under the current program design.

4.3.4.3 Household benefits

Household benefits were calculated as the sum of revenues from sales of milk produced, *m*, including the market value for milk consumed by the household, calves, *k*, and post-lactation cows, *p*. In addition, benefits from energy cost savings were included in present value benefit calculations under program design scenarios that involved distribution of biogas production plants.

The present value of revenues from milk production, $PV\ Revenue_m$, was calculated as:

$$PV\ Revenue_m = \sum_j \frac{Production_m \times Production\ loss\ rate_j \times Price_m}{(1 + Discount\ rate)^T}$$

for $j = traditional\ cowshed, climate\ smart\ cowshed$

Milk production loss was estimated as higher under traditional cowsheds than under climate-smart cowsheds due to a higher risk of mastitis under traditional cowsheds than under climate-smart cowsheds (Iraguha et al., 2015; Juozaitienė et al., 2006). Milk loss under climate-smart cowsheds was largely attributed to lack of milk storage facilities (IFAD, 2016).

The value of the benefit of producing calves was calculated as the sum of the present value of revenues from sale of the third born calf. We assumed that households gave the first born calf to a neighbouring poor household consistent with Girinka program requirements, kept the second born calf to grow the herd size, sold the third born calf, and kept the fourth born calf to serve as a replacement for the mother cow at the end of its lactation cycle. The total number of lactation cycles of a heifer was assumed at between three and five years and the average calving interval was assumed at between 1 and 1.5 years. We assumed that at the end of four calving intervals, a heifer is culled and slaughtered to be consumed or sold for meat (Miklyaev et al., 2017). Thus only the third born calf, born in the third calving interval, seven years after the initial year of the program inclusive, can be sold for income for the household (CIWF, 2012; IFRC, 2016):

$$PV\ Calf\ revenue_{T_k} = \sum_{t_k} \frac{Calf\ price_k}{(1 + Discount\ rate)^{t_k}}$$

$$\text{for } t_k = 7$$

The present value of revenue from selling a post-lactation cow was calculated as the sum of present value of revenues from sales of the first cow at the end of its nine-year lactation cycle, eight years after the initial year of program implementation inclusive, and subsequent sales of post-lactation replacement cows at nine-year intervals over the course of the 25-year period of analysis:

$$PV\ Cow\ revenue_{T_P} = \sum_{t_P} \frac{Cow\ price_P \times Discount\ rate}{(1 + Discount\ rate)^{t_p}}$$

$$\text{for } t_p = 8, 16, 24$$

The assumption is that a cow is sold at a discounted price due to low meat quality (IFC, 2007; IFRC, 2016).

We calculated the present value of energy cost savings to households from substituting expensive traditional energy sources, primarily fuelwood, mainly used for cooking with biogas:

$$PV\ Energy\ cost\ saving_j = \sum_{j} \frac{(Energy\ cost) \times Utilization_j}{(1 + Discount\ rate)^T}$$

$$\text{for } j = traditional\ cowshed, climate\ smart\ cowshed$$

Higher biogas plant utilisation rates were assumed under climate-smart cowsheds than under traditional cowsheds due to lower manure production losses because climate-smart cowsheds enable effective removal and storage of manure. Energy cost savings were only considered under scenarios that augmented distribution of biogas production plants.

The total present value benefit (PVB) per household under each scenario, i, was calculated as:

$$PVB_i = \varepsilon(PV\ Revenue_m) + \eta(PV\ Calf\ revenue_{T_k}) + \theta(PV\ Cow\ revenue_{T_P}) + \lambda(PV\ Energy\ cost\ saving_j)$$

Where, $\lambda=1$ under scenarios with biogas plant distribution, and $\lambda=0$ under scenarios without biogas production plants.

The present value of the net benefit value per household under each scenario, NB_i, was calculated as the difference between the total benefit to the household and total cost to the household. Parameter values used in net benefit calculations were drawn from value ranges provided in Table 4.4. The process of drawing values from value ranges for input into equations for calculating net benefit values to adequately quantify variability in parameter values is described in detail in the following section.

4.3.5 Quantifying variability in parameter values

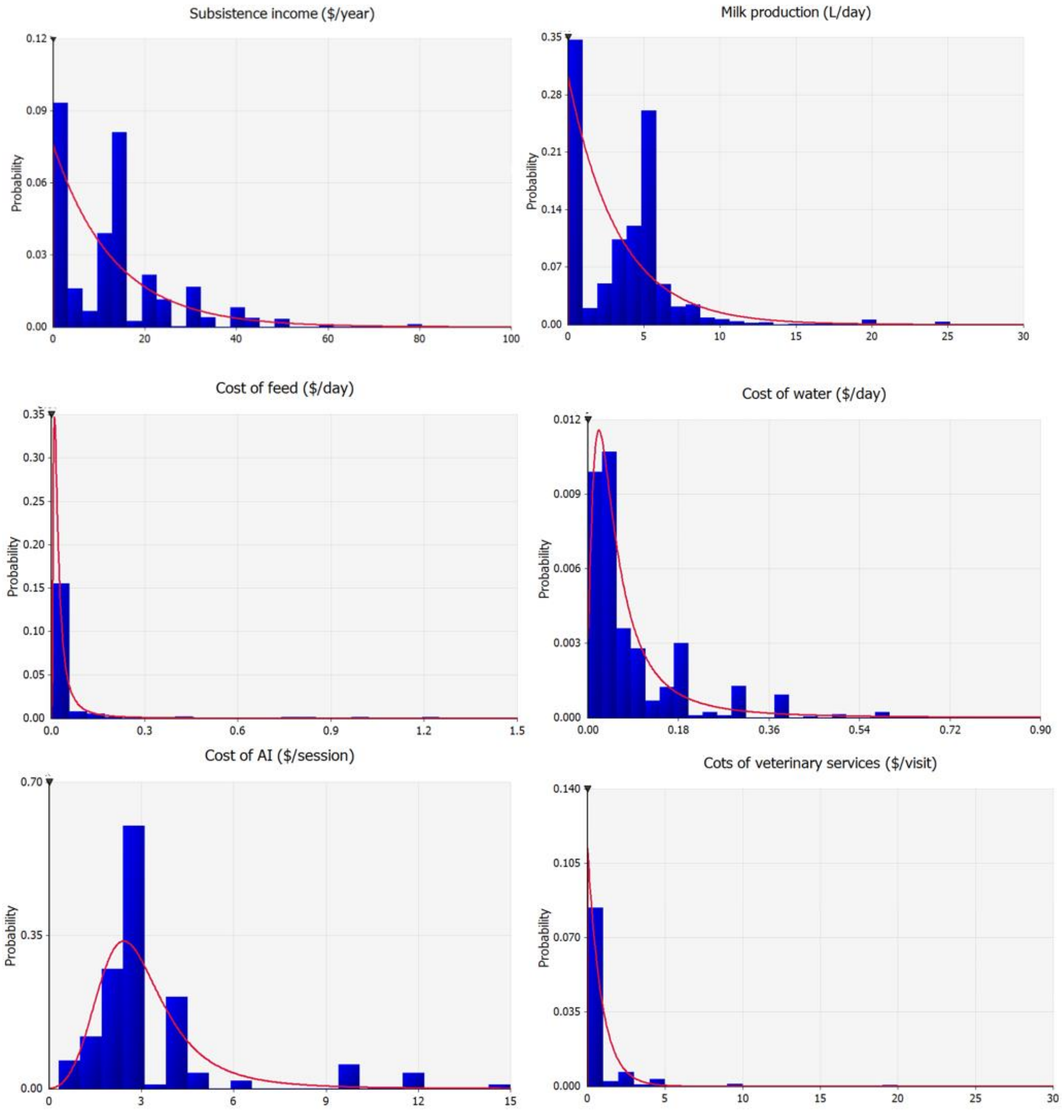
Variability in parameter values used in net benefit calculations was quantified using probability density functions fitted to frequency distributions of observational data from a cross-sectional survey of 1436 households (Table 4.3) and considering secondary data from the literature (Table 4.1). Specifically, probability density functions with the best fit based on chi-squared goodness-of-fit statistical test results were fitted to survey data to quantify variability in income, feeding costs, water costs, AI costs, veterinary service costs, milk consumption and revenue values. Probability density functions of various forms were fitted including exponential, log logistic and Pearson correlation to capture variability in parameter values (Figure 4.4).

Variability in all other parameters obtained from ranges of values collated from reviewed published literature from the case study region (Table 4.3) were assumed to have Beta distribution, a continuous PDF resembling a truncated normal distribution, with a symmetrical bell-shaped density curve about the median value and bounded intervals. This probability density function form is typically used for uncertain parameters with known median and range.

The reader is referred to Kandulu and Connor (2017) for further technical details on choice of appropriate PDF for quantifying uncertainty in parameter values for net benefit calculations. Further, we calculated pair-wise Pearson correlation coefficients to quantify correlations between milk production and the cost of feed, water, and veterinary services as well as milk production and milk price using cross-sectional survey data.

Stochastic Monte Carlo simulations were carried out to draw random parameter values from probability density functions of each parameter and used in equations outlined in the previous section to calculate 1000 probable net benefit values under each scenario, taking into account correlations between correlated parameters. The correlation coefficient between: 1) animal feed expenditure and milk production was calculated as 0.29 consistent with CIAT (2016); 2) water consumption and milk productivity was calculated as 0.30 similar to findings by Kayigema (2013); and 3) veterinary visits and milk production was calculated as 0.21 similar to Argent et al. (2014). Frequency distributions for net benefits were generated from the 1000 probable net benefit values calculated from Monte Carlo simulations to characterise variable net benefit values under each scenario.

Figure 4.4 Fitting probability density functions (red line) to frequency distributions from cross-sectional 2018 survey data from Eastern and Western Rwandan provinces



Source: Authors' design

4.3.6 Sensitivity analysis

We carried out sensitivity analysis to quantify the sensitivity of net benefit estimates to variability in parameter values used to calculate costs and benefits by systematically varying each variable parameter, in turn, within its range of probable values while holding all other uncertain parameters at their median values. Employing a Monte Carlo simulation in a stochastic BCA model enabled assessment of the contribution of variability in values for each parameter to variability in net benefit calculations. Specifically, a Monte Carlo simulation was used to vary each parameter value used in net benefit calculations within the range of its probable values while holding all other parameters at their median values to quantify the relative contribution of each parameter to variability in net benefit estimates.

In addition, we calculated net benefits under various alternative baseline scenarios to accommodate various combinations of initial levels of adoption of heifers, climate-smart cowsheds and biogas plants by households prior to program interventions. First, we considered a baseline scenario where our benchmark household practised subsistence cropping and did not own a heifer because the current Girinka program targets households with no history of livestock ownership by design. In an alternative analysis, we considered a baseline scenario where our reference household already owned a heifer, but received a climate-smart cowshed and a biogas plant. Lastly, we considered a baseline scenario where our reference household already owned a heifer and a biogas plant, but received a climate-smart cowshed.

4.4 Results

Results of our estimates of the net household economic effect of the Girinka program attempt to assess whether: 1) costs imposed on beneficiary households in terms of feed, water, AI and veterinary services are outweighed by the economic benefits to the beneficiary household; 2) alternative program designs with climate-smart technologies can improve the net benefits of the program to beneficiary households; and 3) household net benefit results and conclusions would be robust to alternative baseline 'without project' scenarios.

Without the Girinka program, the few poor rural households that would be able to afford a heifer would be expected to incur a net present value cost equal to USD1660 and realise a present value benefit equal to USD3050 per household on average with a net benefit on their investment calculated as USD1390. Expected present value household costs, benefits, net benefits and benefit-cost ratios under the current Girinka design and three alternative program designs are provided in Table 4.5.

The average net benefit under the current Girinka program was estimated at USD2277 per beneficiary household representing a BCR equal to four to one. The highest BCR equal to five to one would be realised under a scenario that incorporates climate-smart cowsheds and biogas production plants in the current Girinka program.

Table 4.5 Expected present value household costs, benefits, net benefits (USD) and benefit-cost ratio estimates under alternative program designs

Scenario	Program cost	Household cost	Total household benefit	Net household benefit	Household benefit-cost ratio
Current Girinka program	910	763	3,040	2,277	4.0
Girinka + climate-smart cowsheds	957	805	3,280	2,475	4.1
Girinka + biogas plants	3,792	1,185	5,425	4,271	4.6
Girinka + climate-smart cowsheds + biogas	3,839	1,228	6,157	4,929	5.0

Under this scenario, an additional program cost of USD2929 to include distribution and installation of climate-smart cowsheds and biogas production plants in addition to heifers (from USD910 to USD3839) would be expected to yield an incremental present value benefit of USD3117 per household (from USD6157 to USD3040). A scenario that includes distribution and installation of biogas production plants in addition to heifers - without climate-smart cowsheds - was estimated to cost an additional USD2882 per household and to yield an additional USD2385 per household on average.

Our sensitivity analysis considered the incremental net benefit under three alternative baseline ‘without project’ scenarios. Under the first alternative baseline scenario where our benchmark household practised subsistence rainfed cropping and did not own a heifer, the additional net benefit of receiving a lactating heifer, a climate-smart cowshed and biogas production plant was calculated as USD4929 per household and the BCR was equal to five to one. In an alternative analysis where our reference household already owned a heifer, but received a climate-smart cowshed and a biogas plant, the average incremental household net benefit value was calculated as USD2652 and BCR equal to seven to one. Lastly, in a ‘without project’ scenario where our benchmark household already owned a heifer and a biogas plant, receiving a climate-smart cowshed would generate an average present value net benefit of USD689 and a BCR equal to seventeen to one.

Frequency distributions and summary statistics of net benefit values calculated using 1000 random samples from probability density functions of variable cost and benefit parameter values are provided in Figure C.1 in Appendix C. Net benefit value estimates were mostly positive with a very small likelihood of incurring a net cost under the ‘without project’ scenario, where households incurred the cost of a lactating heifer. Net benefit value estimates were highly variable with standard deviations calculated at between 29% and 50% of the expected value.

Figure C.2 in Appendix C shows plots of tornado graphs from quantification of sensitivity of net benefit calculations to variability in parameter values used to calculate benefits and costs under each scenario. Overall, variability in values for milk price and production contributed consistently to variability in net benefit estimates. However, variability in values of even the most sensitive parameters was not found to be important enough to alter key results and conclusion that a substantive increase in household net benefits can be expected under a scenario that includes distribution of climate-smart cowsheds and biogas production plants consistent with to the current Girinka program design. For example, varying milk prices, the most sensitive parameter, between all probable value ranges while holding all other parameter values at their median values, varies net benefit value estimates between USD1229 and USD2988 under the current Girinka program and between USD3617 and USD5942 under a scenario that includes climate-smart cowsheds and biogas plants.

4.5 Discussion

Using a case study in Rwanda’s Eastern and Western provinces, we have evaluated the economic performance of the current Girinka program and three alternative program designs aimed at incorporating distribution of climate-smart cowsheds and biogas plants to the current design which primarily involves distribution of heifers to poor households. Our evaluation framework consisted of a stochastic BCA that explicitly quantified inherent variability in parameter values that influence costs and benefits reflecting heterogeneity across households, in particular,with regard to the cost of animal feed, water and access to AI and veterinary services (Bebe et al., 2002; Kayigema and Rugege, 2014; Mutimura and Everson, 2011).

Our results show that the expected net benefit value for the Girinka program is consistently positive, but highly variable. Whilst incorporating climate-smart cowsheds alone to the current program design would not be expected to generate significant net benefits to households, a complementary package that includes climate-smart cowsheds and biogas production plants would be expected to increase the net benefit to households. Variability in milk production and prices significantly influence variability of net benefit estimates. Variability in the amount of milk produced between households reflects differences in households' cow-feeding intensities due to differences in food supplement affordability, including commercial feed and vitamins (IFRC, 2016; Kayigema, 2013; Kayigema and Rugege, 2014).

Health and social benefits of switching from reliance on fuelwood as the primary source of energy to biogas were not quantified in this study. Inclusion of benefits from reduced risk of respiratory infections, time and effort spent fetching fuelwood and carrying out domestic chores such as preparing fires, cleaning the kitchen, and scrubbing pots and pans traditionally carried out by women and children would be expected to increase the BCR of incorporating biogas production to Girinka. Further, inclusion of the benefit of reduced deforestation and GHG emissions as a result of switching from fuelwood to biogas would also increase BCR estimates (Garfi et al., 2016). A higher net benefit value would also be expected under alternative futures with technological advancements in cowsheds and biogas production plants following a proliferation of cheaper more efficient biogas plants and higher adoption and utilisation rates.

Despite increasing awareness of health and environmental impacts of fuelwood and increased availability of new cleaner alternative sources of energy for household use source than traditional fuelwood, a large number of households in low to middle income countries continue to use fuelwood for cooking. Differences in shadow prices between male and female labour and unequal distribution of tasks between males and females within the household can contribute to low adoption rates of innovations that have an expected net benefit value for households (e.g. Overfield, 1998). Specifically, low adoption rates can reflect women's limited bargaining leverage in household decisions particularly because fuelwood collection is traditionally a female-dominated task. For example, Rahut et al (2016) found that female-headed households are more likely to adopt cleaner energy sources and are less likely to use fuelwood in Africa. A parallel program aimed at empowering women financially through improved access to microcredit for women can increase women's bargaining power in the household and increase the adoption of cleaner energy sources for households.

Our findings indicate that design and implementation of complementary aid program packages that target and address multiple economic, social and environmental outcomes can achieve economic development and poverty alleviation objectives more efficiently than single-objective aid programs. A limitation is that exploration of the effect of various cost-sharing arrangements between government and aid agencies and households on net benefit estimates was considered to be outside the scope of the study. Further, environmental and health benefits and net benefits under alternative futures reflecting technological advancements and widely available, affordable commercial climate-smart technologies have been discussed qualitatively, but were not quantified in this study. Quantification of environmental and health benefits would further reinforce the superiority of incorporating climate-smart technologies to the Girinka and similar livestock donation programs over alternative aid programs for addressing malnutrition and food security and poverty. However, future research efforts should look into quantification of net benefits under alternative means-tested cost-sharing arrangements, and include quantified environmental and health benefits of climate-smart technological innovations.

One limitation of this study is that values obtained from the survey in Table 4.3, in particular for input costs and milk production and price, were likely obtained from clustered samples from farmers in the same village, or from nearby villages, and may not be representative of the entire population of Rwanda's East and West provinces. The sensitivity analysis revealed that whilst net benefit calculations were sensitive to variability in parameter values for input costs and milk production and price, relative net present values and the ranking of the alternative program designs were robust to variability in input costs and milk production and price (Figure C.2 in Appendix C). Thus, our contention is that that our extensive treatment of uncertainty in BCA provided robust results and adequately addressed variability due to heterogeneity across beneficiary households in Rwanda's West and East provinces. Future research should improve on sampling procedures for collecting data in the case study area to improve on the sample to population representativeness of BCA input data.

Another limitation of this study is that GHG emission savings and health benefits were not quantified due to data limitations. Social impacts were also not quantified as this was beyond the scope of the study. Future research can build on this study quantify GHG emission and health benefits of adopting climate-smart technologies. Non-market valuation techniques can also be applied to quantify social impacts to improve on the breadth of quantified costs and benefits

Findings from this study are consistent with growing calls to harness broader environmental and social benefits from livestock donation programs through installation of biogas plants to utilise livestock waste to generate clean energy for domestic use to enhance long-term economic viability of smallholder crop and livestock production systems in poor rural communities (Bedi et al., 2013; Ezeanya and Kennedy, 2016). Our study also makes a strong case for targeted pro-poor poverty reduction programs as an alternative to broader economic growth programs showing that community-scale development programs targeting poor households can have high BCRs with direct quantifiable benefits to poor rural households that can be directly attributed to interventions. This study bears significant relevance following the advent of affordable small-scale renewable energy production technologies in SSA in recent years (Clemens et al., 2018; Gitau et al., 2019; Jagger and Das, 2018) and can serve as a template for quantifying economic impacts of adoption from households' perspective.

4.6 Conclusion

There is an urgent requirement to prioritise adoption of effective adaptation and mitigation efforts in smallholder SSA's agricultural production systems to moderate climate change impacts. Integration of climate change adaptation and mitigation technologies in poverty reduction programs is widely discussed, but quantitative evaluations of the expected net benefit of adopting such technologies from the perspective of households are sparse. This study estimates the net benefit of incorporating climate-smart technological innovations to existing livestock donation poverty reduction strategies. Specifically, the net benefit of incorporating distribution of climate-smart cowsheds and biogas production plants to the current Girinka program was estimated using a case study in Rwanda's East and West Provinces. We found that the expected net benefit value for the Girinka program was consistently positive, but highly variable. Incorporating climate-smart cowsheds alone to the current program design would not be expected to generate significant net benefits to households, but a complementary package that includes climate-smart cowsheds and biogas production plants generated the highest BCR. Variability in milk production and milk price contributed the most to variability in estimates of net benefits. Incorporating alternative program designs to optimise multiple economic, social and environmental objectives would reinforce the superiority of livestock donation programs over single-objective aid programs.

Community-scale pro-poor poverty reduction programs targeted directly at poor households have direct quantifiable benefits to poor rural households that can be directly attributed to interventions. Harnessing broader environmental and social benefits from livestock donation programs through installation of climate-smart cowsheds and biogas plants can enhance long-term economic viability of smallholder crop and livestock production systems in poor rural communities.

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Chapter 5 Improving rural agricultural production and income in low- and middle-income countries using mobile phones

This chapter presents an unpublished manuscript that has been prepared for submission to a journal for publication. Accordingly, the formatting follows the standard journal article format. There is, therefore, some repetition with other chapters in this thesis, particularly the background and conclusion sections.

Abstract

Neo-classical economists have cited technological innovation as by far the most important driver of economic growth and development. Recently, mobile phones have been the most widely adopted and rapidly evolving innovation the world over, including in rural areas of low- and middle-income countries, yet rigorous studies on the influence of mobile phones on rural households' wellbeing are scarce. This study utilises a comprehensive panel dataset that combines national survey data and a spatial climate dataset from Bangladesh, and employs multilevel mixed-effects generalised linear panel regression models to estimate the average marginal effect of mobile phone ownership on rural households' agricultural net returns, yield and production technical efficiency. Results show that the highest returns to policy investments in the area of mobile phone adoption and application in agricultural production can be realised through addressing gender disparities in mobile phone adoption.

Keywords: digital inclusion; information communication technology; rural agricultural outcomes; production technical efficiency; household utility.

Statement of Authorship

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Name of Principal Author (Candidate)	John Kandulu		
Contribution to the Paper	Undertook the literature review. Collected all of the data. Prepared data for analysis and performed econometric analysis in Stata. Interpreted data and wrote the manuscript. Acted as the corresponding author.		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	12/07/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Offered technical assistance with econometric analysis and wrote parts of the manuscript.		
Signature		Date	12/02/2020

5.1 Introduction

Since the 1950s, neo-classical economists have discussed the theoretical basis linking technological advancement with economic growth (Romer, 1986; Solow, 1956), while empirical studies have confirmed technological innovation as the most important driver of economic growth and development since the 1970s (Mansfield, 1972; Nadiri, 1993). Globally, mobile phone technology has emerged as a primary engine of economic growth with mobile phones being the most widely adopted of all information and communication technologies and smartphones being the most rapidly evolving innovation (Steinbock, 2005). The past two decades have witnessed rapid and consistent growth in mobile phone network coverage and subscriptions in rural areas of low- and middle-income countries leading to a reduction in the rural-urban digital gap (Myovella et al., 2020).

Strategic application of mobile phone technology in rural areas of low- and middle-income countries can enable improvements in the economic welfare of poor rural households. For example, mobile phone technology can be applied to facilitate rural farmers' access to production information (Issahaku et al., 2018; Mwalupaso et al., 2019a; Mwalupaso et al., 2019b) and market information (Haile et al., 2019; Khan et al., 2019). Further, mobile phone technology can influence rural households' welfare through its positive association with increased access to off-farm salary incomes (Ma et al., 2018), and remittance income (Kikulwe et al., 2014; Sekabira and Qaim, 2017b).

Some studies have argued that only a small percentage of rural farmers use mobile phones for agricultural production purposes (Chhachhar et al., 2014; Houghton, 2009; Mittal and Tripathi, 2009), although these studies are somewhat dated and other studies have reported significant links between mobile phone use and agricultural production outcomes (see Table D.1 and Table D.2 in Appendix D). For example, the use of mobile phone-based digital financial services has been associated with high farm-input use and net agricultural revenues (Kirui et al., 2012). Mobile phone use has also been linked with mitigating variability in agricultural incomes and increasing nutrition benefits as mobile phone users planted a more diverse basket of crops than non-owners (Aker and Ksoll, 2016). Further, mobile phone application in agricultural production has been found to improve productivity significantly (Issahaku et al., 2018).

Whilst a number of cross-sectional econometric studies have investigated the extent of mobile phone application in agricultural production and the association between mobile phone use and various welfare outcomes (Table D.1 and Table D.2 in Appendix D), rigorous studies on the influence of mobile phone use on agricultural production indicators are scarce. The main objective of this study was to identify the extent of the influence of mobile phone use on Bangladesh rural households' agricultural production and income, including yields, production technical efficiency, and net revenues. Additionally, we estimated the influence of mobile phone use for: 1) households with a female head of house; 2) households with access to off-farm employment opportunities; and 3) households with access to agricultural extension services.

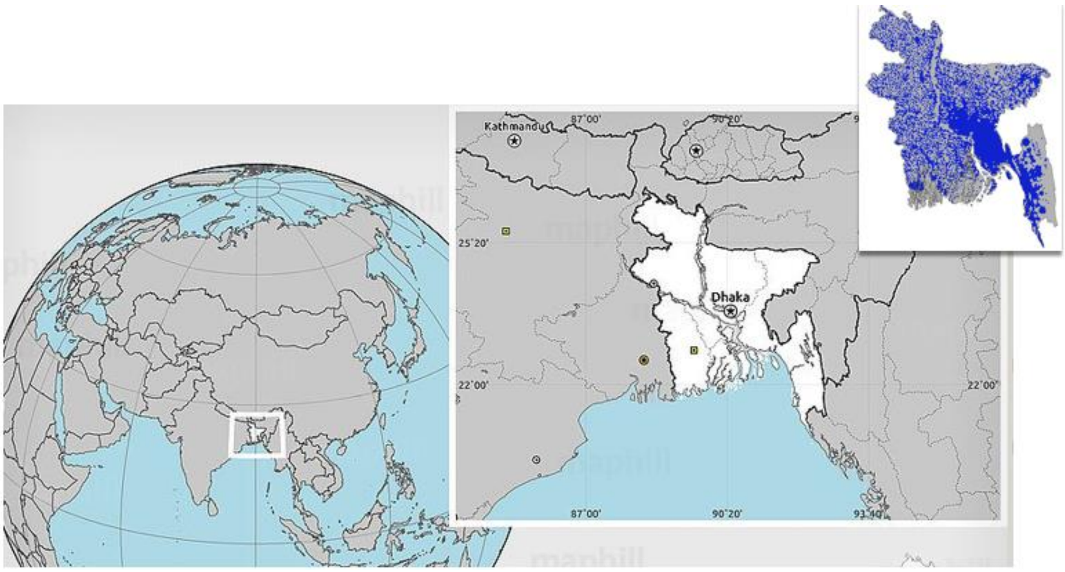
This study utilised a comprehensive panel dataset that combined national survey data and a spatial climate dataset from Bangladesh enabling inclusion of important geospatial control variables typically omitted in reviewed literature, in particular, spatial climate variables, and soil quality. Further, we combined four modelling techniques: 1) machine learning computation to carry out systematic selection of covariates that can most efficiently predict welfare outcome variables; 2) stochastic frontier analysis to measure production technical efficiency; 3) household fixed effects models to control for time-invariant unobserved household characteristics; and 4) mixed-effects generalised linear panel regression models. A rigorous analysis of the influence of mobile phone ownership for rural agricultural outcomes in low- and middle-income countries is of great value to governments, non-governmental organisations and development aid agencies charged with implementing effective rural development and poverty alleviation policies and strategies.

5.2 Case study area description

The case area of focus for this study is rural Bangladesh. Over 60% of Bangladesh's population live in rural areas where the poverty rate is 27% and the average monthly income is USD170 per household (WB, 2018). Most households in rural Bangladesh rely on agriculture for their livelihood with 60% of households involved in small- to medium-scale farming activities, mainly growing rice, cereals, horticulture, and jute (UN data, 2015). Further, most rural areas in Bangladesh are characterised by poor infrastructure with a large rural-urban gap in access to electricity (Moniruzzaman and Day, 2020). The adult literacy rate is lower among women than men in rural areas of Bangladesh by 50%, yet women constitute 46% of Bangladesh's farming population (Islam and Grönlund, 2011).

Despite the high levels of poverty, there is widespread mobile technology use in rural areas, including in the lower income households (Islam, 2011) largely due to rapid growth in network strength and coverage (Figure 5.1).

Figure 5.1 Map of Bangladesh showing 3G network coverage in 2015 (dark blue shaded areas)



<u>Source</u>**:** Adapted from GSMA, (2017,(p. 3)

However, considerable gaps in access to mobile phone technology persist owing to disparities in wealth, literacy, gender, and access to electricity (Alam et al., 2019; Hernandez, 2019; Tran et al., 2015). There is a high concentration of mobile phone network providers in regions with high disposable income and in more urbanised areas with marginal access, typically observed in poorer and more rural areas (Alam et al., 2019). Further, although 74% of people aged 15-65 own mobile phones in Bangladesh, only 18% own smartphones (Hernandez, 2019). Additionally, women are less likely to own a mobile phone in Bangladesh with a gender gap of 34% in mobile phone ownership and use (BBS, 2009).

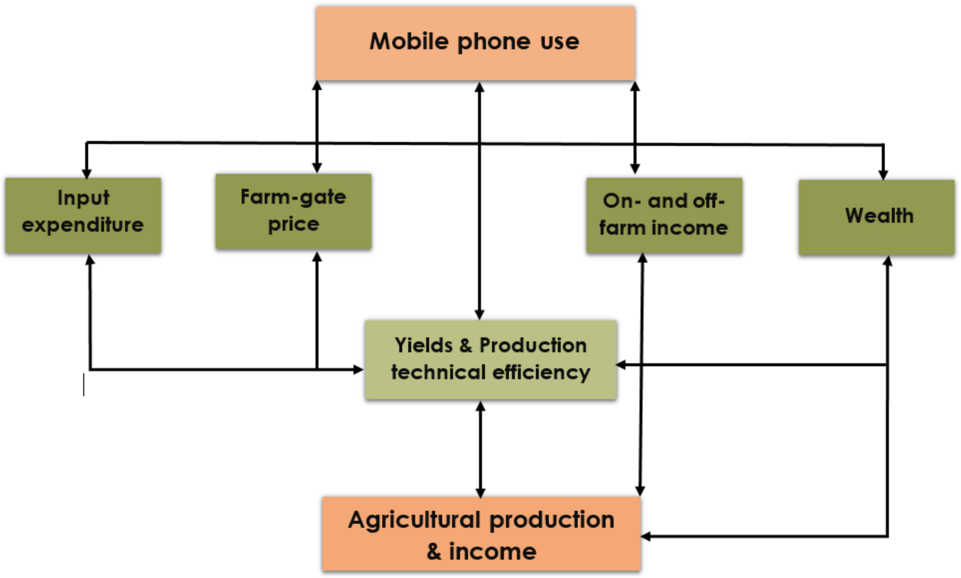
5.3 Method

In what follows, we describe: 1) the conceptual framework and heuristics of possible impact pathways linking mobile use with various household production and income indicators; 2) data and sources; 3) procedures for measuring key variables; and 4) the empirical strategy employed in this study.

5.3.1 Conceptual analytical framework

Figure 5.2 illustrates possible impact pathways through which mobile phone use can influence various household production and income indicators based on literature review findings summarised in Table D.1 and Table D.2 in Appendix D.

Figure 5.2 Heuristic of possible impact pathways through which mobile phone use can influence various agricultural production indicators



Source: Authors' design

The reviewed literature has shown some evidence that mobile phone use can influence agricultural production and income directly through increased production technical efficiency, on- and off-farm incomes, and wealth. Further, mobile phone use can influence agricultural production and income indirectly through its positive correlation with farm-input expenditures and farm-gate prices. Access to market information on farm-gate prices through mobile phone use can influence decisions on farm-input expenditure and investments in production technical efficiency. Figure 5.2 also shows a bidirectional relationship between mobile phone use and all household production and income indicators. For example, the amount of income earned by a household can influence whether or not a household can afford a mobile phone, but mobile phone use can also influence increases in income by improving access to production and market information as well as information on higher earning off-farm employment opportunities.

5.3.2 *Data*

The full list of all variables used, mean and standard deviation values, and data sources are provided in Table 5.2. Further, students' two-sample *t*-test results are provided to illustrate differences in characteristics between mobile phone owners and non-owners based on measures of significance of differences between sample means for a large number of various economic, demographic and geographical variables. Descriptive summary statistics, including mean values, standard deviations, minimum and maximum values for mobile phone owners and non-owners in 2012 and 2015 are presented in Table D.3 and Table D.4 in Appendix D.

The main dataset for this study was the Bangladesh Integrated Household Survey (BIHS). The BIHS is a 2012 and 2015 panel open-access dataset from a national survey funded by the U.S. Agency for International Development (USAID) and implemented by the International Food Policy Research Institute (IFPRI). The BIHS is based on a survey of 6,500 rural households covering 325 sampling units across each of Bangladesh's seven major administrative divisions with equal representation in all of Bangladesh's Upazilas (hereafter, *counties*). The BIHS survey sampling procedure was designed such that each rural household had an equal probability of being selected with the 6,500 rural households drawn randomly from the 325 rural PSUs.

In total, 4,448 households owned a mobile phone in 2012 and 5,013 households owned a mobile phone in 2015 (Table 5.1). A total of 372 households had missing observations and were not used in the analysis. 12,256 observations from 6,128 households were used in analysis for the 2012 and 2015 observational data. Among 1,409 households with a female head of house, 1,316 household-level observations were used providing a total of 2,362 observations for the 2012 and 2015 survey periods. 93 households with a female head of house were not used in the analysis due to missing data.

The BHIS tracked households between 2012 and 2015 experiencing a low attrition rate of 1.26%. The BHIS collected household data on agricultural production and practices, in particular, farm-input expenditure, access to extension services, yields, farm-gate prices, revenues, soil quality, crop choices, demographic and location characteristics, household structure, off-farm incomes and wealth and asset ownership. In addition to BHIS, geospatial climate data, in particular, flood depth, proneness to extreme floods (deeper than 360 cm) and extreme drought events were collected using information from the Centre for Geographic and Information Services (CEGIS) based on a 50-year analysis of Bangladesh's climate and hydrological data between 1959 and 2009. Projections showed that no significant change occurred in modelled spatial distribution, frequency, and severity of extreme flood and drought events across Bangladesh from 2009 to 2015 (Brammer, 2016).

5.3.3 *Measurement of key variables*

Mobile phone ownership, the independent variables of interest, was measured as a binary variable for whether or not at least one adult member of a household owns a functional mobile phone. Three dependent variables were considered, including yield per harvested hectare, production technical efficiency, and net farm revenue. Production technical efficiency scores were computed using stochastic frontier analysis (Alemu et al., 2008; Ma et al., 2018; Mango et al., 2015; Mwalupaso et al., 2019b). The basic intuition behind the frontier modelling approach for predicting production technical efficiency scores is that households with the same level of input of factors of production, including land, labour and physical capital, are benchmarked against a reference household with the highest level of production for the given level of input.

A constant value of 0.1 was added to all observations of the various input costs and net revenue before applying the logarithm transformation. The percentage of observations with zero values for the log-transformed input cost and net revenue variables ranged between 3.77% and 7.12%. The log-transformed variables were preferred because they had a more symmetrical distribution and for more intuitive interpretation of coefficients. In an additional analysis, we applied the inverse hyperbolic sine transformation to values of net revenue, instead of logarithm transformations, to test the sensitivity of instrumental variable estimation and net revenue model estimates to the scale of transformation of zero-value observations (Bellemare and Wichman, 2020; Aihounton and Henningsen, 2021).

Table 5.1 A summary of the total number of observations used in analysis by sub-group

Group	Number of observations
Surveyed households	6,500
Households with no missing observations used in analysis	6,128
Number of observations (2012 and 2015)	12,256
Households that owned mobile phones in 2012	4,448
Households that owned mobile phones in 2015	5,013
Households not used in analysis due to missing observations	372
Households with female head of house	1,409
Households with female head of house used in analysis	1,316
Number of observations from households with female head of house used (2012 and 2015)	2,632
Households with female head of house not used in analysis due to missing observations	93

A production technical efficiency score equal to one is assigned to the reference household with the highest production for each level of input, and all other households are assigned a value between zero and one, commensurate with each household's production for the given level of input. The rationale is that a producer is considered to be performing at the most technically efficient level of production, at a given level of input, if it is no longer possible to produce any further output without using more input. Thus, the role of mobile phone technology is providing households with increased access to new information about alternative agricultural practices to enable technically inefficient households to better utilise available inputs to realise the highest attainable level of production.

5.3.4 Empirical strategy

5.3.4.1. Regression equation

To estimate the influence of owning mobile phones on each of the three dependent variables, *Y*, panel-data regression models with standard errors clustered at the PSU (subdistrict) level.

Table 5.2 Mean, standard deviation (in parentheses), and Student's two-sample t-test results showing the significance of differences between means of mobile phone owners and non-owners for 2012 and 2015 (full summary statistics in Table D.3 and Table D.4 in Appendix D)

	2012		2015	
	Owners	**Non-owners**	**Owners**	**Non-owners**
Outcome variables				
Log of yield (yield in tonnes per harvested area in hectares based on yield-weighted average by crop)	0.92**	0.88	1.30**	0.87
	(0.33)	(0.42)	(0.47)	(0.37)
Production technical efficiency^	0.77***	0.67	0.79***	0.69
	(0.11)	(0.07)	(0.22)	(0.14)
Log net revenues	5.14***	3.03	5.59***	4.01
	(3.40)	(3.22)	(3.54)	(3.12)
Subpopulation of interest				
1 = head of house is female; 0 = otherwise	0.23*	0.27	0.25**	0.29
	(0.42)	(0.41)	(0.44)	(0.49)
Instrumental variables				
4G network tower coverage in upazila	0.63***	0.47	0.77***	0.53
	(0.12)	(0.14)	(0.11)	(0.13)
Total number of major telecommunication providers operating in upazila	2.49***	2.03	2. 57***	2.14
	(0.21)	(0.24)	(0.27)	(0.23)
Explanatory variables				
1 = household had access to electricity; 0 = otherwise	0.57**	0.33	0.64**	0.37
	(0.50)	(0.44)	(0.49)	(0.47)
1 = head of household received no education; 0 = otherwise	0.42***	0.71	0.47***	0.73
	(0.49)	(0.53)	(0.44)	(0.55)
1 = household owns a household; 0 = otherwise	0.93**	0.87	0.93*	0.94
	(0.27)	(0.33)	(0.39)	(0.35)
1 = household received rice subsidy; 0 = otherwise	0.06***	0.02	0.07***	0.03
	(0.14)	(0.17)	(0.12)	(0.11)
Log of cost of hired labour	2.75*	1.73	2.92*	1.87
	(3.30)	(4.00)	(4.12)	(3.84)
Log of total cost of machinery	2.70**	2.31	2.95***	2.23
	(3.74)	(3.61)	(4.44)	(4.18)
Log of total cost of chemicals	1.65***	0.9	2.05***	1.33
	(3.14)	(2.83)	(3.77)	(3.36)
Weighted mean of flood depth (feet)	1.35**	1.01	1.65*	1.37
	(1.98)	(1.57)	(2.29)	(2.49)
1 = household exposed to extreme flooding; 0 = otherwise	0.55**	0.51	0.55*	0.63
	(0.50)	(0.50)	(0.50)	(0.50)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Sources: 1) Bangladesh Integrated Household Survey (BHIS) 2012 and 2015 datasets, 2) Spatial climate data based on CEGIS 1959-2009, 3) NPERF's geospatial time series data on 4G network coverage in Bangladesh (2012 and 2015), and 4) STATISTA's mobile network coverage by service provider as share of population in Bangladesh (2012 and 2015).

^ Calculate using stochastic frontier analysis (SFA) approach

Table 5.2 Mean, standard deviation (in parentheses), and Student's two-sample t-test results showing the significance of differences between means of mobile phone owners and non-owners for 2012 and 2015 (full summary statistics in Table D.3 and Table D.4 in Appendix D) (continued)

	2012		2015	
	Owners	**Non-owners**	**Owners**	**Non-owners**
1 = household exposed to extreme drought events; 0 = otherwise	0.71***	0.72	0.75**	0.74
	(0.47)	(0.47)	(0.47)	(0.45)
Percentage of agricultural land with sand soil	0.15***	0.11	0.15**	0.12
	(0.29)	(0.33)	(0.28)	(0.31)
Percentage of agricultural land with clay soil	0.06	0.07	0.055**	0.03
	(0.21)	(0.23)	(0.17)	(0.15)
Percentage of agricultural land with loam soil	0.23	0.20	0.24	0.22
	(0.37)	(0.36)	(0.36)	(0.35)
Age of household head	43.95***	45.0	45.55***	50.1
	(13.5)	(15.0)	(13.2)	(16.3)
1 = head of household went to university; 0 = otherwise	0.025*	0.00	0.025**	0.00
	(0.14)	(0.041)	(0.13)	(0.037)
1 = head of household's ethnicity is Bengani; 0 = otherwise	0.95***	0.94	0.85***	0.81
	(0.25)	(0.32)	(0.36)	(0.40)
Household size	4.45***	3.79	4.85***	3.93
	(1.64)	(1.49)	(1.77)	(1.73)
Proportion of females in household	0.65***	0.70	0.65***	0.67
	(0.25)	(0.34)	(0.24)	(0.32)
Percentage of land owned	0.17*	0.09	0.25***	0.10
	(0.083)	(0.093)	(0.29)	(0.27)
1 = household owns a cassette or CD player; 0 = otherwise	0.085	0.01	0.065	0.01
	(0.28)	(0.12)	(0.24)	(0.11)
1 = household owns a TV; 0 = otherwise	0.35***	0.07	0.35***	0.07
	(0.47)	(0.25)	(0.47)	(0.26)
1 = household grows jute; 0 = otherwise	0.11***	0.08	0.08*	0.06
	(0.30)	(0.27)	(0.25)	(0.24)
1 = household grows horticultural crops; 0 = otherwise	0.22**	0.11	0.27**	0.12
	(0.38)	(0.34)	(0.36)	(0.33)
Observations	4,448	1,680	5,013	1,115

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

Sources: 1) BHIS 2012 and 2015 datasets, 2) Spatial climate data based on CEGIS 1959-2009, 3) NPERF's geospatial time series data on 4G network coverage in Bangladesh (2012 and 2015), and 4) STATISTA's mobile network coverage by service provider as share of population in Bangladesh (2012 and 2015).

The following equation models the relationship between mobile phone ownership and each of the three dependent variables:

$$y_{it} = C + \alpha M_{it} + \beta X_{it} + \delta T_t + \varepsilon_{it} \qquad \text{Eq. (1)}$$

Where: y_{it} is yield, production technical efficiency, and net revenue for household i at time t; M_{it} is a vector of the binary variable representing mobile phone ownership status for household i at time t; X_{it} is a vector of covariates consisting time-variant household characteristics; and T_t is an indicator variable for time t equal to 1 if year=2015, 0 if year=2012. Time FE models were estimated to control for unobserved time-variant or trend factors such as economic growth, network coverage expansion, changes in signal strength, and droughts. ε_{it} is the random error varying across households and years. Our particular interest was the estimates for α where a positive and significant value would imply that mobile phone ownership status has a positive influence on households' economic welfare. X_{it} included a vector of various independent variables including demographic, economic, and geographic variables. X_{it} also included farm input cost variables for regressions of yield and net revenues, but farm input cost variables were omitted in estimates of production technical efficiency due to multicollinearity because estimation of production technical efficiency scores using stochastic frontier analysis already considered farm input variables. Further, separate regressions were run for a subpopulation of female-headed households.

5.3.4.2. Selecting covariates

We controlled for a large set of demographics, socioeconomic and geospatial household characteristics identified from a review of similar studies to reduce the potential for omitted variable bias. Table D.1 and Table D.2 in Appendix D provide a summary of studies that were reviewed to identify covariates included in the initial models. Specifically, the estimates controlled for the influence of farm-inputs, access to extension services, soil quality, crop choices, demographic and location characteristics, household structure, off-farm incomes, asset ownership and wealth, and geospatial climate variables. First, models with the full set of controls were estimated and tested for multicollinearity. All the covariates had a variance inflation factor of less than five, suggesting no serious multicollinearity (Table D.12 in Appendix D).

Next, a parsimonious regression model was specified based on a systematic variable selection process that utilised machine-learning techniques to select model covariates that would most efficiently predict the four economic welfare dependent variables. Specifically, the most efficient model was specified using least absolute shrinkage and selection operator (LASSO) and Bayesian model averaging (BMA) to determine which control variables to include in the parsimonious model after Kandulu et al. (2019). The selection of control variables used in the models, X_{it}, considered an additional set of geospatial covariates, including flood depth, exposure to extreme floods and drought events, and soil quality measured as the percentage of agricultural land with loam soils. The full set of covariates considered in the models is enumerated and categorised in Table 5.2. Table D.13 in Appendix D provides a detailed discussion of the process of selecting covariates for the parsimonious regression model.

5.3.4.3. Estimation procedure

Three main procedures were undertaken to investigate the influence of mobile phone use on agricultural net revenue, yield and production technical efficiency: 1) testing for endogeneity due to unobserved time-invariant factors that can jointly influence mobile phone ownership and the three dependent variables; 2) conducting Hausman tests to differentiate between fixed and random effects panel regression models; and 3) Selecting a panel regression model that supports specification of survey design features to account for the complex sample design, where the total BIHS sample of 325 PSUs (subdistrict-level boundaries) were allocated among eight strata (seven divisions).

Mobile phone ownership can be correlated with the error term due to intrinsic time-invariant unobserved heterogeneity between owner- and non-owner households, for example, poor farming skills and management abilities (Cameron and Trivedi, 2005; Haile et al., 2019). Specifically, a household's decision on whether or not to own a mobile phone may be correlated with unobserved time-invariant household characteristics that may also be correlated with agricultural net returns, yield and production technical efficiency. Testing and treating for endogeneity thus enables isolation and accurate attribution of the influence of mobile phone ownership on agricultural net returns, yield and production technical efficiency.

We conducted instrumental variable panel regressions to test if mobile phone ownership can be treated as exogenous (Table 5.3). Two instrumental variables were used: 1) mobile phone coverage by upazila, or county, defined as the percentage of the total population who are within range of a 4G mobile cellular signal, irrespective of whether or not they are subscribers; and 2) The total number of major telecommunication providers operating in each upazila. A number of studies have found that adoption of mobile phones in rural areas in Bangladesh and other South Asian countries is affected by various facilitating factors, including network coverage, quality and availability of support services such as subscription, technical support and bill payment centres (Biljon and Kotzé, 2007; Islam and Gronlund, 2011; Jain and Hundal, 2007; Kalba, 2008; Sangwan and Pau, 2005). Further, we conducted weak instruments tests to test the validity of instruments, and exclusion restriction tests to test if the chosen instruments were correlated with the error term in the second-stage regression (Table 5.3). In addition, IV models and parsimonious models were re-estimated using inverse hyperbolic sine transformations (IHS) of net revenue and all the input cost covariates instead of logarithm transformations.

To determine whether or not we needed to control for the influence of household fixed effects, we conducted Hausman tests to test if the difference in fixed effects and random effects coefficient estimates were systematic and statistically significant. Whilst fixed effects models take time-invariant household characteristics into account, random effects models have higher estimation efficiency when time-invariant household characteristics do not significantly influence outcome variables. Accordingly, multilevel mixed-effects generalised linear (random effects) models were preferred because they support specification of survey design features of a panel dataset in Stata. Thus, multilevel mixed-effects generalised linear panel regression models took complex survey design features into account and enabled clustering of standard errors at the PSU level as well as specification of how PSUs were allocated among the eight strata representing Bangladesh's rural agricultural divisions.

5.4 Results and discussion

5.4.1 Endogeneity tests and Hausman test results

Results of two-stage endogenous treatment effect models and instrumental variable estimations for net revenue, yield per harvested area and technical efficiency show significant *p*-values between mobile phone ownership and the instrument in the first-stage reduced form models (Table D.5, Table D.6 and Table D.7 in Appendix D). Additionally, IV estimates were robust to use of either logarithm or HIS transformation of net revenue and input cost covariates (Table D.8, Table D.9 and Table D.10 in Appendix D). Post-estimation instrumental variables test and Hausman test results are presented in Table 5.3. Thus endogeneity and Hausman test results supported use of multilevel mixed-effects generalised linear (random effects) panel regression models with survey design specification.

Table 5.3 Instrumental variables test and Hausman test results, including test statistics, *p*-values and critical values for weak identification tests (in parentheses)

Variables	NR	Yield	TE
Regression results			
Regression method	Panel 2SLS	Panel 2SLS	Panel 2SLS
Control variables	Yes	Yes	Yes
Number of observations	12,256	12,256	12,256
Adjusted R^2	0.55	0.17	0.10
Endogeneity and model test with IV			
Over-identification test (Sargan statistic)[a]	0.117	0.766	1.365
	(0.7321)	(0.3814)	(0.2427)
Weak identification test (C-D Wald F statistic)[b]	46.528	132.88	102.161
	(19.73)	(19.93)	(17.73)
Endogeneity test (Chi-squared statistic)[c]	0.182	13.514	50.031
	(0.6700)	(0.2034)	(0.1963)
Hausman specification test (Chi-squared statistic)[d]	157.85	159.47	177.66
	(0.5397)	(0.4992)	(0.1135)

[a] The joint null hypothesis is that the instruments are valid instruments, or uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.
[b] Weak identification refers to the excluded instruments being correlated with the endogenous regressors, but only weakly. If the test statistic exceeds the 10% critical value (e.g. 19.73 for the net returns model), we can reject the null hypothesis that the instruments are weak.
[c] The null hypothesis is that the specified endogenous regressors (mobile phone ownership) can be treated as exogenous. Failing to reject the null hypothesis suggests that mobile phone ownership is exogenous to the dependent variables.
[d] We cannot reject the null hypothesis that the difference in fixed effects and random effects coefficient estimates is not systematic. Individual-level effects are adequately modelled by a random-effects model. Thus a random effects multilevel mixed-effects generalised linear model may be used.

5.4.2 Influence of mobile phone use on agricultural production and income

Student's two-sample *t*-test results revealed significant differences in mean values of all the three dependent variables between mobile phone owners and non-owners in the two study periods in 2012 and 2015 (Table 5.2). Table 5.4 presents results from six multilevel mixed-effects generalised linear regressions on the three dependent variables with standard errors clustered at the PSU level to investigate the significance of the influence of mobile phone ownership on agricultural net revenue, yield at harvest and technical efficiency. In addition, results on the average marginal effects of mobile phone ownership on net revenue, yield at harvest and technical efficiency are presented for the sampled households and for a subsample of female-headed households.

On average, mobile phone *owners* had 9.5% higher net revenues than non-owners, 1.3% more yields and a higher production technical efficiency score (by 1.6 percentage points). Thus, overall, the average marginal effect of mobile phone ownership on yields and production technical efficiency was significant, but relatively small compared with the average marginal effect on net revenues. A possible explanation for this is that mobile phone ownership influences net revenues through improving access to market information on inputs and commodities which may influence average unit production costs and sale prices received at the market (Figure 5.2, and Table D.1 and Table D.2 in Appendix D).

Table 5.4 Estimates of the average marginal effects (AME) of mobile phone ownership on net revenue, yield and technical efficiency for parsimonious regression models

	AME	SE	t	P>t	P>t (adjusted for Type I Error)	Number of observations
NR	0.091	0.03	2.81	0.01	0.01	12,256
NR (female head of house subpopulation)	0.130	0.07	1.87	0.06	0.10	2,632
Yield	0.013	0.00	2.75	0.01	0.01	12,256
Yield (female head of house subpopulation)	0.119	0.08	1.44	0.14	0.24	2,632
TE	0.016	0.00	9.54	0.00	0.00	12,256
TE (female head of house subpopulation)	0.019	0.00	16.26	0.00	0.00	2,632
Number of PSUs	323					
Number of strata	7					
Design degrees of freedom	316					

Table 5.4 also shows that on average, female heads of house that owned a mobile phone had 14% higher net revenues than non-owners, 13% more yields and a higher production technical efficiency score (by 1.9 percentage points). Overall, the average marginal effect of mobile phone ownership is higher among female-headed household subpopulation than for the entire sample of households. Further, the average marginal effect of mobile phone ownership on production technical efficiency was significant, but relatively small compared with the average marginal effect on net revenues and yields for the subpopulation of female-headed subpopulation. This may imply a significant correlation between production efficiency and yield and between yield and net returns. AME estimates were robust to use of either logarithm or IHS transformations of net returns and input cost covariates with the exception of the yield model (Table D.11 in Appendix D). Specifically, the AME of mobile phone ownership on yield was statistically significant for the model with logarithm transformations at p=0.05, whereas it was not statistically significant for the model with HIS transformations.

5.5 Discussion

Results from this study show that, on average, mobile phone owners have significantly higher agricultural net revenues, yields and production efficiency scores in rural Bangladesh, but households the difference is larger for the subpopulation of female-headed households than for the entire population. This finding is different to findings from other studies in other low- and middle-income countries that have found that males typically realise higher net gains from mobile phone use than females in rural agricultural areas (Owusu et al., 2018; Sekabira and Qaim, 2017a). This finding supports increasing calls to bridge the gender gap in access to mobile phone technology and its application in agricultural production in rural areas of low- and middle-income countries (Abraham, 2018; Anyoha et al., 2018; Koh et al., 2018; Owusu et al., 2017; Sun, 2018).

Based on our findings, policies for addressing the prevailing gender gap in access to and application of information and communication technology in agricultural production (termed, *digital inclusion*) have potential to improve social welfare outcomes in rural areas of low- and middle-income countries. One way to facilitate digital inclusion may be through incentivising productive applications of mobile phone based agricultural information and technology through adult female literacy programs (Aker and Ksoll, 2016) and mobile phone voucher programs targeted at the female-headed households. Coupling this policy with implementation of complementary policies to subsidise mobile phone based digital agricultural-extension services can further improve agricultural production, production technical efficiency and net revenues.

This study contributes to literature on quantitative empirical evaluation of the impact of using information communication technologies on rural livelihoods and well-being in low- and middle-income countries (e.g. Lwoga and Sangenda, 2019). In addition to improving agricultural outcomes, mobile use in rural areas of low- and middle-income countries has also been linked with other social welfare outcomes, including food and nutrition security (e.g. Parlasca et al., 2019), gender equality (e.g. Sekabira and Qaim, 2017) and poverty alleviation (e.g. Sife et al., 2010)

One limitation of this study is that we focused mainly on the influence of basic mobile phones in agricultural production because only 18% of households in rural Bangladesh owned mobile phones with smartphone technology in 2015 (LIRNEasia, 2018). However, the advent of affordable mobile phones with smartphone technology in India and China offers great scope for broader application of mobile phone-based technology in agricultural production. Future research studies should investigate the influence of adoption and application of mobile phones with smartphone technology in agricultural production on agricultural production, production technical efficiency, and incomes.

5.6 Conclusion

This study evaluated the influence of mobile phone ownership on rural households' agricultural production and income in Bangladesh. Our results show that mobile phone technology can significantly improve agricultural net revenues, yields and production technical efficiency. The highest returns to policy investments in the area of mobile phone adoption in rural areas of low- and middle-income countries can be realised through addressing gender disparities in mobile phone adoption. Comprehensive and rigorous quantitative evaluations of the influence of information communication technologies on social welfare outcomes in rural areas of low- and middle-income countries can furnish governments, and aid agencies with useful information for basing effective rural development policies. Rural development agencies can harness consistent upward trends in mobile phone adoption rates and the influx of affordable smartphones, including in rural areas of low- and middle-income countries, by implementing policies that can facilitate and incentivise productive application of mobile phone technology in rural agricultural enterprises.

Chapter 6 Conclusions and policy implications

This thesis describes quantitative evaluations of four disparate rural development investments in the world's poorest regions of South Asia and Africa. This chapter provides a summary of the thesis, presents key findings, and makes a series of policy suggestions. In the final section, a discussion of key limitations of this study and directions for future research is provided.

6.1 Summary of background context and research questions

A consistent increase in the amount of foreign aid disbursements has been directed at funding rural development, yet the actual impact of rural development initiatives on social welfare outcomes among the world's poorest subpopulations remains poorly understood. Two main areas have previously been identified for improvement: 1) high quality evaluations of rural development initiatives to recommend policies that can support effective investments are needed (Qaim, 2010; Qaim and Kouser, 2013); and 2) rural development interventions must be tailored to consider household characteristics and gender dynamics (Curry et al., 2016; Ryan et al., 2017). The objective of this thesis was to: 1) utilise quantitative methods to evaluate the effectiveness of a broad range of rural development investments, including water and energy infrastructure schemes, information communication technological innovations, and microcredit programs; and 2) identify targeted and tailored supporting policies to enhance the effectiveness of investments considering heterogeneous household characteristics and gender dimensions.

Four case studies involving distinct rural development interventions across two spatially and culturally disparate contexts in the world's poorest regions of South-East Asia and Africa were evaluated. Specifically, economic estimation approaches were applied to: 1) compare between regional- and community-scale rural development programs; 2) analyse the importance of considering inadvertent outcomes of rural development aid programs (e.g. unintended impacts on households' education investment decisions), 3) compare between complementary multi-objective program designs and single-objective programs; and 4) assess the difference between targeted and universal rural development interventions.

In what follows, a summary of overall thesis findings is provided, policy suggestions and implications are discussed, key contributions to the body of literature on evaluation of rural development programs are described, thesis limitations are outlined, recommendations for future research opportunities are provided, and overall conclusions are drawn.

6.2 Main findings

The overall thesis finding common to all four evaluation studies is that targeted packages of complementary rural development interventions tailored to consider differences in household characteristics are more effective than universal single objective initiatives that do not explicitly consider the importance of various socio-economic factors (e.g. gender of head of household). In what follows, the main findings from each of the four case study evaluations, described in detail in Chapters 2, 3, 4 and 5, are discussed.

The first case study in Chapter 2 utilised a stochastic benefit-cost analysis to estimate the net benefit of a proposed multimillion-dollar centralised large-scale irrigation scheme covering 548,916 hectares of agricultural land in Lao PDR between 2009 and 2030. The large-scale irrigation scheme was compared with an alternative investment in decentralised smaller farm-scale pump-based irrigation schemes that would service an equivalent of the targeted total effective irrigated area. Overall, small-scale irrigation schemes performed better than large-scale investments with a higher expected net benefit value, a higher benefit-cost ratio, lower environmental costs, and higher head count poverty reduction rates. Further, the study found that large-scale irrigation investments are likely to suffer from low utilisation rates, in particular, under user-pays cost-sharing arrangements. Consequently, rural communities may not take full ownership and responsibility of maintaining large-scale investments, which can ultimately result in stranded infrastructural assets (Bos and Gupta, 2019; Lenz et al., 2017). Additionally, farm-scale irrigation investments offer the flexibility to target and prioritise poorest beneficiary rural communities and households when accompanied by targeted and tailored support policies to deliver on multiple social welfare outcomes, including increased net agricultural production, head-count poverty reduction, and reducing gender inequality. Another finding from this study is the opportunity cost of proposed investments, namely that alternative investments were made in road construction, electricity and education in Lao PDR; this could improve opportunities for higher-paying off-farm employment which would be more effective in reducing head-count poverty than large-scale irrigation schemes.

The second evaluation study in Chapter 3 employed quasi-experimental econometric techniques to evaluate the inadvertent causal impact of microcredit participation and incomes on households' educational investment decisions based on a 2010 Bangladesh Census dataset that surveyed 60,903 people in 12,240 households. The motivation for this study was to understand the possible unintended secondary impacts of microcredit initiatives besides the primary objectives of reducing poverty and improving gender inequality. Specifically, this study assessed the causal influence of microcredit participation and increasing microcredit on the probability of children's school enrolment, distinguishing between boys and girls, and between younger and older siblings. A key finding from this study was that the impact of microcredit on households' educational investments depended on the gender and age of the child. Specifically, microcredit participation did not significantly influence the likelihood of school enrolment for boys, but it increased girls' enrolment. Additionally, microcredit income had a stronger positive influence on girls' and younger siblings' enrolment than on boys' and older siblings' enrolment. Further, this study revealed that commonly omitted geospatial control variables and inadequate treatment of endogeneity in econometric evaluations may bias estimates of the influence of microcredit on household education investments.

The third case study in Chapter 4 applied stochastic benefit-cost valuation methods to estimate the net benefit of a proposed initiative to integrate the distribution of climate change adaptation and mitigation technological innovations to existing livestock donation programs per household in Rwanda in 2018. Specifically, this study evaluated the net benefit to beneficiary households under a national livestock donation program that has been operational since 2006 with the primary objective of improving food and nutrition security in rural areas. Whilst the program has reported significant benefits since its inception, prohibitive livestock-husbandry costs imposed on beneficiary households can erode the program benefits, including high costs of veterinary services, water, feed, and artificial insemination. Results from the evaluation of the current program were compared with estimates of the net benefit of incorporating a complementary package that includes climate-smart cowsheds and biogas production plants to the distribution of livestock. The study showed that incorporating a complementary package that includes climate-smart cowsheds and biogas production plants to the distribution of livestock could realise a higher program benefit-cost ratio. One key study finding was that harnessing broader economic, environmental, social and health benefits from livestock donation programs through installation of climate-smart technological innovations could generate positive economic, environmental, and health benefits. Specifically, use of biogas in rural households, a cleaner source of energy than traditional fuelwood, could reduce deforestation, GHG emissions and the risk of respiratory infections in particular among women and children who are traditionally charged with cooking duties.

The fourth case study in Chapter 5 utilised empirical econometric estimation methodologies to evaluate the causal impact of addressing the gender digital gap on social welfare outcomes based on repeat national surveys of 6,500 rural households in Bangladesh between 2012 and 2015. Particularly, an evaluation of the causal influence of mobile phone ownership on various rural households' economic welfare outcomes, including income and productivity, was carried out considering differences in the gender of the head of household. This study was motivated by the fact that mobile phones have been the most widely adopted and rapidly evolving information communication technological innovation, including in rural areas of developing countries where there is potential to harness productive use of mobile phone based technological innovations to improve social welfare outcomes among the world's poorest subpopulations. Key findings showed that mobile phone ownership can significantly improve economic welfare outcomes among rural households with the highest benefits expected from: 1) addressing gender disparities in mobile phone adoption and use; 2) applying mobile phone technology to the dissemination of digital agricultural extension information; and 3) prioritising agricultural regions that do not have access to off-farm employment opportunities.

6.3 Policy implications

This thesis provides four main policy implications from key findings of the case studies, namely:

1. Policies that encourage investments in small-scale rural development programs may be more beneficial than large-scale regional interventions.
2. Policies that facilitate adequate consideration of foreseeable inadvertent impacts (i.e. unintended impacts in other sectors besides the primary sector of interest) may improve the overall effectiveness of rural development aid programs.
3. Policies that encourage complementary multi-objective rural development program designs may enhance program effectiveness.
4. Policies that support targeted and tailored rural development interventions may have the ability to improve program effectiveness.

The main policy implications from each of the four evaluated case studies are discussed next in the context of broader findings from evaluation literature.

6.3.1 Small-scale programs may be the most effective

The main policy recommendation from the first case study was that Lao PDR, and other countries in similar contexts, seemed to benefit more substantially from policies that encourage investments in farm-scale pump irrigation over large-scale irrigation. Some evaluation studies have reported results that support the implementation of policies that incentivise small community- or household-scale infrastructure investments over large-scale regional infrastructure investments citing prohibitive connection fees and user-tariffs typically associated with large-scale investments as the main cause for low utilisation rates among the poorest households (Lenz et al., 2017). Further, rural development investments that consist solely of technological or infrastructure investments without being accompanied by supporting complementary policies interventions may be ineffective (Lenz et al., 2017; Qaim, 2010; Qaim and Kouser, 2013).

6.3.2 Need for consideration of inadvertent consequences

A key policy implication from the second case study was that microcredit initiatives may have broader secondary social welfare outcomes across multiple other sectors, such as the education sector, that ought to be considered besides the primary poverty-alleviation and gender-equality objectives. Policies that encourage rural development initiatives that demonstrate adequate consideration of broad social welfare outcomes across multiple sectors beyond the primary objective of the program are thus recommended. Specifically, the study found that microcredit could influence substitution effects in households' educational investments may favour girls and younger siblings in the absence of appropriate mitigating policies. Microcredit initiatives may thus need to be accompanied by policies that are tailored in favour of boys and older siblings, such as conditional education cash-transfers, to mitigate the impact of inadvertent adverse incentives that can result in age and gender disparities in children's educational attainment. Further, microcredit initiatives may also need to account for the amount of loan incomes accessed by the poorest rural households, in addition to increasing microcredit participation to avoid inadvertent facilitation of gender preferences in households' child-education choices.

6.3.3 Need for complementary multi-objective program designs

The design of rural development policies may result in perverse incentives and undesirable social welfare outcomes that could erode expected program net benefits (Curry et al., 2016; Gibson, 2015; Ryan et al., 2017). Gibson (2015), for example, found that use of poorly targeted conditional cash transfers to incentivise household education investments in Latin America in the early 2000s resulted in distorting households' work choices thereby reducing the net gains from the intervention. Rural development policies should consider promoting complementary multi-objective programs over single-objective programs to mitigate unintended undesirable social welfare outcomes.

6.3.4 Targeted and tailored program designs may be the most effective

The main policy implication from the third case study also advocates exploration of various policies that can facilitate effective cost-sharing arrangements between government, aid agencies and rural households to enhance the likelihood of beneficial adoption of climate-smart technological innovations. Particularly, consideration of incentive-based policies that can support favourable cost-sharing arrangements, such as subsidies and conditional cash transfers, could mitigate impediments to adoption of production technological innovations. Further, flexible policy arrangements to recover program costs, including interest-free instalment-payment plans for beneficiary households may perform better at enhancing adoption than inflexible user-pay arrangements. Similarly, the fourth case study suggested that targeted incentive policies for enhancing mobile phone application in the provision of extension agricultural services prioritising regions that do not have access to off-farm employment opportunities and poor households headed by a female may yield large social welfare gain.

Other studies have also found that packages of rural development policy interventions that are targeted and tailored to prioritise and address unique characteristics of the poorest households seem to be the most effective at improving social welfare outcomes and alleviating poverty (Paris and Rola-Rubzen, 2019; Ryan et al., 2017). Specifically, targeted policies that facilitate the reallocation of scarce rural development funds considering differences in the structure of the household, including the gender of the household head, number of dependents, and the distribution of gender and age of children, may deliver superior social welfare outcomes.

6.4 Literature and methodological contribution

Development economists have often questioned the lack of comprehensive and rigorous quantitative rural development evaluations and the allocation of scarce rural development financial resources (Banerjee and Duflo, 2011; IFAD, 2019; Masset et al., 2012). This thesis contributes to the evaluation literature by providing some additional case study evidence in two spatially and culturally disparate contexts in the world’s poorest regions, using a variety of quantitative methods that take household characteristics, location and gender dynamics into account. In what follows, a description of how the four thesis case studies contributed to the evaluation literature is provided.

A key contribution from these studies was the demonstration of quantitative treatment of uncertainty due to factors such as heterogeneous beneficiary household characteristics; lack of reliable primary data; issues with choosing costs and benefits to include in the evaluation; and parameter values to use in net benefit calculations. The first and third case studies described how stochastic BCA techniques were applied to evaluate the net social benefit of current and proposed rural development programs. These case studies illustrate an approach for carrying out a transparent BCA of rural development initiatives in the absence of primary data by specifying value ranges for uncertain parameters based on secondary information from a review of similar peer-reviewed evaluation studies and through probabilistic treatment of multiple uncertainties.

Further, studies on the impact of community-level interventions in rural areas of low- and medium-income countries rely on community-level survey data. Poor infrastructure and remoteness often make data collection in regional, rural and remote areas of low- and medium-income countries prohibitively expensive. To address this impediment, statistics agencies typically employ multi-stage clustered sampling procedures involving selection of Primary Sampling Units (PSUs) and stratification. Households within the same PSU are typically correlated because households in nearby locations (e.g. villages) in most low- and medium-income countries share similar unobserved factors. As such, observations within a cluster (e.g. PSU) are usually similar and observations from different clusters are typically different (Gibson, 2019). There is a challenge with addressing spatial correlations between sampled households because few surveys collect high spatial resolution spatial data on household locations with the exception of Gibson (2011). As such, complex survey design features, including sample weights, clustering and stratification, should be considered to control for the effects of unobserved correlated neighbourhood variables. Specifying survey design characteristics also enables drawing inferences about both the sample and the population.

In addition, a lack of primary data and transparency with the process of treating uncertain parameters and parameter values in BCAs of rural development programs has been noted in the evaluation literature (Farrow, 2013; McClintock and Griffith, 2010; Molle, 2008). One of the main challenges in the evaluation of prospective rural development interventions is that proposed investments are inherently characterised by uncertainty because they typically involve long economic lives (Hurley et al., 2014; PC, 2010). Another barrier to conducting rigorous quantitative evaluations is the lack of detailed primary data on important parameters that influence social welfare outcome variables of interest (WB, 2010). Adequate treatment of uncertainty thus contributes to the estimation of robust BCA results that can provide substantive confidence and reliable information to underpin the process of designing effective rural development policies in the absence of reliable primary data.

Another contribution to the BCA evaluation literature made by the two case studies (see Chapters 2 and 4) was the employment of systematic sensitivity analysis involving Monte Carlo simulation to quantify the sensitivity of program net benefit estimates to uncertainties in parameter values. The most common treatment of uncertainty in parameter values employed in the BCA evaluation literature involves deterministic adjustment of a select few parameter values based on subjective judgement on a finite set of plausible future scenarios (Almansa and Martínez-Paz, 2011). Several studies have acknowledged that this approach does not exhaustively quantify the sensitivity of BCA outcomes to uncertain parameter values (Gentilello et al., 2005; Nichol et al., 2003; Salling and Leleur, 2011).

These two BCA evaluation case studies illustrated an approach that utilised Monte Carlo simulation to quantify the relative contribution of each parameter to variability in net benefit estimates. Specifically, the sensitivity of net benefit estimates to variability in parameter values was quantified by systematically varying each variable parameter, in turn, within its range of probable values while holding all other uncertain parameters at their median values. Adequate treatment of uncertainty can help with producing robust results and decisive conclusions from BCA evaluations, thereby providing confidence in reliable BCA results as a basis for informing effective rural development policies.

The second case study and fourth study described how household-level empirical econometric analyses were applied to evaluate the impact of current and proposed rural development initiatives on various social welfare outcomes taking heterogeneous household characteristics into account. Since the 1980s, review studies on observational research methods have showed that econometric modelling results can be sensitive to non-systematic specification and omitted-variable bias which can result in reduced confidence in evaluation results (David, 1980; Leamer, 1983). On the other hand, use of a large set of covariates can introduce high likelihood of multicollinearity due to inclusion of highly correlated confounding covariates that may not necessarily improve the explanatory power of a regression model. Traditional non-systematic treatment of econometric model uncertainty typically involving a series of ad hoc robustness testing exercises as a basis for including or dropping some controls from the baseline model has been widely criticised in the evaluation literature (Bruns and Ioannidis, 2016; Young and Karr, 2011). The two econometric case studies contributed to the evaluation literature by demonstrating how model-selection and omitted variable bias can be reduced by controlling for the largest set of socio-economic and geospatial characteristics based on the reported sets of controls used in the reviewed evaluation literature. Further, these studies illustrated the process of specifying parsimonious econometric models based on a systematic process for selecting model covariates that would most efficiently predict the social welfare outcomes of interest. Specifically, the influence of choice of estimation models and control variables used on evaluation results were exhaustively modelled by utilising machine learning operations based on a systematic process of testing all possible combinations of control variables used. Additionally, the two studies tested the sensitivity of results to the choice of the estimation model and covariates used in predictions of the causal influence of rural development initiatives on various social welfare outcomes.

The systematic comprehensive approach for treating model uncertainty demonstrated in the abovementioned econometric evaluation studies improves on commonly applied methods that typically involve a series of ad hoc robustness testing exercises as the basis for including or dropping control variables (Ioannidis, 2008). The contention from the two econometric evaluation case studies is that econometric evaluations on the causal influence of rural development interventions on social welfare outcomes that can demonstrate adequate consideration of a comprehensive set of control variables and robustness of results to the choice of model and covariates provide a strong basis for designing effective rural development policies.

6.5 Study limitations

One key challenge faced in carrying out BCA evaluations of rural development programs was a lack of primary and secondary data. The lack of data limited the set of costs and benefits that were quantified for inclusion in calculations of net benefit values. A comprehensive dataset would have enabled a more comprehensive quantification of the opportunity of rural development interventions and a broader set of expected environmental and social costs and benefits. Assessment of broader opportunity costs and environmental and social costs and benefits would further enrich the information base for designing effective rural development policies. However, inclusion of opportunity costs of alternative proposed investments would likely not change relative net return estimates in the two BCA case studies because the opportunity costs of all investments would have to be included and would therefore likely offset each other. Further, it was shown in both BCA evaluations that key conclusions from net benefit estimates were not likely to change by including more environmental and social benefits and inclusion of omitted benefits would further reinforce key findings.

Across all four case studies, the effect of various cost-sharing arrangements between government and aid agencies and households was discussed qualitatively, but was not quantified. Additionally, expected changes in the impact of proposed rural development investments under alternative futures reflecting projections on the expected rates of technological advancements and diffusion were only discussed qualitatively in this study. Further, this thesis did not explicitly make a distinction between different types of uses of proposed technological innovations, such as productive and consumptive uses, and among different types of productive uses due to lack of observational data.

In addition, correlations between neighbouring household choices and the effect of interaction between households in close proximity were not explicitly considered due to data limitations, because the datasets used did not provide exact household locations. However, peer-reviewed econometric modelling techniques were utilised to reduce bias due to omitted unobserved spatial correlations in the two empirical econometric case studies, including village-level control variables and household fixed effects estimation.

Further, use of a relatively old cross-sectional dataset in the second evaluation study (see Chapter 3) in the absence of the 2015 BIHS dataset, the most recent dataset, limited the scope of causal econometric inference methods that could be employed to provide a stronger and more robust basis for establishing the causal influence of microcredit on educational outcomes.

6.6 Future research opportunities

There are several opportunities for future research to build on methods, findings and gaps from this thesis. One opportunity for future research identified from the application of BCA to evaluate rural development intervention is the evaluation of net benefits under alternative means-tested cost-sharing arrangements between households, governments and development agencies. Future BCA studies can also build on this thesis by using market and non-market valuation methods to quantify broader social, environmental and health costs, and benefits of existing and proposed rural development initiatives. Further, quantification of the opportunity cost of current and proposed rural development investments would provide a stronger basis for informing effective rural development policies. For example, the opportunity cost of a household's choice not to adopt proposed technological innovations that can substitute time-intensive production methods can be estimated as the value of foregone utility from the additional spare time that could be allocated to alternative activities based on local minimum wage values.

Another opportunity for future studies of rural development interventions is to build on the BCA methods presented in this thesis by explicitly considering expected changes in the impact under alternative futures reflecting projections in the expected rates of technological advancements and technological diffusion. Future studies could utilise computable general equilibrium models to estimate the impact of rural development investment options on regional economies, including multiplier effects on regional economies and broader cross-sectoral benefits, to provide a stronger basis for informing effective rural development policies. Further, future evaluation studies could extend this study by explicitly distinguishing between various expected consumptive and productive uses of proposed technological innovations for improving rural social welfare outcomes.

There is also an opportunity for future econometric evaluation studies to extend the application of methods presented in this thesis by utilising spatial correlation econometric models to quantify the influence of correlated household choices with nearby households to inform effective policies that consider intra- and inter-household dynamics. Future studies could use an updated panel dataset comprising repeated household surveys in HIES 2010 and 2015 to build on the evaluation of the causal influence of microcredit on educational outcomes and thus provide further policy insights.

6.7 Overall conclusion

This thesis presented four case study evaluations of various distinct rural development interventions across two spatially and culturally disparate contexts in the world's poorest regions of South-East Asia and Africa. Overall, we suggest four potential findings from all of these evaluation case studies. First, effective rural development investments and policies should consider impacts on a broad set of cross-sectoral rural social welfare outcomes. Second, targeted and tailored policy interventions that consider heterogeneous household characteristics and gender dynamics may perform better than universal interventions. Third, community-scale rural development programs may perform better than large-scale regional rural development schemes. Fourth, complementary multi-objective policy packages that make provisions for foreseeable inadvertent adverse impacts of rural development interventions may perform better than single-objective intervention. Given growing calls to restructure foreign aid administration from large bilateral flows of foreign aid transfers to modest aid flows targeting rural development programs, this thesis provides some insights for improved social welfare of households South-east Asia and Africa.

Appendix A Supplementary material for Chapter 2

A detailed description of how multiple retrospective studies were synthesised to obtain value ranges for each of key input parameters for each of the three component models in the order in which they feature in Table 2.1 follows.

A.1 Irrigation net return model parameters

Key parameters that determine the expected irrigation net returns typically include planned irrigation area, base year rice yield, expected growth rate in rice yields, base year rice price, expected rate of growth of rice price, base year production cost, and the expected rate of growth of production cost Table 2.1 follows

As discussion of how the value ranges for each of these parameters was estimated follows.

Planned_area

Best current estimates state there are currently 166,000 hectares of irrigation in Lao, PDR (MRC, 2009). Bartlett et al. (2012) reported that the Lao government proposed a strategy to increase the size of irrigated area in the Nam Ngum Basin by more than 100 000 hectares between 2012 and 2030, or 5556 hectares per year over 20 years, to raise food production mostly through expansion of rice production. The Lower Mekong Basin Development Plan (MRC, 2009) proposed a more ambitious target to increase irrigated cropping area in Lao, PDR by between 284 820 hectares and 548 916 hectares by 2030 representing a median value of 416 868 hectares, or 12 543 hectares per year over the 20-year period. We estimate the annual rate of expansion at 9049 hectares by calculating the average between the conservative estimate of 5556 hectares (Bartlett et al., 2012) and the optimistic estimate of 12 543 hectares (MRC, 2009).

Land_utilisation

Evidence shows that the total land area targeted for new irrigation development is typically greater than the total land area actually utilised for irrigated agricultural production observed are often less than standard levels planned for in most irrigation feasibility studies in the Mekong Region (de Walle and Gunewardena, 2001; Molle, 2008). This is because most irrigation schemes are designed such that capital costs for setting up water delivery infrastructure from dams to farms are incurred by foreign aid agencies and O&M costs are in principle recovered by charging participation fees to irrigators (Molle, 2008). In practice however, participation fees are beyond the means of most irrigators and only a fraction of eligible farmers equipped with irrigation water delivery infrastructure participate in irrigation schemes (de Walle and Gunewardena, 2001). Most schemes are therefore not economically viable largely due to the fact that stranded infrastructure and poor maintenance effectively reduce the area to which water is efficiently delivered. Further, the ADB (2005) observed that past Lao PDR irrigation development project feasibility studies typically set optimistic cropping intensity targets much higher than observed in practice.

The parameter *Land_utilisation* represents land utilisation rate described as the ratio of the area that is actually irrigated to planned irrigation expansion area adjusting for observed participation rates and cropping intensities. The study by ADB (2005) observed that feasibility studies for most irrigation development projects in the Lao PDR assumed irrigated land utilisation rates of between 100 and 130% of irrigation command area. In practice however, lower dry season cropping intensities were observed between 41% and 55%. Consistent with this estimate, the Lao Government (2008) revealed estimates for land utilisation rates between 49% and 58% giving an overall range for land utilisation rates at between 41% and 58%. We used a broader range of land utilisation rate estimated at between 40% and 80% to encompass land area utilisation rates from the low-end of historical data to optimistic future utilisation rates higher than currently observed whilst correcting for the optimism bias observed in most irrigation development project plans.

Base_year_rice_yield

MRC (2009) estimated average dry season rice yields in Lao PDR at 3.8 tonnes per hectare. ADBI (2008) estimated commercial irrigated rice yields at between 2.6 and 3.3 tonnes per hectare for non-contract and contract rice production respectively. SiliPhouthone et al. (2012) reported average dry season rice yields at 3.0 tonnes per hectare and Lao Government (2008) estimated average irrigated rice yields as ranging between 2.7 and 4.0 tonnes per hectare for gravity and pump-lift irrigation respectively. We used the overall range of values for the irrigated rice yields estimated in the cited studies between 2.6 and 4.0 tonnes per hectare.

Yield_growth_rate

MRC (2009) projected the rate of growth of rice yields at 3.0% from 2010 to 2030 whilst Yu and Fan (2009) estimated a growth rate of 2.0% between 2000 and 2008 assuming linear growth. This translates to an overall range of between 2.0% and 3.0% yield growth rate assuming a simple annual growth rate, or between 1.6% and 2.4% assuming a compound annual growth rate. We assume compound growth rates in this analysis.

Base_price

MRC (2009) estimated the average price of rice in Lao PDR at between USD0.21/kg for ‘normal’ rice and USD0.28/kg for ‘high-quality’ rice. This is roughly consistent with SiliPhouthone et al. (2012) who estimated the average price of rice at USD0.27/kg and ADBI (2008) at between USD0.19/kg and USD0.22/kg. The overall range of rice price values can be derived from these values as ranging from USD0.19/kg to USD0.28/kg. FAO (2013) reported historical trends in international prices for rice from 1996 to 2012 averaging between USD0.46/kg and USD0.60/kg from 1996 to 2007 before the global food price hike, then spiking to up to USD1.10/kg in 2008 and dropping again to USD0.62/kg between 2009 and 2012 with further decline in prices expected after 2012. Part of the difference between relatively lower locally reported prices and the higher prices reported by FAO (2013) can be explained by a mark-up in price along the supply chain with FAO (2013) likely reporting prices observed further along the supply chain than local farm gate prices. We used a wide, but conservative range representing generally lower farm gate price between USD0.15/kg and USD0.62/kg to accommodate high variations in domestic and international rice prices (FAO, 2013) and price variation across glutinous and non-glutinous rice varieties both of which are produced in Lao, PDR (ADBI, 2008). The median price assumption USD0.39 is higher than some local farm gate estimates but less than very high recorded prices further along the supply chain at the global level and for non-glutinous rices varieties.

Price_growth_rate

IFPRI (2001) considered optimistic and pessimistic global scenarios for food supply, demand, trade and security and made projections on the expected rate of growth or decline in the price of rice from 2001 to 2020. Key factors considered in describing the two scenarios included population growth rates, the likelihood of a technological evolution in the time horizon considered, expected rate of environmental degradation, irrigation growth, and projected changes in trade policies. IFPRI (2001) projected that annual rice prices would decline by 44% under an optimistic scenario where increases in supply outstrip growth in demand. Rice prices were projected to grow by 45% under the pessimistic scenario where demand was projected to increase and supply decrease over the same period. Using these estimates, compound annual price growth rates were calculated as ranging between -1.5% and 1.5%.

Base_cost

The average production cost for irrigated rice in Lao PDR was estimated at USD608/ha by MRC (2009) and at USD650/ha by SiliPhouthone et al. (2012) thus a range of production costs from USD608/ha to USD650/ha was used in this analysis. This cost aggregates a wide range of farm input costs including seeds, fertiliser, herbicides, and insecticides, and a wide range of farm labour costs including land preparation, nursery planting and pulling, transplanting, weeding, harvesting, irrigation and fertiliser application, and cost of farm machinery including harvesters and threshers (SiliPhouthone et al., 2012).

Cost_growth_rate

MRC (2009) projected the average growth rate of production cost, *Cost_growth_rate*, at between USD607 and USD746 per year based on expected growth rates in the cost of material inputs, labour, and mechanization between 2010 and 2030. The annual cost growth rate can be calculated using these estimates at 1.0% assuming compound annual growth or 1.3% assuming simple annual. We used a range of compound growth rate values between 0.0% and 2.0% with a median value of 1.0% was used in this analysis.

A.2 Irrigation capital and O&M cost model

Estimates for the expected cost of setting up, operating and maintaining new irrigation infrastructure investments depends on irrigation infrastructure capital set-up costs, O&M costs, and assumptions about the rate of land utilisation. Next we discuss how the value ranges for each of these parameters were estimated. Note that the process of estimating the value for the rate of land utilisation, *Land_utilisation*, was discussed in the previous section where we described key parameter inputs into the irrigation net returns model.

Capex

Capital set-up costs for large-scale irrigation investments typically include capital costs of infrastructure for storing, pumping, conveying, and delivering water from surface and/or groundwater sources to the farm gate. Capital set-up costs to expand irrigation based on an average unit cost of civil works were estimated by ADB (2005) at USD4707 and USD6049 and at between USD4672 and USD9345 by (UN, 2001). The overall range from the cited studies of USD4707 and USD9345 was used in this analysis.

OM

Operation and maintenance costs typically include energy costs and regular maintenance, replacements and repairs. ISMR (2002) estimated O&M costs at between USD210/Ha and USD514/Ha per year for a case study in the Mekong River Basin. We used these estimates in the absence of alternative data sets on O&M costs for irrigation expansion in Lao, PDR.

A.3 Cost of reductions in fish yields

Obstruction to upstream and downstream fish passage is considered one of the greatest threats of dam construction and the resultant impacts on fisheries is widely expected to be significant (Hecht and Lacombe, 2014; ICEM, 2010; Khoa et al., 2002; Minh, 2001; MRC, 2010). Qualitative studies have identified several hydrological factors that would affect natural fish migration patterns and consequently annual fish catches from the Mekong as a result of disruptions to natural flow regimes. These include but are not limited to flood level, duration, timing and regularity and changes in dry season discharge. Long-distance migratory fish species comprising 40% to 70% of the total fish catch in the Mekong basin would be impeded by dam construction (Hecht and Lacombe, 2014).

Key parameters determining the monetary value of the effect of irrigation on wetland-based fisheries include the expected level of decline in fish catch and the market price of fish. The values for these parameters were estimated in turn as follows.

Decline_in_catch

The impact of irrigation development on wetland based fisheries in Laos, *Decline_in_catch*, was estimated using results from two studies: ICL (2002) who estimated that reservoir construction on floodplain fish catches would cause a decline in fish catch of between 3.0% and 4.0%; and Kyophilavong (2008) who estimated that reducing the volume of water used for irrigation over a total dry season rice cultivation area of up to 598.4ha would lead to an increase in the annual value of aquaculture resources in Lao wetlands by up to USD48560. Kyophilavong (2008) assumed a price of USD1.5/kg thus an average annual fisheries productivity loss of 54kg per hectare irrigated can be calculated.

ICL (2002) estimated that a project designed to irrigate an area of 1021 hectares in Huay Thouat catchment, Lao PDR, would reduce flows to nearby downstream wetlands in Xe Champhone leading to a loss of 48 ha of temporary floodplain and reductions in fisheries yields. ICL (2002) assumed an average annual fisheries productivity loss of 130kg/ha irrigated. We used the overall range of possible values from the cited studies for Decline_in_catch estimated at between 54kh/ha and 130 kg /ha.

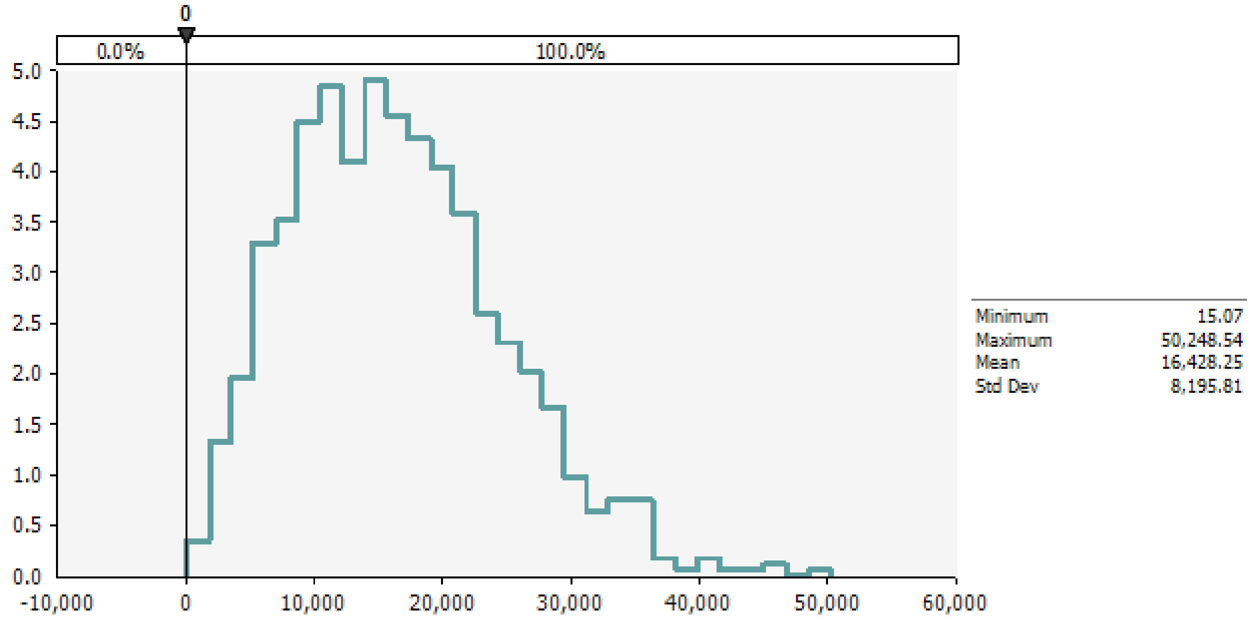
Fish_price

Estimates for the range of possible fish prices, *Fish_price* (USD/kg) were obtained from data reported by MRC (2002), Costanza et al. (2011) and Sumaila et al. (2007). MRC (2002) reported an average farm-gate price of USD1.38/kg for cultured fish and USD0.89/kg for captured fish in the Lower Mekong Basin while Costanza et al. (2011) reported fish prices ranging between USD0.84/kg and USD3.15/kg in Southeast Asia. Sumaila et al. (2007) observed that the price of fish in Southeast Asia is highly variable over time and across fish species from less than USD1.14/kg to more than USD4.56/kg. We used the overall range from the cited studies of between USD0.84/kg and USD4.56/kg.

A.4 Farm irrigation returns

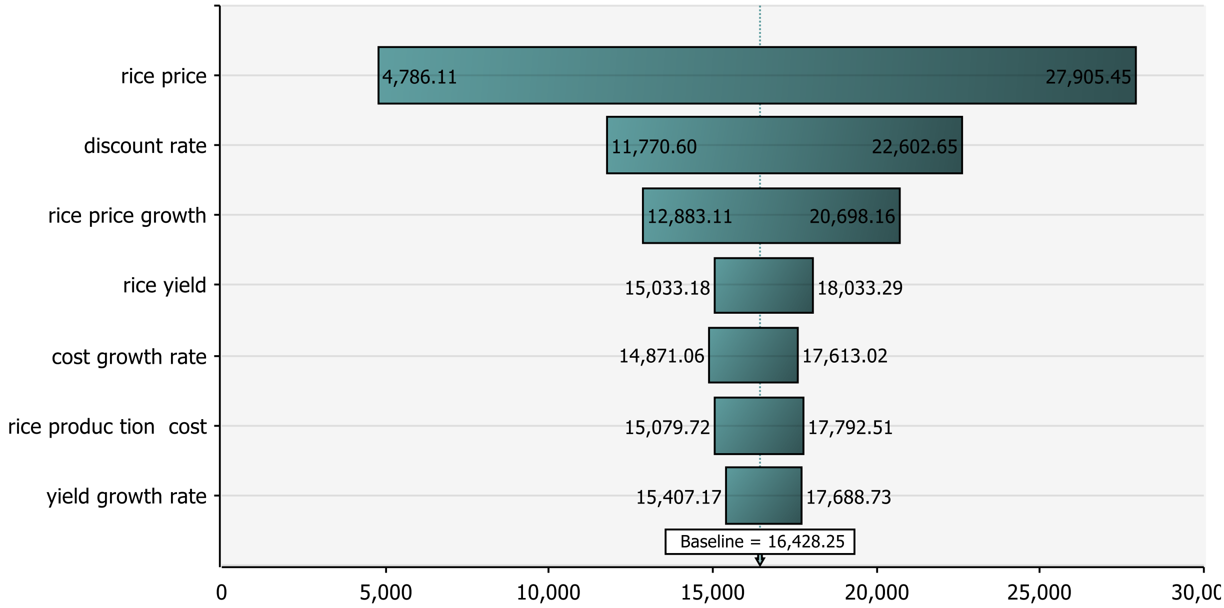
Estimates of on-farm production costs and returns depend on baseline yield, cost, price assumptions and expected escalation of these factors in real terms over the investment horizon considered. Figure A.1 in Appendix A shows our estimate of dry season irrigated rice return as a 30-year net present value. Figure A.2 in Appendix A is an evaluation of uncertain factors that contribute to variation in estimates of irrigation net returns. The figure shows that rice price futures most importantly influence future potential dry season rice net returns in Laos.

Figure A.1 Irrigated rice production net returns per hectare expressed as 30-year net present value



Source: Authors' design

Figure A.2 Irrigated rice production returns per hectare sensitivity analysis

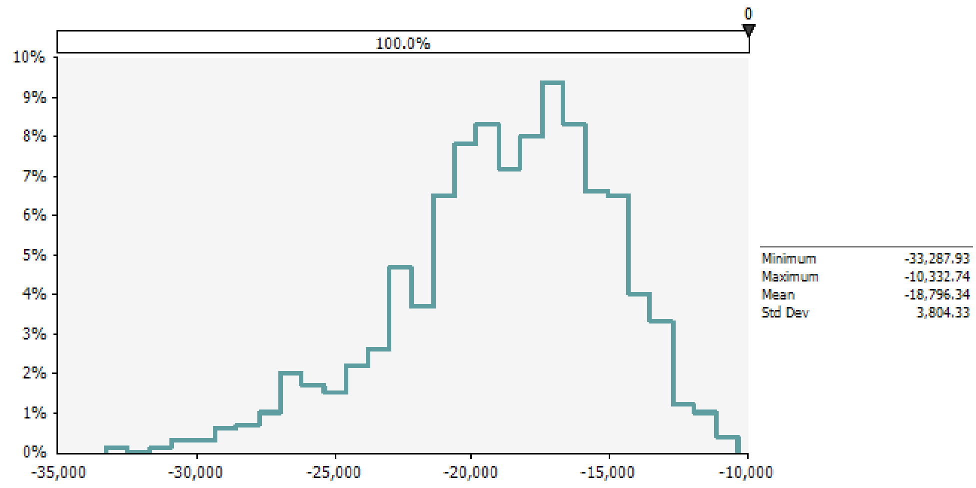


Source: Authors' design

A.5 Irrigation infrastructure cost

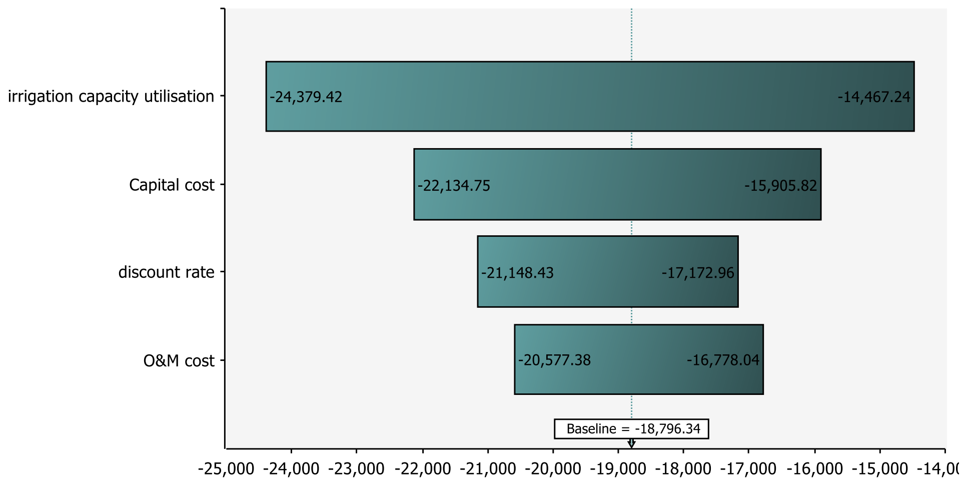
Estimates of capital and O&M costs of large-scale irrigation schemes were based on experience in Laos as well as in neighbouring countries with similar projects in the Mekong Basin. Historical ex-post project evaluation reports provided ranges of costs on a per hectare irrigation command area basis which were adjusted to 2014 prices. Estimating these costs on a per-hectare irrigated basis required accounting for typical past patterns of potential irrigation command area underutilisations. Figure A.3 in Appendix A shows our estimate of the likely range of cost per hectare command area actually utilised for capital plus thirty-year discounted O&M costs. Figure A.4 shows partial factor sensitivity analysis of this cost estimate. The analysis shows that capital and O&M costs of large-scale irrigation infrastructure are high relative to irrigation net returns from rice production and that this cost is particularly sensitive to utilisation rates. Low utilisation leads to high per hectare costs and small gross margins for irrigated rice production. Historically, low utilisation rates have been observed in contexts where farmers are charged a fee to irrigate. The fee is typically charged to recover O&M costs.

Figure A.3 Net present value of capital and O&M costs of large-scale irrigation schemes (USD/hectare)



Source: Authors' design

Figure A.4 Partial sensitivity analysis of net present value of capital and O&M costs over 30 years

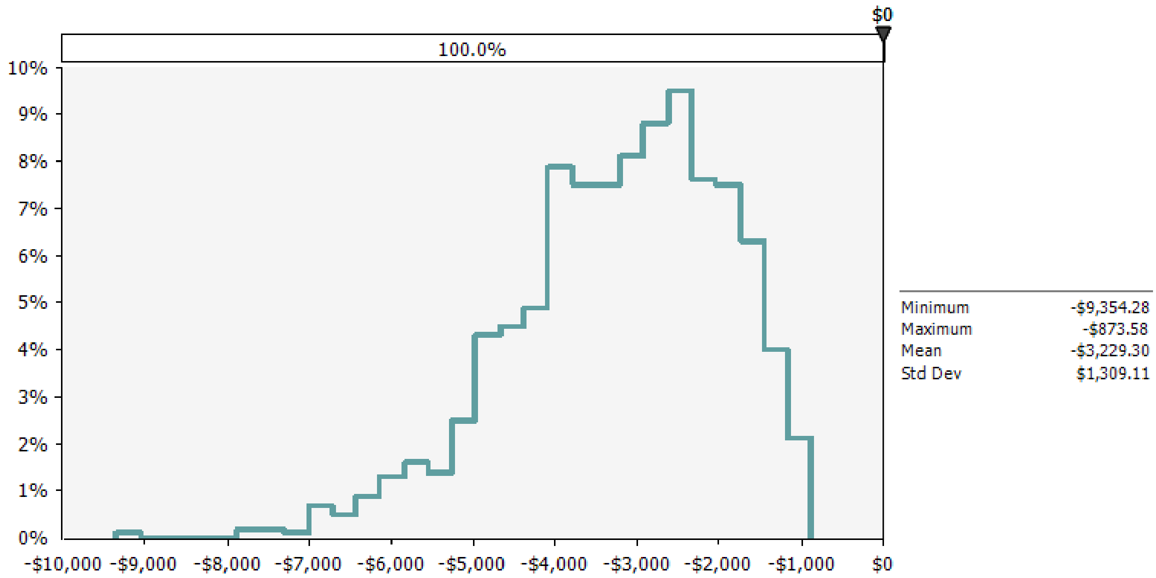


Source: Authors' design

A.6 Wetland fish and forage loss cost

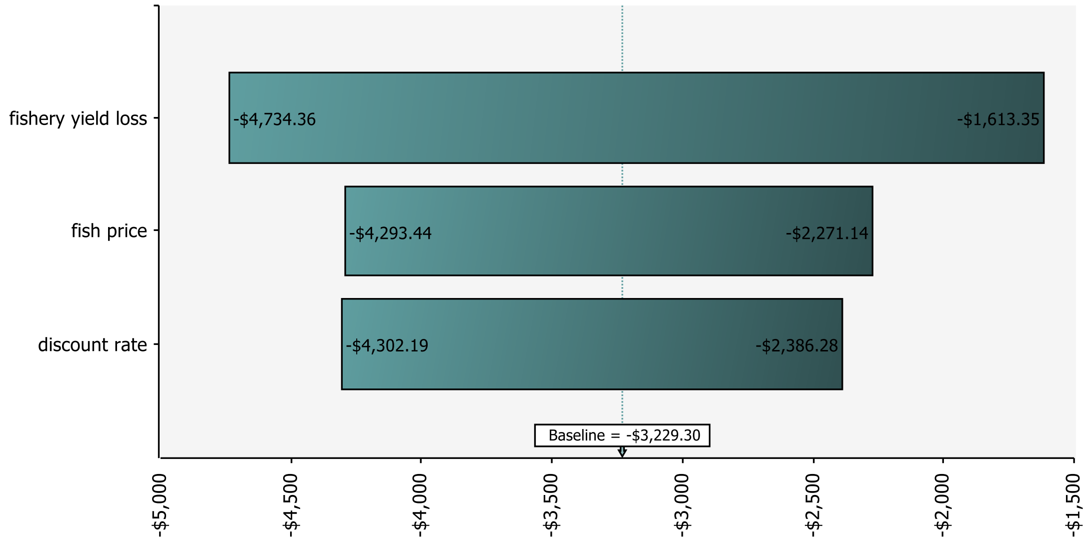
Irrigation can cause reduced inflows to wetlands which in turn can reduce wetland area. This can lead to a decline in yields from wetland fishing and forage efforts by household in the Nam Ngum Basin. A range of values for the cost of fish loss were estimated considering alternate fish prices (whole sale versus market prices). The estimated 30-year net present value of the cost of losses in fish and forage for every hectare of rice irrigated is shown in Figure A.5 in Appendix A. Figure A.6 in Appendix A shows results of partial factor sensitivity analysis of this cost estimate. The sensitivity analysis shows that costs associated with potential for loss of fish and forage livelihoods are particularly sensitivity to the uncertainly understood relationship between increased irrigation water diversion and reduced fish catch opportunity.

Figure A.5 The cost of losses in wetland fish and forage for every hectare of rice irrigated



Source: Authors' design

Figure A.6 Wetland fish and forage loss cost per hectare irrigated sensitivity analysis



Source: Authors' design

A.7 Results of correlation tests

Table A.1 Comparative statistical analysis of benefit-cost ratio model results under three correlation assumptions

Scenario description	mean	min	max	stdev
Large-scale irrigation investment				
No correlation	0.52	0.04	1.47	0.36
Weak correlation	0.53	0.04	1.50	0.38
Strong correlation	0.54	0.02	1.69	0.39
Small farm-scale pump irrigation investment				
No correlation	1.39	0.09	3.47	0.99
Weak correlation	1.41	0.07	3.68	1.12
Strong correlation	1.41	0.05	3.90	1.14

A.8Data used to analyse impacts of aid investments on economic returns and head-count poverty reductions

Table A.2 Benefit-cost ratio estimates (BCRs) and head-count poverty reductions (HCPR) for various countries, regions, and sectors after Fan et al. (2007)

Country/Region/Sector	BCR	HCPR	HCPR
Vietnam			
Northern uplands			
Irrigation	0.21	0.12	12.03
Roads	1.87	1.53	153.04
Education	0.95	0.66	65.60
Red River delta			
Irrigation	0.40	0.08	7.93
Roads	3.26	0.91	91.38
Education	2.08	0.49	49.40
Central north			
Irrigation	0.22	0.15	14.90
Roads	3.27	3.12	311.57
Education	1.01	0.81	81.28
Central coast			
Irrigation	0.21	0.13	12.99
Roads	2.44	2.16	215.58
Education	1.23	0.92	92.31
Highlands			
Irrigation	0.28	0.08	8.37
Roads	3.09	1.31	130.54
Education	1.97	0.70	70.14
Southeast			
Irrigation	1.33	0.28	27.85
Roads	3.30	0.99	98.64

Table A.2 Benefit-cost ratios (BCRs) and head-count poverty reductions (HCPR) for various countries, regions, and sectors after Fan et al. (2007) (continued)

Country/Region/Sector	BCR	HCPR	HCPR
Education	4.66	1.18	117.64
Mekong River delta			
Irrigation	0.37	0.06	5.68
Roads	3.40	0.74	74.14
Education	2.08	0.38	38.24
Thailand			
Northeast			
Irrigation	0.76	0.21	21.05
Roads	1.23	4.83	483.39
Education	1.26	0.35	34.74
Electricity	8.66	12.53	1,253.02
North			
Irrigation	1.11	0.05	5.22
Roads	1.23	0.83	82.71
Education	2.92	0.14	13.71
Electricity	8.04	1.99	198.57
Central			
Irrigation	0.55	0.02	1.74
Roads	0.44	0.19	19.48
Education	2.89	0.09	9.08
Electricity	2.59	0.43	42.79
South			
Irrigation	0.62	0.05	4.53
Roads	1.24	1.30	130.12
Education	2.51	0.19	18.53
Electricity	5.48	2.12	211.99
India			
Agricultural R&D	13.45	0.32	32.20
Irrigation	1.36	0.04	3.70
Roads	5.31	0.47	47.18
Education	1.39	0.16	15.63
Power	0.26	0.01	1.45
Soil & Water conservation	0.96	0.09	8.61
Health	0.84	0.10	9.72
Anti-poverty programs	1.09	0.07	6.78

Appendix B Supplementary material for Chapter 3

Table B.1 Summary review of studies on determinants of household education investment in developing countries (showing the weight of evidence by each variable)

Variable	Finding
Gender of household head	Male headed households have a higher enrolment rate than female-headed households (Ahiakpor and Swaray, 2015)
Gender of household head	Households with a large number of people enrol less children in school (Burney and Irfan, 1995; Deng et al., 2014; Guimbert et al., 2008)
Missing parent	Households with either no father or mother invest less in education than households with both parents (Glick and Sahn, 2000; Huisman and Smits, 2009; Tansel, 2002; Young, 2010)
Number of children	The higher the number of children in a household, the less likely a child is to be enrolled in school (Zimmerman, 2001)
Number of younger siblings	Children with a large number of younger siblings are less likely to be enrolled in school than children who do not have younger siblings (Connelly and Zheng, 2003; Glick and Sahn, 2000; Huisman and Smits, 2009; Lincove, 2015; Rosati and Rossi, 2003; Zeng et al., 2012)
Child's gender	Boys are more likely to be in school than girls (de Carvalho Filho, 2012; Grimm, 2011; Hazarika and Viren, 2013; Kabubo-Mariara and Mwabu, 2007)
Income and expenditure	Household with high income and expenditure levels spend more on education and spend more children to school than poor households (Bainbridge et al., 2005; Burney and Irfan, 1995; Deng et al., 2014; Grimm, 2011; Guimbert et al., 2008; Kurosaki et al., 2006; Song et al., 2006; Zhao and Glewwe, 2010)
Employment sector	Parents employed in agriculture invest more in education than in other sectors (Grimm, 2011; Huisman and Smits, 2009)
Self-employment	Households with a self-employed head invest less in education than those with the household head employed in the labour market (Guimbert et al., 2008; Tansel, 2002).
Parents' education	Parents’ education attainment positively influences a household's education investment (Ahiakpor and Swaray, 2015; Glick and Sahn, 2000; Kabubo-Mariara and Mwabu, 2007; Kurosaki et al., 2006; Rosati and Rossi, 2003)

Table B.1 Summary review of studies on determinants of household education investment in developing countries (showing the weight of evidence by each variable) (continued)

Variable	Finding
Parents' employment	Parents' employment status also has an effect on education investment (Bainbridge et al., 2005; Deng et al., 2014; Huisman and Smits, 2009)
Migrating parent	Households with a migrating parent spend more on education (Hu, 2012), but have lower likelihood of enrolment (Yang and Fan, 2012)
Housing characteristics	Households with big brick houses invest more in education than those in small houses made from traditional building materials (Hazarika and Viren, 2013; Kabubo-Mariara and Mwabu, 2007)
Ethnicity	Some ethnicities have higher school enrolment rates than others (Bainbridge et al., 2005; Connelly and Zheng, 2003; Glick and Sahn, 2000; Guimbert et al., 2008; Kurosaki et al., 2006)
Literacy	Literate communities invest more in children's education than illiterate communities (Burney and Irfan, 1995; Connelly and Zheng, 2003; Hazarika and Viren, 2013; Kurosaki et al., 2006)
Religion	Some religions invest more in children's education than others (Lincove, 2015)
Location	Rural communities invest less in education than urban communities (Connelly and Zheng, 2003; Huisman and Smits, 2009; Kabubo-Mariara and Mwabu, 2007; Rosati and Rossi, 2003; Tansel, 2002; Zimmerman, 2001)
Parents' expectations	Households that expect their children to do well in school, get a good job, and provide financial help in future are most likely to invest in education than households that do not have these expectations (Ahiakpor and Swaray, 2015; Zhao and Glewwe, 2010)
Distance to nearest school	The longer the distance to the nearest school the lower the likelihood of enrolment (Guimbert et al., 2008; Huisman and Smits, 2009; Kabubo-Mariara and Mwabu, 2007; Lincove, 2015; Zhao and Glewwe, 2010; Zimmerman, 2001)
Quality and quantity of teachers	High teacher-student ratio and teacher qualification and experience positively influence school enrolment rates (Guimbert et al., 2008; Huisman and Smits, 2009; Kabubo-Mariara and Mwabu, 2007; Zhao and Glewwe, 2010)
Quality of school infrastructure	Good quality school infrastructure positively influences household education investment (Guimbert et al., 2008; Zhao and Glewwe, 2010)

Table B.2 Full regression results for the influence of microcredit income on children's likelihood of school enrolment (with geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P>*z*	P>*z* (adjusted for Type I Error)
Age	-0.081	0.001	1.44	0.000	0.000
Girl	0.027	0.008	2.37	0.072	0.072
Non-biological child	0.945	0.073	2.86	0.000	0.000
Microcredit income received	***0.002***	***0.001***	***1.73***	***0.000***	***0.000***
Remittances income	0.001	0.002	0.67	0.505	0.505
Wage and salary income	-0.014	0.002	-2.64	0.000	0.000
Revenues from own enterprises	-0.005	0.002	-1.11	0.000	0.000
Mother attended private school	-0.087	0.654	-2.64	0.107	0.107
Mother's school years	0.023	0.005	1.71	0.000	0.000
Father attended private school	0.097	0.042	1.81	0.000	0.000
Father's school years	0.020	0.004	2.58	0.000	0.000
Mother's age	0.001	0.028	0.73	0.471	0.471
Mother ill this year	0.028	0.017	0.68	0.144	0.144
Father's age	-0.001	0.059	6.91	0.000	0.000
Father ill this year	0.053	0.015	-1.81	0.070	0.070
Islam	0.041	0.027	0.57	0.253	0.253
Household size	0.060	0.007	3.08	0.000	0.000
Proportion of females	0.244	0.032	-9.33	0.000	0.000
Female head	-0.118	0.065	-1.81	0.070	0.070
Children under 5	-0.021	0.027	1.15	0.153	0.153
Proportion of people over 66	-4.833	0.132	-17.66	0.000	0.000
Number of non-biological children	-0.394	0.032	-9.33	0.000	0.000
Thana minimum daily wage	-0.015	0.002	-7.64	0.000	0.000
Total active months	-0.006	0.004	-1.45	0.165	0.165
Employed in agriculture	-0.043	0.003	-3.38	0.002	0.002
Drinking water supplied	-0.033	0.016	0.78	0.433	0.433
Electricity	0.051	0.005	2.35	0.012	0.012
Urban	0.001	0.003	0.51	0.608	0.608
Prone to severe flooding	-0.722	0.204	-7.64	0.000	0.000
Prone to severe drought	0.077	0.048	2.11	0.035	0.035
Horticulture district	-0.020	0.015	-0.44	0.174	0.174
School Feeding Program district	0.024	0.017	0.64	0.525	0.525
Constant	0.749	0.089	1.73	0.000	0.000
Number of observations	9,162				

Table B.3 Full regression results for the influence of microcredit income on boys' likelihood of school enrolment (with geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P>*z*	P>*z* (adjusted for Type I Error)
Age	-0.074	0.001	-3.68	0.000	0.000
Non-biological child	1.120	0.101	4.14	0.000	0.000
Microcredit income received	***0.002***	***0.001***	***1.84***	***0.047***	***0.047***
Remittances income	0.004	0.003	1.46	0.064	0.064
Wage and salary income	-0.017	0.003	-5.93	0.000	0.000
Revenues from own enterprises	-0.008	0.002	-1.31	0.000	0.000
Mother attended private school	-0.014	0.039	-2.04	0.413	0.413
Mother's school years	0.027	0.007	2.83	0.005	0.005
Father attended private school	0.118	0.068	2.74	0.006	0.006
Father's school years	0.019	0.006	3.12	0.002	0.002
Mother's age	-0.0008	0.002	-1.27	0.794	0.794
Mother ill this year	0.085	0.003	3.12	0.047	0.047
Father's age	-0.001	0.002	-1.48	0.140	0.140
Father ill this year	0.032	0.055	0.82	0.410	0.410
Islam	0.054	0.013	2.94	0.074	0.074
Household size	0.06475	0.007	4.94	0.000	0.000
Proportion of females	-0.397	0.104	-3.33	0.001	0.001
Female head	-0.092	0.086	-1.93	0.054	0.054
Children under 5	-0.002	0.046	1.19	0.235	0.235
Proportion of people over 66	-4.644	0.217	-7.95	0.000	0.000
Number of non-biological children	-0.297	0.039	-7.66	0.000	0.000
Thana minimum daily wage	-0.017	0.003	-5.93	0.000	0.000
Total active months	-0.005	0.008	-0.89	0.372	0.372
Employed in agriculture	-0.054	0.007	-1.72	0.009	0.009
Drinking water supplied	-0.024	0.046	0.78	0.317	0.317
Electricity	0.06**	0.003	1.27	0.077	0.077
Urban	-0.03	0.038	-0.25	0.806	0.806
Prone to severe flooding	-0.571	0.002	-2.24	0.058	0.058
Prone to severe drought	0.033	0.068	1.05	0.295	0.295
Horticulture district	-0.021	0.030	-2.13	0.034	0.034
School Feeding Program district	0.023	0.034	0.24	0.844	0.844
Constant	0.8***	0.126	2.08	0.000	0.000
Number of observations	4,737				

Table B.4 Full regression results for the influence of microcredit income on girls' likelihood of school enrolment (with geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P>*z*	P> *z* (adjusted for Type I Error)
Age	-0.084	0.003	-28.46	0.000	0.000
Non-biological child	0.776	0.098	7.91	0.000	0.000
Microcredit income received	***0.003***	***0.001***	***1.78***	***0.037***	***0.037***
Remittances income	-0.0003	0.002	-0.49	0.624	0.624
Wage and salary income	-0.007	0.000	-2.93	0.000	0.000
Revenues from own enterprises	-0.002	0.003	-0.4	0.689	0.689
Mother attended private school	-0.091	0.042	-3.07	0.134	0.134
Mother's school years	-0.007	0.007	-0.98	0.328	0.328
Father attended private school	0.119	0.061	1.94	0.053	0.053
Father's school years	0.022	0.006	3.54	0.000	0.000
Mother's age	0.002	0.002	0.88	0.377	0.377
Mother ill this year	-0.05	0.003	0.88	0.377	0.377
Father's age	-0.002	0.002	-0.76	0.448	0.448
Father ill this year	0.075	0.001	1.82	0.057	0.057
Islam	0.04267	0.000	4.48	0.178	0.178
Household size	0.074	0.012	4.31	0.000	0.000
Proportion of females	0.773	0.106	9.46	0.000	0.000
Female head	-0.197	0.009	-1.25	0.021	0.021
Children under 5	-0.051	0.008	1.14	0.095	0.095
Proportion of people over 66	-4.871	0.211	-4.53	0.000	0.000
Number of non-biological children	-0.287	0.041	-6.92	0.000	0.000
Thana minimum daily wage	-0.010	0.002	-4.09	0.000	0.000
Total active months	-0.006	0.029	-0.21	0.835	0.835
Employed in agriculture	-0.023	0.017	-0.72	0.229	0.229
Drinking water supplied	-0.05	0.074	-1.43	0.154	0.154
Electricity	0.039	0.033	-0.72	0.172	0.172
Urban	0.034	0.038	1.22	0.221	0.221
Prone to severe flooding	-0.752	0.002	-2.21	0.038	0.038
Prone to severe drought	0.155	0.071	2.20	0.028	0.028
Horticulture district	-0.024	0.032	-0.75	0.711	0.711
School Feeding Program district	0.018	0.335	0.82	0.630	0.630
Constant	0.537	0.141	4.51	0.000	0.000
Number of observations	4,425				

Table B.5 Full regression results for the influence of microcredit income on children's likelihood of school enrolment (without geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P> *z*	P> *z* (adjusted for Type I Error)
Age	-0.080	0.002	-3.05	0.000	0.000
Girl	0.027	0.004	1.97	0.032	0.037
Non-biological child	0.934	0.074	5.59	0.000	0.000
Microcredit income received	***0.022***	***0.002***	***2.11***	***0.003***	***0.004***
Remittances income	0.001	0.002	0.71	0.478	0.558
Wage and salary income	-0.001	0.000	-1.76	0.000	0.000
Revenues from own enterprises	-0.003	0.002	-1.89	0.053	0.062
Mother attended private school	-0.161	0.066	-0.44	0.157	0.183
Mother's school years	0.015	0.004	1.79	0.000	0.000
Father attended private school	0.156	0.042	3.68	0.000	0.000
Father's school years	0.020	0.005	4.39	0.000	0.000
Mother's age	0.0004	0.002	0.43	0.667	0.778
Mother ill this year	0.029	0.038	0.40	0.691	0.806
Father's age	-0.001	0.002	-0.91	0.364	0.425
Father ill this year	0.051	0.038	0.46	0.648	0.756
Islam	0.037	0.002	3.57	0.087	0.102
Household size	0.058	0.008	5.30	0.000	0.000
Proportion of females	0.213	0.061	4.57	0.000	0.000
Female head	-0.089	0.005	-3.73	0.000	0.000
Children under 5	0.016	0.027	1.34	0.181	0.211
Proportion of people over 66	-4.793	0.151	-32.57	0.000	0.000
Number of non-biological children	-0.285	0.032	-2.76	0.000	0.000
Thana minimum daily wage	-0.016	0.002	-3.44	0.000	0.000
Total active months	-0.006	0.002	-7.45	0.165	0.193
Employed in agriculture	-0.037	0.001	-1.97	0.001	0.002
Drinking water supplied	-0.110	0.055	-1.99	0.047	0.055
Electricity	0.490	0.003	1.88	0.009	0.011
Urban	0.001	0.025	0.90	0.367	0.428
Constant	0.913	0.090	10.09	0.000	0.000
Number of observations	9,162				

Table B.6 Full regression results for the influence of microcredit income on boys' likelihood of school enrolment (without geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P> *z*	P> *z* (adjusted for Type I Error)
Age	-0.062	0.002	-32.62	0.000	0.000
Non-biological child	0.871	0.103	10.81	0.000	0.000
Microcredit income received	***0.017***	***0.002***	***3.11***	***0.003***	***0.003***
Remittances income	0.003	0.002	2.28	0.122	0.142
Wage and salary income	-0.078	0.049	-3.22	0.824	0.961
Revenues from own enterprises	-0.007	0.001	-1.84	0.046	0.054
Mother attended private school	-0.01	0.025	-0.94	0.451	0.526
Mother's school years	0.027	0.007	3.09	0.002	0.002
Father attended private school	0.116	0.068	2.83	0.075	0.088
Father's school years	0.019	0.006	3.06	0.002	0.002
Mother's age	-0.001	0.003	-0.27	0.923	1.077
Mother ill this year	0.092	0.005	1.84	0.097	0.113
Father's age	-0.001	0.002	-1.02	0.306	0.357
Father ill this year	0.027	0.057	0.36	0.717	0.837
Islam	0.029	0.028	0.55	0.884	1.031
Household size	0.055	0.011	4.21	0.000	0.000
Proportion of females	-0.356	0.103	-3.45	0.001	0.001
Female head	-0.122	0.090	-1.35	0.077	0.090
Children under 5	-0.002	0.040	-0.15	0.885	1.033
Proportion of people over 66	-4.711	0.214	-22.04	0.000	0.000
Number of non-biological children	-0.288	0.042	-6.91	0.000	0.000
Thana minimum daily wage	-0.019	0.003	-6.79	0.000	0.000
Total active months	-0.004	0.008	-0.55	0.580	0.677
Employed in agriculture	-0.046	0.012	-1.72	0.086	0.100
Drinking water supplied	-0.03	0.076	-1.54	0.122	0.142
Electricity	0.057	0.003	1.46	0.083	0.097
Urban	-0.025	0.038	-0.19	0.806	0.940
Constant	1.102	0.128	8.58	0.000	0.000
Number of observations	4,737				

Table B.7 Full regression results for the influence of microcredit income on girls' likelihood of school enrolment (without geospatial variables; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P>*z*	P>*z* (adjusted for Type I Error)
Age	-0.068	0.004	-2.12	0.000	0.000
Non-biological child	0.829	0.098	7.89	0.000	0.000
Microcredit income received	***0.026***	***0.002***	***2.78***	***0.044***	***0.051***
Remittances income	-0.0007	0.003	-0.21	0.835	0.974
Wage and salary income	-0.003	0.003	-0.93	0.190	0.222
Revenues from own enterprises	-0.001	0.003	-0.66	0.512	0.597
Mother attended private school	-0.081	0.089	-0.92	0.360	0.420
Mother's school years	0.006	0.007	-0.92	0.640	0.747
Father attended private school	0.112	0.062	1.82	0.068	0.079
Father's school years	0.022	0.006	3.53	0.000	0.000
Mother's age	0.002	0.002	0.69	0.489	0.571
Mother ill this year	-0.050	0.051	-0.37	0.710	0.828
Father's age	-0.002	0.002	-0.57	0.568	0.663
Father ill this year	0.072	0.010	0.57	0.568	0.663
Islam	0.040	0.047	0.03	0.974	1.136
Household size	0.065	0.013	3.97	0.000	0.000
Proportion of females	0.791	0.109	9.27	0.000	0.000
Female head	-0.185	0.004	-1.14	0.061	0.071
Children under 5	-0.060	0.048	-1.07	0.284	0.331
Proportion of people over 66	-4.803	0.246	-20.97	0.000	0.000
Number of non-biological children	-0.280	0.042	-6.71	0.000	0.000
Thana minimum daily wage	-0.014	0.006	-1.87	0.110	0.128
Total active months	-0.006	0.008	0.56	0.573	0.669
Employed in agriculture	-0.021	0.034	-0.26	0.792	0.924
Drinking water supplied	-0.084	0.079	-1.46	0.144	0.168
Electricity	0.043	0.030	-0.99	0.218	0.254
Urban	0.055	0.038	1.45	0.147	0.172
Constant	0.594	0.139	4.26	0.000	0.000
Number of observations	4,425				

Table B.8 Full regression results for the influence of microcredit income on children's likelihood of school enrolment (parsimonious model; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P> *z*	P> *z* (adjusted for Type I Error)
Microcredit income received	***0.026***	***0.009***	***2.95***	***0.003***	***0.004***
Non biological child	0.925	0.073	12.71	0.000	0.000
Age	-0.078	0.0022	-5.96	0.000	0.000
Mother's school years	0.010	0.0052	2.08	0.038	0.051
Father's school years	0.023	0.0044	5.21	0.000	0.000
Household size	0.040	0.0069	5.88	0.000	0.000
Proportion of females	0.410	0.0602	6.81	0.000	0.000
Proportion of people over 66	-4.733	0.1422	-3.29	0.000	0.000
Number of non-biological children	-0.275	0.0316	-8.74	0.000	0.000
Log of district minimum daily wage	-0.014	0.0015	-10.28	0.000	0.000
Father's age	-0.0003	0.0008	-0.33	0.741	0.988
Father ill this year	0.020	0.0290	0.71	0.479	0.639
Prone to severe floods	0.094	0.2458	0.38	0.702	0.936
Constant	0.802	0.0581	11.80	0.000	0.000
N	9,162				

Table B.9 Full regression results for the influence of microcredit income on boys' likelihood of school enrolment (parsimonious model; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P> *z*	P> *z* (adjusted for Type I Error)
Microcredit income received	***0.021***	***0.013***	***1.58***	***0.071***	***0.095***
Non biological child	1.094	0.100	10.95	0.000	0.000
Age	-0.072	0.0024	-12.73	0.000	0.000
Mother's school years	0.024	0.0072	3.34	0.001	0.001
Father's school years	0.022	0.0061	3.77	0.000	0.000
Household size	0.044	0.0097	4.58	0.000	0.000
Proportion of females	-0.337	0.1020	-3.31	0.001	0.001
Proportion of people over 66	-4.408	0.1737	-14.38	0.000	0.000
Number of non-biological children	-0.277	0.0403	-6.89	0.000	0.000
Log of district minimum daily wage	-0.017	0.0021	-8.65	0.000	0.000
Father's age	-0.001	0.0010	-1.26	0.208	0.277
Father ill this year	0.044	0.0428	1.04	0.299	0.399
Prone to severe floods	0.084	0.3299	0.26	0.799	1.065
Constant	0.917	0.0768	11.95	0.000	0.000
N	4,737				

Table B.10 Full regression results for the influence of microcredit income on girls' likelihood of school enrolment (parsimonious model; with standard errors, *p*-values and *z* values)

Variable	Y = Enrolled in school	SE	*z*	P> *z*	P> *z* (adjusted for Type I Error)
Microcredit income received	***0.033***	***0.013***	***2.54***	***0.011***	***0.015***
Non biological child	0.761	0.097	7.84	0.000	0.000
Age	-0.081	0.0041	-9.65	0.000	0.000
Mother's school years	-0.003	0.0069	-0.52	0.604	0.805
Father's school years	0.024	0.0061	3.98	0.000	0.000
Household size	0.046	0.0102	4.58	0.000	0.000
Proportion of females	0.991	0.1057	9.38	0.000	0.000
Proportion of people over 66	-5.021	0.2474	-12.30	0.000	0.000
Number of non-biological children	-0.268	0.0419	-6.41	0.000	0.000
Log of district minimum daily wage	-0.011	0.0019	-5.77	0.000	0.000
Father's age	0.0006	0.0011	0.64	0.521	0.695
Father ill this year	0.0002	0.0419	0.01	0.995	1.327
Prone to severe floods	0.133	0.3507	0.38	0.704	0.939
Constant	0.566	0.0958	5.91	0.000	0.000
N	4,425				

Table B.11 Comparing two-stage endogenous treatment effect model estimates for the logarithm and IHS transformation models for microcredit participation

Variable	Coefficient^^		SE^^		t^^		P>t^^		P>t (adjusted for Type I Error) ^^	
Transformation	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**
First-stage results: dep. variable is microcredit participation										
Interaction between household's eligibility status and the availability of a microcredit facility in a village	3.65	3.68	0.32	0.32	11.4	11.5	0.00	0.00	0.00	0.00
The average travel distance to microcredit facilities in a village	0.03	0.03	0.01	0.03	2.73	2.07	0.01	0.01	0.01	0.01
Second-stage results: dep variable is likelihood of school enrolment										
Microcredit participation	0.031	0.034	0.01	0.01	1.98	2.34	0.05	0.02	0.06	0.03
Observations	16,699	16,699								
Number of clusters (degrees of freedom) (PSUs)	612	612								
F statistic	38.94	47.69								
Prob > *F*	0.00	0.00								

Table B.12 IV Comparing estimations for the logarithm and IHS transformation models for microcredit income received

Variable	**Coefficient^^**		**SE^^**		**t^^**		**P>t^^**		**P>t (adjusted for Type I Error) ^^**	
Transformation	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**
First-stage results: dep. variable is microcredit income received										
Interaction between household's eligibility status and the availability of a microcredit facility in a village	0.01	0.03	0.02	0.02	0.42	0.77	0.03	0.01	0.04	0.01
The average travel distance to microcredit facilities in a village	0.13	0.17	0.01	0.04	20.01	23.37	0.00	0.00	0.00	0.00
Second-stage results: dep variable is likelihood of school enrolment										
Microcredit income received	0.05	0.03	0.10	0.142	0.52	0.77	0.00	0.00	0.00	0.00
Observations	16,699	16,699								
Number of clusters (degrees of freedom) (PSUs)	612	612								
F statistic	38.94	47.69								
Prob > *F*	0.00	0.00								

Table B.13 Comparing average marginal effects of microcredit participation on the probability of school enrolment with logarithm and IHS transformation of income and expenditure covariates

	AME ^	**AME ^^**	**SE^^**	**t^^**	**P>t^^**	**P>t (adjusted for Type I Error) ^^**	**Number of observations^^**	**Number of PSUs^^**
Child	0.003	0.002	0.003	0.63	0.411	0.620	16,999	609
Boys	0.003	0.002	0.007	0.43	0.594	0.732	8,669	608
Girls	**0.009***	**0.012***	**0.001**	**0.47**	**0.070**	**0.091**	8,030	606
Age 5-9	**0.019***	**0.021***	**0.005**	**1.70**	**0.050**	**0.069**	6,810	604
Age 10-14	**0.017***	**0.011***	**0.003**	**1.58**	**0.063**	**0.090**	6,748	606
Age 15-17	0.028	**0.003****	**0.000**	**0.11**	**0.031**	**0.035**	3,141	576

^With logarithm transformation (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
^^With IHS transformation.

Table B.14 Comparing estimates of the AMEs of microcredit income on school enrolment with logarithm and IHS transformation of income and expenditure covariates

Model description	**Child (n=9,162)**	**Boy (n=4,737)**	**Girl (n=4,425)**	**Age 5-9 (n=3,743)**	**Age 10-14 (n=3,708)**	**Age 15-17 (n=1,711)**
With log transformations	***0.026*****	***0.020****	***0.033****	***0.0850******	*-0.0398*	*-0.0578*
With IHS transformations	***0.017*****	***0.011****	***0.030****	***0.0748****	*-0.0158*	*-0.0380*

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

B.1 Results from variable selection process

Multicollinearity test results from estimates of variance inflation factors (VIF) from the microcredit participation model for all children with the full set of controls are presented in Table B.15. Results of the final set of covariates that were selected after carrying out LASSO and BMA operations are presented in Table B.16. Out of a total of 28 variables from the original model, 21 variables were selected after running the LASSO operation and based on the average of more than four million regressions, the BMA procedure identified 12 important controls with a posterior inclusion probabilities (PIP) of greater than 0.5 out of the 21 variables. Table B.16 presents the posterior inclusion probabilities (PIP) from BMA analysis of each regressor selected after carrying out LASSO analysis. The PIP for microcredit loan income is 0.9 suggesting strong evidence that microcredit loan income is an important predictor of school enrolment. The influence of microcredit participation on the likelihood of a child being enrolled was found to be positive and significant. Microcredit income is also found to have a positive significant effect on school enrolments. In fact, post BMA regression results show an overall slightly stronger positive influence of microcredit income.

Table B.15 VIF estimates from multicollinearity test from the microcredit participation model for all children with the full set of controls

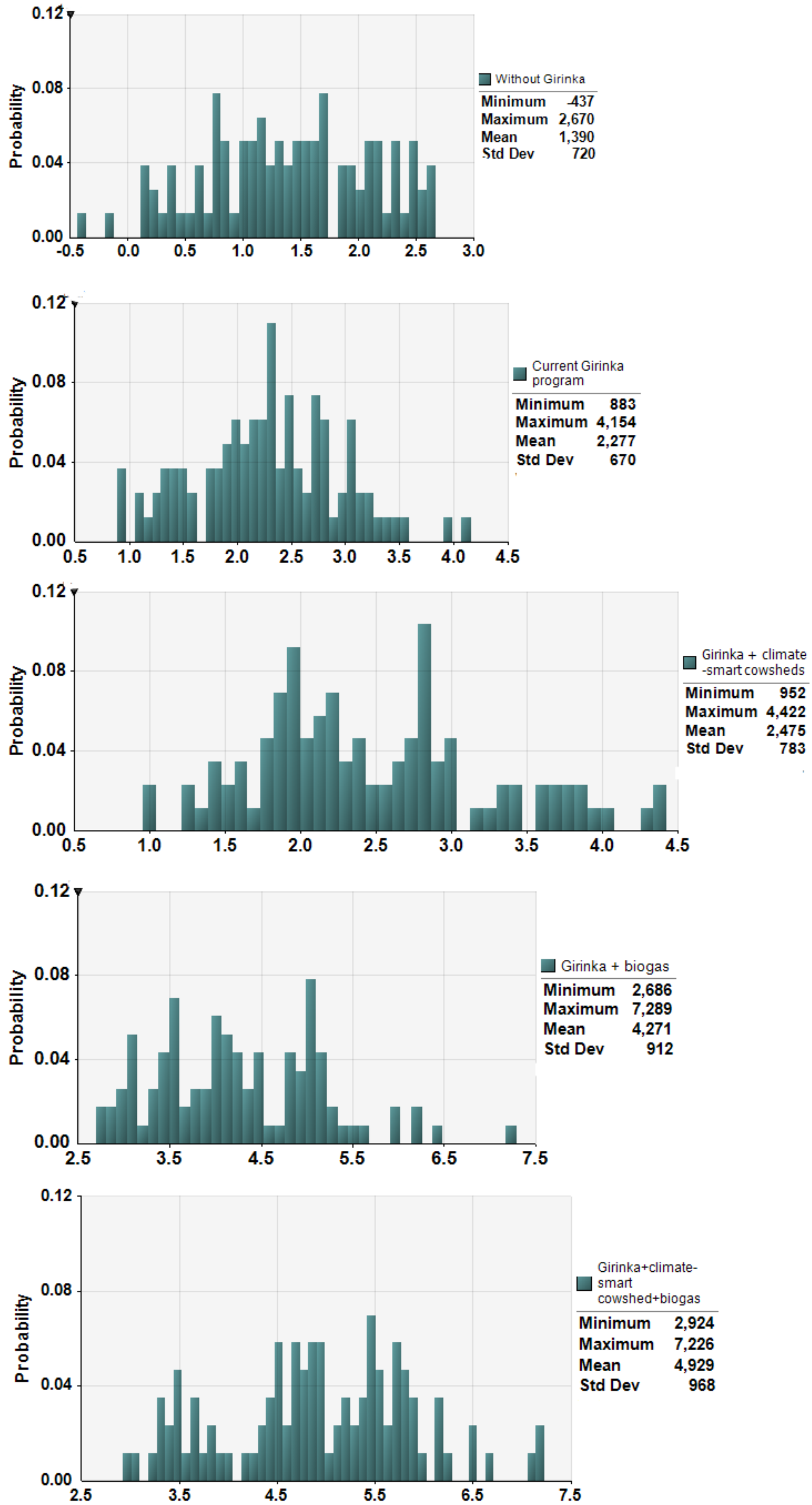
	VIF	1/VIF
Child characteristics		
Age	1.15	0.87
Girl	1.31	0.76
Non-biological child	1.71	0.59
Household income		
Microcredit participation	1.05	0.95
Remittances income	1.99	0.50
Wage and salary income	1.59	0.63
Revenues from household enterprises	1.78	0.56
Parent characteristics		
Mother attended private school	1.83	0.55
Mother's school years	3.55	0.28
Father attended private	2.13	0.47
Father's school years	3.61	0.28
Mother's age[1]	1.03	0.97
Mother ill this year	1.88	0.53
Father's age	1.05	0.96
Father ill this year	1.68	0.59
Islam	3.21	0.31
Household structure		
Household size	1.64	0.61
Proportion of females	1.6	0.63
Female head	1.18	0.85
Number of under 5 children	1.46	0.68
Proportion of people over 66	1.1	0.91
Number of non-biological children	1.34	0.75
Thana minimum daily wage	2.2	0.45
Employment characteristics		
Total active months	2.26	0.44
Employed in agriculture	1.13	0.89
Housing characteristics		
Drinking water supplied	1.09	0.91
Electricity	1.06	0.95
Location		
Urban		
Prone to severe flooding	1.12	0.89
Prone to severe drought	1.3	0.77
Horticulture district	1.06	0.94
School Feeding Program district	1.03	0.97
Mean VIF and 1/VIF	1.65	0.61

Table B.16 PIP estimates from BMA analysis conducted after LASSO operation to identify covariates used in the parsimonious models with PIP>0.5 (in bold text)

Selected after LASSO and BMA	PIP
Microcredit participation	**1.0**
Age	**1.0**
Non biological child	**1.0**
Mother's school years	**1.0**
Father attended private school	0.0
Father's school years	**0.9**
Islam	0.1
Household size	**1.0**
Proportion of females	**1.0**
Female heads of house	0.0
Number of under 5 children	0.2
Proportion of people over 66	**1.0**
Number of non-biological children	**1.0**
Log of district minimum daily wage	**1.0**
Total active months	0.1
Horticultural district	0.2
Mother ill this year	0.2
Father's age	**1.0**
Father ill this year	**0.7**
Drinking water supplied	0.3
Prone to severe floods	**0.6**
Prone to severe drought	0.1

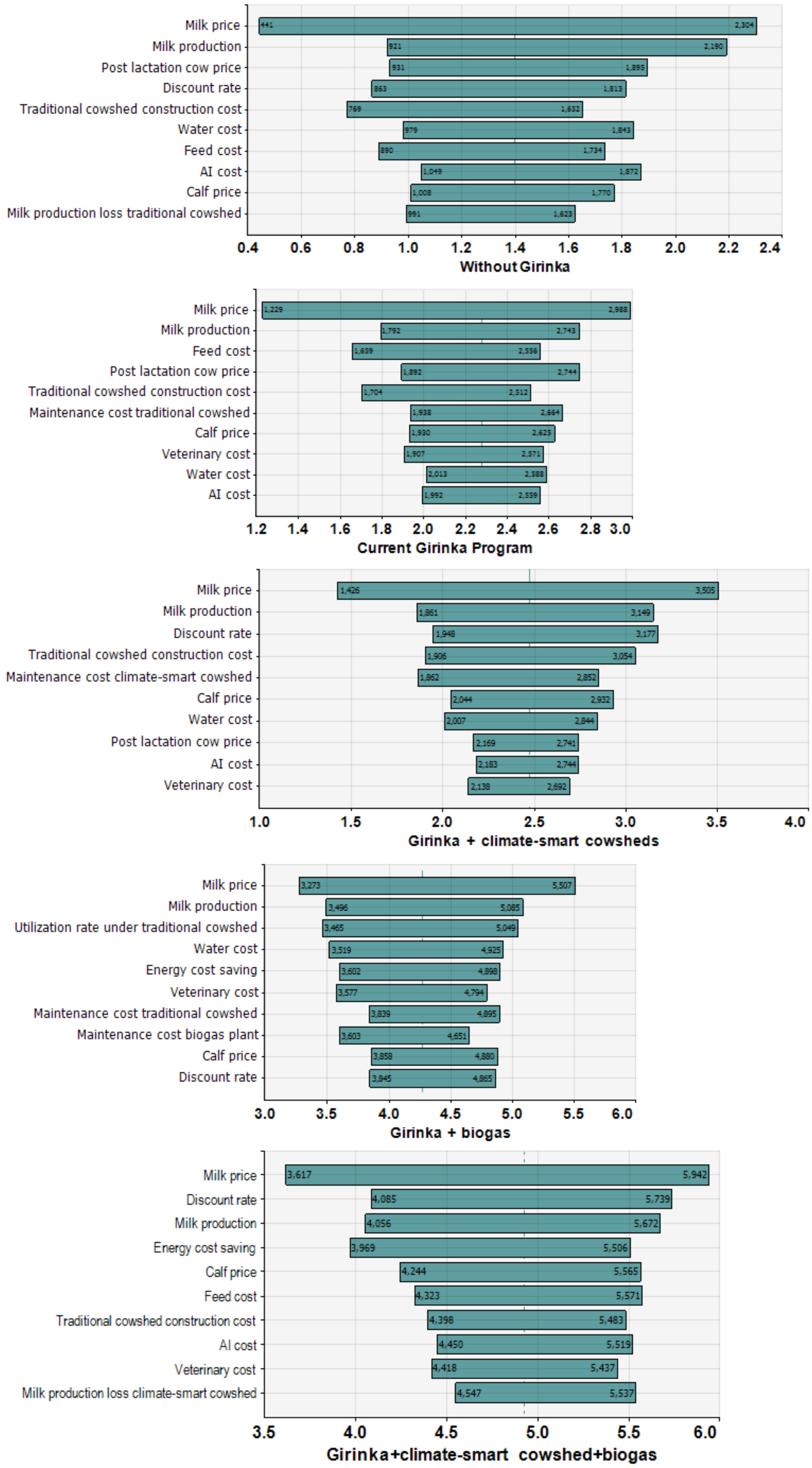
Appendix C Supplementary material for Chapter 4

Figure C.1 Net present value of net benefits (x-axis values measured in '000USD) without Girinka, with Girinka and under three alternative program designs



<u>Source:</u> Authors' design

Figure C.2 Sensitivity of net benefit calculations (x-axis values measured in '000USD) to variability in parameter values under alternative program designs



Source: Authors' design

Appendix D Supplementary material for Chapter 5

Table D.1 Summary of heuristics of possible impact pathways linking mobile use with various household production and income indicators

Outcome variables	Impact mechanism
Production and production technical efficiency	Mobile phones can improve household production because households with mobile phones have better access to information through extension services regarding production inputs and technologies. Mobile phones contribute to the improvement of farmers' productivity and consequently their agricultural output level should increase (Issahaku et al., 2018; Mwalupaso et al., 2019a; Mwalupaso et al., 2019b)
Farm-input costs	Mobile phone users purchase more farm inputs. One important pathway is through an increase in the amount of remittances received through mobile-based money transfers (Kikulwe et al., 2014)
Price received	Farmers that use mobile phones receive higher commodity prices than nonusers through arbitrage because they have access to market information (Aker and Ksoll, 2016; Haile et al., 2019; Khan et al., 2019; Sife et al., 2010; Tadesse and Bahiigwa, 2015)
Farm income	Income effects can result from better access to information, better access to production inputs and technologies, better access to output markets, and better prices (Kikulwe et al., 2014; Parlasca et al., 2019)
Off-farm income	Mobile phone use can increase salaried incomes through access to information on available off-farm employment. High off-farm incomes can, in turn, increase access to loans and consequently profits from household enterprises (Ma et al., 2018)
Wealth	Increased incomes from mobile phone use increased on- and off-farm incomes can increase the amount of asset owned by a household (Kikulwe et al., 2014; Sekabira and Qaim, 2017b)

Table D.2 A summary of literature on possible impact pathways through which mobile phone use can influence various household production and income indicators

Factors	Expected direction of influence and supporting literature
Farm-input costs & farm-gate price	Mobile phone users spend more on farm inputs than nonusers (Chhachhar et al., 2014; Kante et al., 2019; Kikulwe et al., 2014; Ogutu et al., 2014). Farmers that use mobile phones receive higher commodity prices than nonusers (Haile et al., 2019; Khan et al., 2019; Sife et al., 2010; Wyche and Steinfield, 2016). Majority of farmers do not use mobile phones for getting marketing information on commodity prices (Tadesse and Bahiigwa, 2015).
Production and production technical efficiency	Mobile phone ownership and use improve households' productivity, production technical efficiency (Masuka et al., 2016; Mittal and Tripathi, 2009; Ogutu et al., 2014)
On- and off-farm income and wealth	Increase in mobile phone use has increased on-farm income (Kikulwe et al., 2014; Ma et al., 2018; Muto and Yamano, 2009) and earned and non-earned off-farm (Kirui et al., 2012; Sekabira and Qaim, 2017b)and wealth (Beuermann et al., 2012; Houghton, 2009)
Gender disparity	Males realise higher gains from mobile phone use than females (Owusu et al., 2017). female mobile phone use has stronger positive associations with social welfare than if males alone use mobile phones (Sekabira and Qaim, 2017a)
On- and off-farm employment	Mobile phone users are more likely to access off-farm employment than nonusers (Kikulwe et al., 2014; Ma et al., 2018; Sekabira and Qaim, 2017b). Households with better access to off-farm employment and consequently higher off-farm incomes are more likely to afford mobile phones than households without access to off-farm employment.
Agricultural extension services	Mobile phone users realise higher gains from agricultural extension services than nonusers (Tata and McNamara, 2018; Tumbo et al., 2018; Wright et al., 2016).

Table D.3 Descriptive summary statistics from 2012 BIHS data

	Owners (*n=4,448*)				Non-owners(*n=1,680*)			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Log of yield	0.92	0.33	0.21	1.63	0.88	0.42	0.04	1.80
Production technical efficiency	0.77	0.11	0.53	1.01	0.67	0.07	0.52	0.82
Log net revenues	5.14	3.40	-2.24	12.45	3.03	3.22	-2.30	10.11
1 = head of house is female; 0 = otherwise	0.23	0.42	0.00	1.00	0.27	0.41	0.00	1.00
4G network tower coverage in upazila	0.63	0.12	0.37	0.89	0.47	0.14	0.16	0.77
Total number of major telecommunication providers operating in upazila	2.49	0.21	2.04	2.94	2.03	0.24	1.53	2.56
1 = household had access to electricity; 0 = otherwise	0.57	0.50	0.00	1.00	0.33	0.44	0.00	1.00
1 = head of household received no education; 0 = otherwise	0.42	0.49	0.00	1.00	0.71	0.53	0.00	1.00
1 = household owns a household; 0 = otherwise	0.93	0.27	0.00	1.00	0.87	0.33	0.00	1.00
1 = household received rice subsidy; 0 = otherwise	0.06	0.14	0.00	1.00	0.02	0.17	0.00	1.00
Log of cost of hired labour	2.75	3.30	-4.28	9.78	1.73	4.00	-2.30	10.45
Log of total cost of machinery	2.7	3.74	-5.15	10.93	2.31	3.61	-2.30	9.89
Log of total cost of chemicals	1.65	3.14	-5.01	8.50	0.9	2.83	-2.30	7.07
Weighted mean of flood depth (feet)	1.35	1.98	0.93	5.69	1.01	1.57	0.41	4.42
1 = household exposed to extreme flooding; 0 = otherwise	0.55	0.50	0.00	1.00	0.51	0.50	0.00	1.00
1 = household exposed to extreme drought events; 0 = otherwise	0.71	0.47	0.00	1.00	0.72	0.47	0.00	1.00
Percentage of agricultural land with sand soil	0.15	0.29	0.07	0.79	0.11	0.33	0.08	0.80
Percentage of agricultural land with clay soil	0.06	0.21	0.03	0.50	0.07	0.23	0.04	0.57
Percentage of agricultural land with loam soil	0.23	0.37	0.06	1.04	0.2	0.36	0.05	0.97
Age of household head	43.95	13.50	14.52	72.44	45	15.00	12.15	77.85
1 = head of household went to university; 0 = otherwise	0.025	0.14	0.00	1.00	1	0.04	0.00	1.00
1 = head of household's ethnicity is Bengani; 0 = otherwise	0.95	0.25	0.00	1.00	0.94	0.32	0.00	1.00
Household size	4.45	1.64	1.01	8.03	3.79	1.49	0.66	6.99
Proportion of females in household	0.65	0.25	0.11	1.20	0.7	0.34	0.14	1.45
Percentage of land owned	0.17	0.08	0.00	0.35	0.09	0.09	0.00	0.29
1 = household owns a cassette or CD player; 0 = otherwise	0.085	0.28	0.00	1.00	0.01	0.12	0.00	1.00
1 = household owns a TV; 0 = otherwise	0.35	0.47	0.00	1.00	0.07	0.25	0.00	1.00
1 = household grows jute; 0 = otherwise	0.11	0.30	0.00	1.00	0.08	0.27	0.00	1.00
1 = household grows horticultural crops; 0 = otherwise	0.22	0.38	0.00	1.00	0.11	0.34	0.00	1.00

Table D.4 Descriptive summary statistics from 2015 BIHS data

	Owners (*n=5,013*)				Non-owners (*n=1,115*)			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Log of yield	1.30	0.47	0.28	2.30	0.87	0.37	0.07	1.67
Production technical efficiency	0.79	0.22	0.32	1.27	0.69	0.14	0.39	1.00
Log net revenues	5.59	3.54	-1.84	13.02	4.01	3.12	-2.30	10.72
Subpopulation of interest								
1 = head of house is female; 0 = otherwise	0.25	0.44	0.00	1.00	0.27	0.49	0.00	1.00
Instrumental variables								
4G network tower coverage in upazila	0.77	0.11	0.53	1.01	0.53	0.13	0.25	0.81
Total number of major telecommunication providers operating in upazila	2.57	0.27	1.99	3.15	2.57	0.23	2.09	3.05
Explanatory variables								
1 = household had access to electricity; 0 = otherwise	0.64	0.49	0.00	1.00	0.37	0.47	0.00	1.00
1 = head of household received no education; 0 = otherwise	0.47	0.44	0.00	1.00	0.73	0.55	0.00	1.00
1 = household owns a household; 0 = otherwise	0.93	0.39	0.00	1.00	0.94	0.35	0.00	1.00
1 = household received rice subsidy; 0 = otherwise	0.07	0.12	0.00	1.00	0.03	0.11	0.00	1.00
Log of cost of hired labour	2.92	4.12	-5.94	11.90	1.87	3.84	-2.30	10.09
Log of total cost of machinery	2.95	4.44	-6.37	12.45	2.23	4.18	-2.30	11.18
Log of total cost of chemicals	2.05	3.77	-6.21	10.16	1.33	3.36	-2.30	8.59
Weighted mean of flood depth (feet)	1.65	2.29	0.37	6.57	1.37	2.49	0.35	6.62
1 = household exposed to extreme flooding; 0 = otherwise	0.55	0.50	0.00	1.00	0.63	0.50	0.00	1.00
1 = household exposed to extreme drought events; 0 = otherwise	0.75	0.47	0.00	1.00	0.74	0.45	0.00	1.00
Percentage of agricultural land with sand soil	0.15	0.28	0.06	0.74	0.12	0.31	0.05	0.78
Percentage of agricultural land with clay soil	0.06	0.17	0.03	0.42	0.03	0.15	0.02	0.39
Percentage of agricultural land with loam soil	0.24	0.36	0.05	1.01	0.22	0.35	0.05	0.97
Age of household head	45.55	13.20	16.91	73.67	50.1	16.30	15.22	85.63
1 = head of household went to university; 0 = otherwise	0.03	0.13	0.00	1.00	0.0001	0.04	0.00	1.00
1 = head of household's ethnicity is Bengani; 0 = otherwise	0.85	0.36	0.00	1.00	0.81	0.40	0.00	1.00
Household size	4.85	1.77	1.04	8.69	3.93	1.73	0.14	7.70
Proportion of females in household	0.65	0.24	0.14	1.17	0.67	0.32	0.12	1.35
Percentage of land owned	0.25	0.29	0.00	0.86	0.10	0.27	0.00	0.69
1 = household owns a cassette or CD player; 0 = otherwise	0.07	0.24	0.00	1.00	0.01	0.11	0.00	1.00
1 = household owns a TV; 0 = otherwise	0.35	0.47	0.00	1.00	0.07	0.26	0.00	1.00
1 = household grows jute; 0 = otherwise	0.08	0.25	0.00	1.00	0.06	0.24	0.00	1.00
1 = household grows horticultural crops; 0 = otherwise	0.27	0.36	0.00	1.00	0.12	0.33	0.00	1.00

Table D.5 Results of the instrumental variable estimation for Net revenue

Variable	Coefficient	SE	t	P>t	P>t (adjusted for Type I Error)
First-stage results: dep. variable is Own mobile phone					
4G network coverage by upazila as a share of the population in Bangladesh	1.32	0.08	16.36	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.17	0.77	2.24	0.03	0.05
Second-stage results: dep variable is net return per hectare per year					
Mobile phone ownership	0.98	0.17	5.62	0.00	0.00
Log of cost of hired labour	0.058	0.03	2.31	0.02	0.04
Log of total cost of machinery used	-0.064	0.05	-1.32	0.19	0.32
Log of current land area used for agricultural production	0.346	0.08	4.11	0.00	0.00
Log of total cost of irrigation	0.028	0.02	1.46	0.14	0.25
Log of cost of inorganic fertilizer	0.451	0.05	8.92	0.00	0.00
Log of cost of organic manure	0.078	0.02	3.17	0.00	0.00
Log of cost of chemicals	-0.032	0.03	-1.17	0.24	0.42
Female head of house	-0.604	0.24	-2.52	0.01	0.02
Age of household head	-0.005	0.01	-0.59	0.55	0.95
Head of household went to University	-0.404	1.01	-0.40	0.69	1.18
Does this household have an electricity connection?	-0.116	0.17	-0.70	0.49	0.83
Log of household loan	-0.005	0.02	-0.30	0.76	1.31
Log of household total savings	0.036	0.02	2.20	0.03	0.05
Log of remittance income received in the last 12 months	-0.042	0.02	-1.97	0.05	0.08
Household grows jute	2.406	0.24	10.21	0.00	0.00
Horticultural household	2.157	0.17	12.68	0.00	0.00
Use hybrid rice variety	-0.203	0.78	-2.60	0.01	0.02
Use pure rice variety	0.042	0.01	4.45	0.00	0.00
Household size	0.010	0.07	0.15	0.88	1.51
Ethnicity = Bengani	-0.366	1.35	-0.27	0.79	1.35
Head of household received no education	-0.202	0.22	-0.92	0.36	0.62
Household owns a TV	-0.029	0.19	-0.16	0.88	1.50
Are you are getting subsidy for Rice?	0.682	0.2429496	2.81	0.005	0.01
Weighted mean flood depth (feet)	0.048	0.0313085	1.54	0.123	0.21
Employed off-farm	-0.565	0.1755848	-3.22	0.001	0.00
Observations	12,256				
Adjusted R^2	0.17				
F-test statistic	44.41				
F-test critical value	23.51				
Prob > F	0.000				

Table D.6 Results of the instrumental variable estimation for Yield

Variable	Coefficient	SE	t	P>t	P>t (adjusted for Type I Error)
First-stage results: dep. variable is Own a mobile phone					
4G network coverage by upazila as a share of the population in Bangladesh	1.130	0.12	9.62	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.0197	0.009	2.17	0.03	0.05
Second-stage results: dep variable is net return per hectare per year					
Mobile phone ownership	0.00	0.00	2.37	0.02	0.03
Log of cost of hired labour	0.007	0.00	5.83	0.00	0.00
Log of total cost of machinery used	0.001	0.00	0.23	0.82	1.40
Log of current land area used for agricultural production	0.125	0.01	22.52	0.00	0.00
Log of total cost of irrigation	0.003	0.00	3.89	0.00	0.00
Log of cost of inorganic fertilizer	0.013	0.00	5.44	0.00	0.00
Log of cost of organic manure	0.004	0.00	3.11	0.00	0.00
Log of cost of chemicals	0.003	0.00	2.08	0.04	0.06
Female head of house	-0.038	0.02	-2.39	0.02	0.03
Age of household head	0.000	0.00	0.16	0.87	1.49
Head of household went to University	-0.008	0.06	-0.15	0.88	1.51
Does this household have an electricity connection?	-0.004	0.01	-0.49	0.62	1.07
Log of household loan	-0.001	0.00	-0.57	0.57	0.98
Log of household total savings	0.003	0.00	3.02	0.00	0.00
Log of remittance income received in the last 12 months	0.001	0.00	0.43	0.67	1.14
Household grows jute	0.014	0.01	1.26	0.21	0.35
Horticultural household	0.025	0.01	3.16	0.00	0.00
Use hybrid rice variety	-0.084	0.02	-5.46	0.00	0.00
Use pure rice variety	0.252	0.10	2.58	0.01	0.06
Household size	-0.003	0.00	-0.76	0.45	0.77
Ethnicity = Bengani	0.080	0.09	0.93	0.35	0.60
Head of household received no education	0.024	0.01	1.85	0.07	0.11
Household owns a TV	0.029	0.01	2.72	0.01	0.01
Are you are getting subsidy for Rice?	0.025	0.0108557	2.32	0.02	0.03
Weighted mean flood depth (feet)	0.000	0.0016512	0.05	0.962	1.65
Employed off-farm	-0.014	0.0093164	-1.46	0.144	0.25
Observations	12,256				
Adjusted R^2	0.14				
F-test statistic	120.79				
F-test critical value	12.35				
Prob > F	0.000				

Table D.7 Results of the instrumental variable estimation for production technical efficiency

Variable	Coefficient	SE	t	P>t	P>t (adjusted for Type I Error)
First-stage results: dep. variable is Own a mobile phone					
4G network coverage by upazila as a share of the population in Bangladesh	1.243	0.09	14.28	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.002	0.00	2.77	0.006	0.01
Second-stage results: dep variable is net return per hectare per year					
Mobile phone ownership	0.01	0.00	2.53	0.01	0.02
Log of cost of hired labour	-0.002	0.00	-2.41	0.02	0.03
Log of total cost of machinery used	0.005	0.00	2.84	0.01	0.01
Log of current land area used for agricultural production	-0.013	0.00	-3.67	0.00	0.00
Log of total cost of irrigation	-0.001	0.00	-1.66	0.10	0.17
Log of cost of inorganic fertilizer	0.006	0.00	2.99	0.00	0.01
Log of cost of organic manure	-0.005	0.00	-5.34	0.00	0.00
Log of cost of chemicals	0.005	0.00	4.18	0.00	0.00
Female head of house	-0.021	0.01	-2.04	0.04	0.07
Age of household head	0.000	0.00	0.31	0.75	1.29
Head of household went to University	-0.025	0.04	-0.60	0.55	0.95
Does this household have an electricity connection?	-0.029	0.01	-4.25	0.00	0.00
Log of household loan	0.001	0.00	1.12	0.26	0.45
Log of household total savings	0.001	0.00	1.21	0.23	0.39
Log of remittance income received in the last 12 months	0.000	0.00	-0.30	0.77	1.32
Household grows jute	-0.011	0.01	-1.13	0.26	0.44
Horticultural household	0.002	0.01	0.27	0.79	1.35
Use hybrid rice variety	0.022	0.01	2.29	0.02	0.04
Use pure rice variety	0.000	0.01	-0.05	0.96	0.06
Household size	-0.003	0.00	-1.07	0.29	0.49
Ethnicity = Bengani	-0.014	0.06	-0.24	0.81	1.39
Head of household received no education	0.016	0.01	1.67	0.09	0.16
Household owns a TV	0.001	0.01	0.18	0.86	1.47
Are you are getting subsidy for Rice?	-0.031	0.009478	-3.27	0.001	0.00
Weighted mean flood depth (feet)	0.004	0.0012577	3.31	0.001	0.00
Employed off-farm	0.012	0.007175	1.64	0.101	0.17
Observations	12,256				
Adjusted R^2	0.11				
F-test statistic	18.29				
F-test critical value	11.78				
Prob > F	0.000				

Table D.8 Comparing IV estimations for the logarithm and IHS transformation models of net revenue

Variable	Coefficient^^		SE^^		t^^		P>t^^		P>t (adjusted for Type I Error) ^^	
Transformation	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**
First-stage results: dep. variable is Own a mobile phone										
4G network coverage by upazila as a share of the population in Bangladesh	1.32	1.27	0.08	0.04	16.36	14.07	0.00	0.00	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.17	0.14	0.77	0.63	2.24	2.01	0.03	0.01	0.05	0.07
Second-stage results: dep variable is net return per hectare per year										
Mobile phone ownership	0.98	0.77	0.17	0.12	5.62	4.23	0.00	0.00	0.00	0.00
Observations	12,256	12,256								
F statistic	44.41	56.91								
Prob > *F*	0.00	0.00								

Table D.9 Comparing IV estimations for the logarithm and IHS transformation models of yield

Variable	Coefficient^^		SE^^		t^^		P>t^^		P>t (adjusted for Type I Error) ^^	
Transformation	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**
First-stage results: dep. variable is Own a mobile phone										
4G network coverage by upazila as a share of the population in Bangladesh	1.13	1.09	0.12	0.07	9.62	8.65	0.00	0.00	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.02	0.02	0.01	0.01	2.17	1.97	0.03	0.00	0.05	0.00
Second-stage results: dep variable is net return per hectare per year										
Mobile phone ownership	0.00	0.00	0.00	0.00	2.37	2.33	0.02	0.01	0.03	0.02
Observations	12,256	12,256								
F statistic	19.14	23.17								
Prob > *F*	0.00	0.00								

Table D.10 Comparing IV estimations for the logarithm and IHS transformation models of technical efficiency

Variable	**Coefficient^^**		**SE^^**		**t^^**		**P>t^^**		**P>t (adjusted for Type I Error) ^^**	
Transformation	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**	**Log**	**IHS**
First-stage results: dep. variable is Own a mobile phone										
4G network coverage by upazila as a share of the population in Bangladesh	1.24	1.11	0.09	0.03	14.28	11.23	0.00	0.00	0.00	0.00
Total number of major telecommunication providers operating by upazila	0.02	0.03	0.00	0.00	2.27	2.17	0.01	0.00	0.01	0.00
Second-stage results: dep variable is net return per hectare per year										
Mobile phone ownership	0.01	0.03	0.00	0.01	2.53	1.74	0.01	0.00	0.01	0.00
Observations	12,256	12,256								
F statistic	18.29	22.40								
Prob > *F*	0.00	0.00								

Table D.11 Comparing estimates of the average marginal effects of mobile phone ownership on net revenue, yield and technical efficiency with logarithm and IHS transformations of net revenue and input cost covariates

	AME ^	**AME ^^**	**SE^^**	**t^^**	**P>t^^**	**P>t (adjusted for Type I Error) ^^**	**Number of observations^^**
NR	**0.091*****	**0.087*****	0.02	2.31	0.00	0.00	12,256
NR (female head of house subpopulation)	**0.130****	**0.116****	0.09	1.69	0.03	0.04	2,632
Yield	**0.013****	0.007	1.05	2.44	0.11	0.12	12,256
Yield (female head of house subpopulation)	0.119	0.021	0.11	1.37	0.16	0.17	2,632
TE	**0.016*****	**0.012*****	0.00	9.42	0.00	0.00	12,256
TE (female head of house subpopulation)	**0.019*****	**0.013*****	0.00	9.97	0.00	0.00	2,632

^With logarithm transformation (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
^^With IHS transformation.

D.1 Results from variable selection process

Multicollinearity test results from estimates of variance inflation factors (VIF) from the microcredit participation model for all children with the full set of controls are presented in Table D.12.

Table D.12 VIF estimates from multicollinearity test from models with the full set of controls

	Log of yield	Production technical efficiency	Log net revenues
Mobile phone ownership	1.21	4.90	3.22
Log of cost of hired labour	1.69	4.56	1.91
Log of total cost of machinery used	4.93	2.66	4.92
Log of current land area used for agricultural production	3.32	1.45	2.64
Log of total cost of irrigation	1.41	3.19	2.15
Log of cost of inorganic fertilizer	2.12	4.52	1.38
Log of cost of organic manure	4.83	3.95	4.88
Log of cost of chemicals	1.04	1.71	4.97
Female head of house	4.51	4.63	1.04
Age of household head	1.05	4.50	4.83
Head of household went to University	4.69	2.24	1.05
Does this household have an electricity connection?	4.49	1.44	4.85
Log of household loan	1.96	1.16	4.64
Log of household total savings	4.58	4.79	2.12
Log of remittance income received in the last 12 months	4.77	1.44	1.69
Household grows jute	2.15	2.13	4.33
Horticultural household	4.80	1.05	4.72
Use hybrid rice variety	1.38	1.05	3.32
Use pure rice variety	4.53	1.51	1.41
Household size	1.91	1.03	4.51
Ethnicity = Bengani	4.08	4.84	2.13
Head of household received no education	4.55	4.53	4.80
Household owns a TV	3.22	4.72	4.78
Are you are getting subsidy for Rice?	2.13	4.66	1.44
Weighted mean flood depth (feet)	2.64	2.16	1.02
Employed off-farm	1.44	2.04	1.96

Results of variable selection using LASSO and BMA operations are presented in Table D.13. All the 26 variables were selected after running the LASSO operation. The BMA procedure, based on the average of more than three million regressions, confirmed all 26 controls as important with posterior inclusion probabilities (PIP) of between 0.7 and 1.0 for all the 26 variables. Table D.13 presents the posterior inclusion probabilities (PIP) from BMA analysis of the 26 regressors selected after carrying out LASSO analysis.

Table D.13 Variable selection using LASSO and BMA and VIF

Selected using LASSO	PIP
Mobile phone ownership	1.0
Log of cost of hired labour	1.0
Log of total cost of machinery used	1.0
Log of current land area used for agricultural production	1.0
Log of total cost of irrigation	1.0
Log of cost of inorganic fertilizer	1.0
Log of cost of organic manure	1.0
Log of cost of chemicals	1.0
Female head of house	0.7
Age of household head	1.0
Head of household went to University	1.0
Does this household have an electricity connection?	1.0
Log of household loan	0.9
Log of household total savings	0.7
Log of remittance income received in the last 12 months	0.8
Household grows jute	1.0
Horticultural household	0.7
Use hybrid rice variety	0.8
Use pure rice variety	0.9
Household size	0.7
Ethnicity = Bengani	0.7
Head of household received no education	0.8
Household owns a TV	0.9
Are you are getting subsidy for Rice?	0.7
Weighted mean flood depth (feet)	1.0
Employed off-farm	1.0

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