THESIS

RURAL PROSPERITY INITIATIVE: PROPENSITY-SCORE ANALYSIS OF INCOME AND CROP PRODUCTION EFFECTS FROM A COMPREHENSIVE MICRO-IRRIGATION PROGRAM IN ZAMBIA

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ABSTRACT

RURAL PROSPERITY INITIATIVE: PROPENSITY-SCORE ANALYSIS OF INCOME AND CROP PRODUCTION EFFECTS FROM A COMPREHENSIVE MICRO-IRRIGATION PROGRAM IN ZAMBIA

This study seeks to expand the current literature of the impacts of technology adoption for smallholder farmers. It does so through an empirical investigation of the relationship between micro-irrigation technology investment, farmer-group enrollment and five key income and crop-production indicators of smallholder farmer-households in four rural Zambian regions. Micro-irrigation technologies were purchased by farmer-households, and were not randomly assigned. As such, the paper utilizes a propensity-score matching methodology to reduce self-selection bias, thereby estimating the causal effects of micro-irrigation technology investment on household incomes and crop production. By stratifying the sample, impacts were estimated for six combinations of treatment using three distinct matching algorithms. Regional and gender-specific treatment effects were estimated for the impact of farmer-group enrollment with micro-irrigation investment, and for the incremental impact of micro-irrigation investment when the farmer-household is already enrolled in a farmer-group. The study finds robust and positive effects of micro-irrigation investment and farmer-group enrollment on total crop incomes and total crop revenues, for the whole sample. Regional impacts of technology investment are less robust because of sample size limitations, but remain positive and

significant in two of the four intervention areas. Female- and male-headed households both had positive and robust impacts on crop incomes, but female-headed household treatment effects were larger in magnitude. The findings of this study suggest that investment in micro-irrigation technologies and enrollment in a farmer-group lead to higher crop incomes for smallholder farmers in Zambia, and may reduce gender gaps in farmer earnings.

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IDE has an incredible team of committed and passionate people working to promote tangible changes in the lives of the rural poor. Everyone working or volunteering for IDE deserves to be thanked. Specifically, I would like to express my appreciation to Stuart Taylor - IQ Director of IDE - for giving me an opportunity to conduct this analysis and for all of his hard work in the field in Zambia and in the offices of IDE, not to mention his continued advocacy for the importance of rigorous impact evaluation. Sudip Mahapatra - Data Manager for IDE – for his professional data management and for answering my endless questions and emails. Daniel Kanyembe - M&E Coordinator for IDE - for doing such an amazing job in carrying out the sampling plan, for handling all of the survey and sampling procedures in the field and for answering all my tedious questions about said processes. From the IDE team, I would also like to thank Lucy Pieterse for her GIS support and for producing the RPI intervention area maps that were used throughout the evaluation.

From Colorado State University, I would like to thank my main advisor, Stephan Kroll, for his ongoing advice and support throughout my program as well as his mastery of the English language. His easy-going attitude and witty banter have made this process enjoyable, fulfilling and fun. Gregory Graff, for opening my eyes to the non-academic possibilities this type of research will allow. Stephan Weiler, for taking the time to help an unknown student take a step towards something they are passionate about. I would like to express my appreciation to Christopher Goemans as well, for the leadership he has offered in my personal and professional growth.

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TABLE OF CONTENTS

SECTION 1: INTRODUCTION

For the last two decades a large portion of international development efforts have been spent on agricultural growth. Agricultural growth and increased crop production has been shown to increase on-farm income and household welfare in the developing world (Mellor et al., 1985). Further research indicates that agricultural growth has indirect benefits leading to increases in employment, lower prices for food staples and backward and forward linkages with other parts of the economy (Berdague et al. 2002 and Irz et al. 2001). A large amount of research has been conducted on the impacts from adoption of hybrid yielding seed varieties (HYV) and advanced agricultural practices (Kumar, 1994; Lin, 1994; Pender and Gebremedhin, 2008; Pinstrup-Anderson and Hazell, 1985). Although the use of HYVs and advanced agricultural practices yielded promising results, Shah et al. (2002) found that a general lack of development of water resources for smallholder irrigation was the constraining factor for rural development undermining a number of developmental strategies during the green revolution. More recent empirical evidence argues for the increased need for irrigation solutions for the world's poor. Furthermore, irrigation projects have had positive impacts on agricultural production and household welfare amongst small-scale farmers (Dillon, 2008; Adiote et al. 2007; Mangsoni, 2008 and Enterprise Works).

Access to irrigation provides farmers with a reliable water source during those critical times of the year when high-value, labor-intensive vegetables can be grown and sold for higher market prices thus creating the potential for additional crop incomes, a more diversified crop portfolio, enhanced output quality, lower cultivation costs and less dependence on rain-fed agricultural systems (Namara et al. 2005). Additionally, irrigation reduces unforeseen production shocks by allowing a wider range of smoothing mechanisms to be used, which in turn reduce the distressed sales of crops and assets (Dillon, 2008). Lastly, low-cost, reliable micro-irrigation technologies could help rural women more effectively meet their water needs, while simultaneously increasing household labor productivity, and reduce the gender gap in crop incomes between male- and female-headed households (Upadhyay, 2004).

International Development Enterprises (IDE) is a non-governmental organization that develops income-generating products for small-scale farmers in developing countries. In 2006, IDE partnered with the Bill and Melinda Gates Foundation to implement the Rural Prosperity Initiative (RPI) in Zambia to improve household welfare of farming families living under the 2USD per day poverty line. By promoting sustainable supply chains for micro-irrigation products, fostering additional market opportunities for small-scale farmers, and implementing an agro-educational program for many of their clients, IDE strives to increase household welfare and crop production.

Since 2006, the RPI program in Zambia has reached over 5,000 families, facilitated linkages between small-scale farmers and major produce buyers, and developed a network of 30 women's farmer groups.[1] In the process, many farmer-

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[1] IDE Annual Report 2009, www.IDEorg.org

households have reported increased crop earnings, more diversified crop portfolios, and greater access to market outlets. The current evaluation effort began in 2010 by administering a comprehensive survey to 960 farmer-households throughout five distinct intervention zones[2] in Zambia. That survey collected recall-based baseline measures for the 2009 crop year, as well as end-line measures for the 2010 crop year. A program timeline is shown in Figure 1.

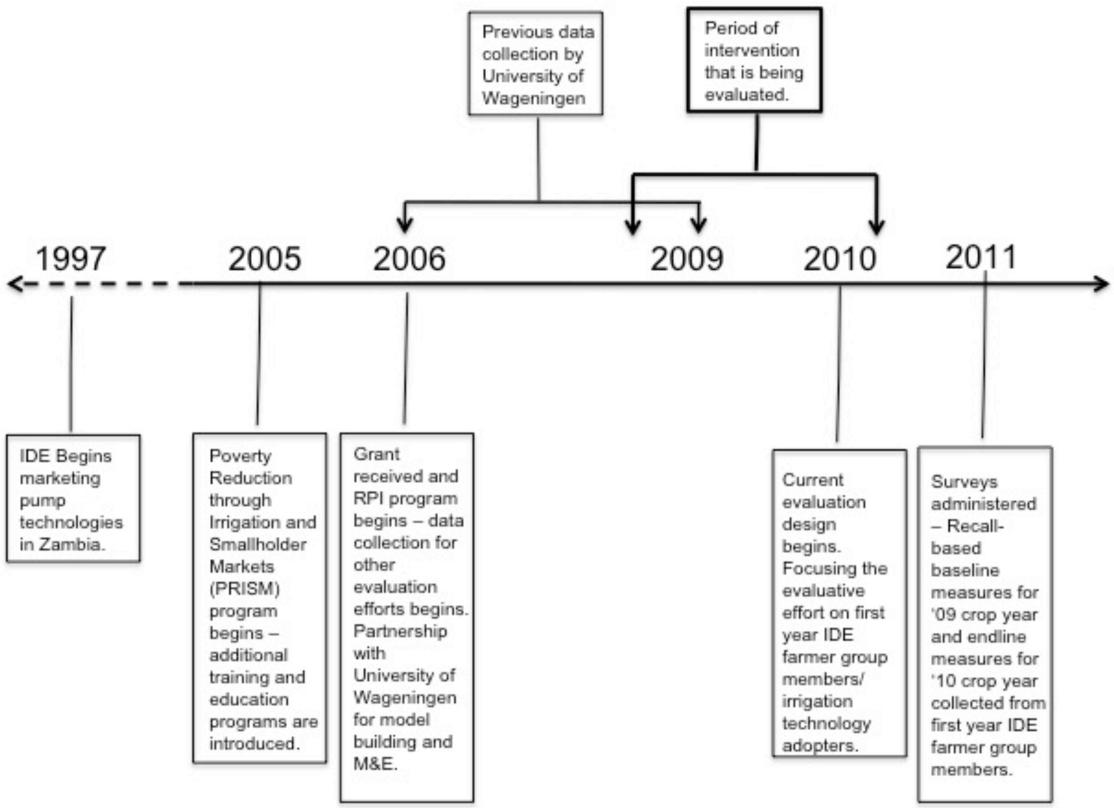

Figure 1: IDE Intervention Timeline

The study described herein attempts to measure the impact of IDE farmer group participation and training, as well as the impact of irrigation technology adoption. For programmatic and theoretical reasons, IDE and the researcher were interested in regional

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2 Intervention zones are referred to as RPI Areas for the rest of the paper, and include: Kabwe, Lusaka, Kafue, Choma and Livingstone.

and gender-specific impacts from agricultural education programs and irrigation technology investment as well. This leads to five primary research questions for the present study:

(1) *Have farmers receiving the IDE treatment experienced greater income growth over the intervention period relative to those who have not?*
(2) *What are the full treatment effects for each RPI Area?*
(3) *What is the income difference between a treated farmer with an irrigation technology and treated farmer that has not adopted an irrigation technology*
(4) *What is the income difference between treated farmer with training and pump compared to a treated farmer with just training experience?*
(5) *What are the full treatment effects for male-headed households[3] compared to full treatment effect for female-headed households?*

The current evaluation utilizes ex-post household demographic, crop production and household income data collected in five RPI areas within Zambia. Because IDE operates with a market driven developmental model, farmer-households must choose to participate in trainings and, optionally, to invest in irrigation technologies. From an analysis perspective, this “free choice” results in the following pair of challenges: First, there are numerous forms of treatment that farmer-households could self-select. Either they may choose to simply join an IDE farmer group and participate in agri-educational programs; or, alternatively, they may both join an IDE farmer group and adopt an irrigation technology. The result is a spectrum of treatments that further complicates the impact evaluation process. Second, treatment (i.e.,, IDE farmer group participation and/or irrigation technology adoption) is not randomly allocated to farmer households, and, as a result, several identification problems exist. The primary bias associated with non-random impact evaluations is that selection bias from non-mandatory program participation could be correlated with household characteristics, geographic

[3] Head of household will be abbreviated by HHH throughout the paper.

characteristics, pre-treatment crop production characteristics, or pre-treatment technological endowments, to name a few. Because the program intervention efforts were not intentionally randomized, the distribution of observable and unobservable characteristics between treatment and control groups will not be statistically equivalent, and impact estimates may be biased upwards or downwards (Dillon, 2005).

To resolve the first issue, the present study creates, from the original total sample, a multitude of treatment and control group samples in order to estimate treatment effects for six primary types of IDE treatment.[4] The strategy is repeated for two additional stratifications of interest: RPI area and gender, thus enabling the estimation of specific treatment effects for each RPI area and for male-versus female-HHHs. The second issue is resolved by utilizing a propensity-score matching (PSM) methodology that matches farmer-households based on their observable pre-treatment characteristics, resulting in the creation of a balanced treatment and control group sample to be used for impact estimation, thereby reducing selection bias (Heckman et al. 1997; Smith and Todd, 2005; Caliendo and Kopeinig, 2008; Dehijia and Wahba, 2002). To control for potential compounding of fixed effects occurring during the intervention period, five distinct difference-in-differences (DID) impact indicators were used to estimate IDE impacts on the target population. The robustness of the propensity-score matching estimates was ensured by using three matching estimators (nearest-neighbor, radius matching, and kernel Epanechnikov) to calculate the treatment effects.

Estimates for the impact of irrigation technology adoption were robust across matching estimators and ranged between 262-534USD total crop income increases

[4] This is explained in greater detail in Section 6.

between the 09-10 crop years for enrolled farmer group members, depending on the irrigation technology. Additional impacts on total crop revenues ranged from 230USD to 347USD. Significant differences in impact estimates were found for each RPI area, where Kabwe and Choma/Livingstone areas were most positively impacted, suggesting potential sensitivity of irrigation programs to geographic and climactic factors. Impact estimates for female-HHHs were larger than male-HHHs when irrigation technologies were adopted, signifying the necessity of irrigation technology adoption if a reduction in the gender income gap is the goal of intervention.

Utilizing an accepted quasi-experimental methodology, this research contributes to the applied irrigation literature by estimating impact of the combinations of agricultural training and irrigation technology investment. Furthermore, geographic and gender-specific effects are estimated to provide IDE a more nuanced study to be used for ongoing program development. Additional motivation for the current study is to build on the impact assessment literature, and to introduce propensity-score matching methods to the rural development and micro-irrigation literature streams.

The organization of this thesis is as follows: the second section provides a brief literature review on rural development and technology adoption, and continues with a review of micro-irrigation benefits, specifically. In section three, the reader is provided with a brief overview of IDE activities in Zambia, a summary of the target population and the primary hypotheses of interest for the current paper. Section four outlines the theoretical problems with evaluating impacts and provides the reader with the theoretical underpinnings for the propensity-score matching methodology that is used to estimate the treatment effects. Specific methodologies, including sample design, sampling plan, survey instrument are discussed in section 5. Recall modeling efforts and the income model used to calculate the household income indicators are presented in section six. Section seven provides standard data discussion and socio-demographic, crop production and household income statistics for all stratifications of interest. Selection model results and estimated treatment effects for the whole sample, RPI Areas and genders are presented in section eight. A brief discussion of the treatment effects, as well as the current limitations of the study, follows in section nine. A final section concludes the paper.

SECTION 2: LITERATURE REVIEW

2.1 - Adoption

Agricultural growth is a promising path to end poverty in much of sub-Saharan Africa. Approximately 66% of sub-Saharan Africans live and work in rural areas, and nearly 90% of the population within rural areas is inherently linked to agricultural success, both physically and financially. Utilizing agriculture as a vehicle for economic growth in rural areas will require a productivity revolution in smallholder farming (World Development Report, 2008). Land area holdings are fairly rigid in the developing world, which further emphasizes the increased need for yield-increasing technologies (Hossain, 1989). Much of the existing research has been spent on the diffusion of technologies and higher-yielding seed varieties (HYV). The present study, however, is not concerned with the diffusion of technologies, but rather with, the specific impacts on the farmer-household after the technology has been adopted.

Agricultural technology adoption benefits farmer-households in a number of ways: by raising the productivity and diversity of smallholder farms, thereby increasing household incomes, increasing employment by promoting the production of high value, labor-intensive produce; decreasing food costs and increasing food diversity within the region, which indirectly benefits the farmer-household (Hossain et al. 1994). Many technological innovations that seemed promising were met with partial success, as measured by empirical analyses on their rates of adoption (Feder et al. 1985). Lack of access to credit, inadequate farm size, risk aversion, inconsistent supply of complementary inputs and household labor mobility has all been shown to inhibit farmer-household investment in agricultural innovations. Although the current research does not seek to model adoption explicitly, the selection-modeling component of the propensity-score analysis will utilize *a priori* information on what household characteristics are significant in determining technology adoption.

Adeoti et al. (2007) summarizes many of the critical farmer-household characteristics influencing irrigation technology adoption in the developing world. There are four primary classes: Physical and natural characteristics - area of land under cultivation, farmers with land less than one acre, pre-adoption income/wealth and access to water year around. Human assets - quality and quantity of household labor, where age of household head and years of education of household head were proxies for the quality of labor and household size and the dependency ratio were proxies for quantity of labor. Social assets - membership in a farmer cooperative and the number of extension visits or trainings. Financial assets - farmer access to formal or informal credit, capital assets and the quality and ownership status of the home (Nowak and Korshig, 1983 and Mendola, 2005). The current study utilizes this stream of literature in designing the survey instrument and constructing the selection model.

The "Green Revolution" was a global development strategy that focused on increasing crop production efficiencies in the developing world, by developing high yielding varities (HYV), encouraging the use of synthetic fertilizers and pesticides and introducing much of the world to advanced management techniques. Beginning in the 1960's, the vast majority of rural development and technology adoption research focused on these activities, and the amount of research that was published in the wake of the "Green Revolution" is overwhelming, with the majority being focused on HYVs (Kumar, 1994; Lin, 1994; Pender and Gebremedhin, 2008; Pinstrup-Anderson and Hazell, 1985; Qaim and Zilberman, 2003). Despite a growing collection of literature on hybrid seed adoption in the developing world, many questions concerning their specific impacts remain unanswered, not to mention the consistent and, often times, inappropriate underlying assumptions that the farmer-household has access to irrigation.

Shah et al. (2002) found that a general lack of development of water resources for smallholder irrigation undermined a number of developmental strategies during the "Green Revolution." Furthermore, staple grain prices were very high during the period just before the Green Revolution, making large-scale irrigation and genetically modified seed programs extremely popular. Smaller scale farmer households do not have the capacity to implement the commercial farming practices that were encouraged during the Green Revolution. For rural development to continue having impacts the smallholder farm must be targeted. New methods of agricultural development and additional, smaller-scale, agricultural technologies must be developed and their impacts must be better understood. The purpose of this paper, therefore, is to explore the welfare impact of irrigation technology adoption and agricultural training on household income and crop production.

2.2 - Micro-irrigation Benefits

Lack of access to water and irrigation is one of the leading deterrents to agricultural productivity in sub-Saharan Africa. Limited access to water limits the diversity of crops and also reduces the stability of yields among smallholder farmers. There is a strong belief that crop yields from marginalized land in sub-Saharan Africa could be doubled, and in many cases quadrupled, when management practices are changed and irrigation is accessible (Rockstrom et al. 2003; Rockstrom et al. 2006). It becomes obvious that providing sufficient access to irrigation to allow farmers to grow diversified crops through the dry season is an extremely important consideration, both in the farmer's individual adoption decision and the overarching developmental program. Of course, large-scale commercial irrigation strategies would not be feasible to a dollar-a-day farmer in the developing world. Many initiatives have begun developing small-scale, affordable solutions to the basic irrigation problem. These solutions, which may take the form of a manually operated pump, mechanical pump, small gravity-fed drip irrigation system or a gravity-fed sprinkler system, have become collectively known as *micro-irrigation*.

Empirical evidence from Bangladesh on the impact of micro-irrigation shows that the adoption of affordable pump technologies, coupled with micro-credit services, have allowed poor households to improve their livelihoods significantly (Shah et al. 2002). Additional research on a specific type of micro-irrigation technology utilized an irrigation deficit indicator and found that open wells provided only temporary relief during dry season spells (Bruere et al. 2003). In India, however, micro-irrigation technologies are seen as a solution to increasing water scarcity, as they result in a more efficient use of irrigation water. Consequently, these technologies are increasing crop yields, crop diversity, farmer health and household incomes, more so than traditional flood irrigation practices (IWMI, 2006).

Using a gross margin analysis, Mangisoni (2008) estimated the household incomes of treadle pump irrigation technology in Malawi.[5] Mean net family incomes for adopting households were significantly higher than for non-adopting households. Similarly, he found that the non-adopting households experienced more severe poverty, as measured by a Malawian poverty index. Adiote et al. (2007) used a Heckman two-step procedure to first estimate an adoption model, where the number of extension visits served as the identification variable, and to estimate a poverty impact model. Estimated income impacts were 393USD/hectare. Although this is indeed an appropriate statistical solution to the problem of self-selection, the procedure relies on a very strong assumption that the unobserved determinants of poverty and adoption are jointly normally distributed, with zero means and constant variances (Mendola, 2007). Additional treadle pump studies have taken place throughout Africa. In Mali, adopters have increased their incomes from 444USD per farmer-household to 801USD per farmer-household (Enterprise Works, 2004). In Burkina Faso, a household survey-based before/after analysis showed that irrigated area increased 140% with the adoption of the treadle pump (Enterprise Works, 2003). And, in Niger markets, gardeners were able to increase incomes from 185USD to 1,164USD over a period of six years after adoption (Agence Nigerienne, 2005). Although these results are promising, there were little to no controls for self-selection bias. Despite their impressive results, the treatment effects of the treadle pump may be biased upward because an appropriate counterfactual was not used.

[5]The treadle pump is a human-powered irrigation device that sits on top of a well. Pumping is activated by stepping up and down on treadles, which drive pistons, creating cylinder suction that draws groundwater to the surface. Treadle pumps free farmers from dependence on rain-fed irrigation, provide capacity to raise crops in two growing seasons per year, and help farmers maximize return on their small plots of land. Pump prices, including installation, range from US$20 – $100 based on country of purchase and type of pump (ide.org).

SECTION 3: PROGRAM OVERVIEW

3.1 - History of IDE activities in Zambia

International Development Enterprises (IDE) is a non-profit organization that develops affordable technologies to help the rural poor increase their incomes. The first technology that IDE founder Paul Polak developed was an improved donkey cart in a Somalian refugee camp in 1982. From there, IDE began to implement affordable income-generating generating solutions in Bangladesh by developing and marketing the first manually operated treadle pump to rural farmers. To date, IDE has sold over 1.5 million treadle pumps in Bangladesh alone, creating nearly 1.4 billion dollars in net additional income per year.[6] After the wave of success in Bangladesh, IDE began to expand their developmental programs by marketing the first scalable and affordable drip irrigation systems in Nepal and India, and designing a community-owned coconut processing plant in Vietnam. In 1997, IDE began their first set of programs in Africa. Offering a suite of micro-irrigation products and services, IDE continues to develop their Africa programs, by learning from rural farmers what they need and how they can better their lives by increasing their household production. According to the IDE website, efforts have helped more than 19 million farmers and entrepreneurs lift themselves above the 1 USD/day poverty threshold.

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[6] IDEorg.org/OurStory/History.aspx

IDE began to develop sustainable supply chains and market avenues for treadle pumps in Zambia in 1997. IDE chose to market treadle pumps because they are appropriately sized for small scale farming efforts and are affordable to low-income rural households, like those found in Zambia. Treadle pumps are lightweight and durable, which allows for easy use among children as well which encourage the increased involvement of household labor in crop production. In early 2005, IDE began the "Poverty Reduction through Irrigation and Smallholder Markets (PRISM)" program. This was the first program in Zambia that emphasized the importance of household data collection for future monitoring and evaluation efforts. Research on IDE's impact on Zambia households was conducted using the PRISM dataset and concludes that IDE technologies do in fact increase average income by $250 per year (Hiller, 2007).

In 2006, IDE received funding from the Bill and Melinda Gates foundation to start the the Rural Prosperity Initiative (RPI) program. The RPI program spans over six countries (Ethiopia, Zambia, Bangladesh, Myanmar, Nepal and Vietnam), and seeks to build smallholder incomes, by providing affordable technologies to rural farmer households. In addition, IDE has developed a number of marketing and agricultural training courses that are disseminated to rural farmers using a farmer group model. Although the RPI program is similar to the PRISM program, there is an increased emphasis on program efficiency, cost effectiveness, gender equality and impact evaluation. The current research is carried out with these goals in mind.

As part of the RPI program, comprehensive monitoring and evaluation efforts must be carried out. IDE has specifically stated that the goal of the current research effort is to "clearly and credibly describe the attributable impact of IDE's efforts on farmer income and other crop-production related outcomes, and to provide actionable recommendations for IDE's future implementation improvements and further evaluative research." This identifies three major components that must be taken into consideration during this research: what is the target population? What are the indicators that will be used to determine impact? And, what additional sub-hypotheses are of interest? The following three sub-sections address these three issues.

3.2 - Target Population

The target population for the intervention is rural farmer households in Zambia living under the 2USD/day poverty threshold. For the sake of comparison, Zambia has a total population equal to 13,046,500 with 61% residing in rural areas. Although the incidence of poverty has declined over the last decade with 64% of the total population being in poverty, 78% of the rural population is still severely impoverished.[7]

According to the most recent Economic Census report[8], there was an increase of 27% in the working age population in rural areas from 1990-2000, compared to 15.7% in urban areas, where 62% of the total labor force is in rural areas. Furthermore, unemployment rates are nearly 13% for Zambia as a whole, and of those that are employed, 81.3% of workers are either self-employed or unpaid family workers.[9] This further supports the need for rural intervention programs that can utilize the abundance of household-labor for income-generating activities.

IDE has identified five RPI areas that were selected based on presiding market conditions and viability of program support. Each RPI area has varying degrees of IDE

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[7] *Central Statistical Office, Living Conditions Report: 2010 Census preliminary reports*. Published by Zamstats.gov

[8] A more recent census was carried out in 2010, but very few results have been published from this census.

[9] *Economic Characteristics Report: 2000 Census*. Published by Zamstats.gov.

presence. RPI regions are distributed throughout the country and do not correlate with any specific political boundaries. However, all five of the RPI regions are contained within the Lusaka, Central and Southern provinces of Zambia. RPI areas and political boundaries that were created using ArcMap can be seen in Appendix A. Using political boundaries as a framework, the poverty rates for Lusaka, Central and Southern provinces are 52%, 77% and 76%, respectively. When the population is considered, to give the distribution of the poor population among provinces, Lusaka and Copperbelt provinces contain the highest percentage of the poor population with 15% and 18%, respectively.[10]

District, ward and population statistics for each RPI area are shown in Table 1. The first RPI District, Kabwe, is situated in the Central Province of Zambia. In general, the Central Province is relatively water rich, contains two major markets, and does not have major topographical barriers to travel or trade. Compared to the other RPI areas, Kabwe has the most favorable road infrastructure as well. The Lusaka and Kafue RPI areas are located in the Lusaka Province and are less water abundant compared to the Central Province. In addition, the Lusaka Province only has one major market and has less desirable soil conditions, compared to the Central Province. Lastly, the Choma and Livingstone RPI Areas are situated in the Southern Province where water is less available, the weather is less favorable and the road infrastructure is less than that found in the other RPI areas. Choma, however, has a large market center that is easily accessible to farmers. Because of these geographic and demographic differences, stratified treatment effects are calculated and presented for each RPI District individually in later sections.

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[10] *Housing and Household Characteristics Analytical Report: 2000 Census of Population and Housing*. Published by Zamstats.gov.

Table 1: Geographic, Clientele and Sample Statistics, By RPI Area.

RPI Area	Primary Province	# of Districts	# of Wards	# of IDE Clients reported since 2007		Size of Current Sample
				Full⊗	Partial⊗	
1: Kabwe	Central	3	19	1,623	2,437	210
2: Lusaka	Lusaka & Central	3	8	725	1,088	215
3: Kafue	Lusaka & Southern	3	15	1,044	1,567	216
4: Choma	Southern	3	24	1,521	2,281	109
5: Livingstone	Southern	2	7	867	867	103

⊗ Some IDE Clients are considered partial clients if they only have a pump and have not attended meetings, of if they only attend trainings and have not invested in a pump technology.

RPI areas are utilized for stratification purposes, both during sampling and for the estimation of treatment effects. It is important to note, however, that IDE has facilitated an additional cluster, beyond districts and wards, referred to as farmer groups. Although farmer groups are not spatially explicit, they were heavily relied upon for sampling purposes and will be discussed in later sections. There are over 100 IDE farmer groups within Zambia, each is composed of approximately 30 IDE clients. Each farmer group elects a leader, who is responsible for attending educational training clinics put on by IDE field staff. The farmer-group leaders are then responsible for disseminating learned information to the rest of their respective farmer group participants. Although IDE goes to great lengths to ensure dissemination among farmer-group participants, there are still differences between the accuracy of disseminated information.

The evaluation effort is specifically interested in household-level income and production effects of IDE technologies and training. Therefore, a thorough understanding of the household composition is needed. 80% of rural households in Zambia have a male HHH. The average household size for the whole population is 5 members. 40% of the population has completed primary school, and 39% of the rural population has not received any schooling. Single families occupy 78% of housing units in rural areas and nearly 91% of rural homes are owned by the family. Not surprisingly, however, 91% of homes are self-built and have little external value, which makes access to credit extremely difficult for many farmer-households. Approximately 46% of rural households are composed of mud bricks[11] and 29% are made of pole and dagga[12]. Another important consideration for IDE's, or any, intervention effort is how many rural households have access to electricity. Only 2% of rural households in Zambia have access to electricity, and nearly 89% of households utilize biomass[13] for cooking and warmth. Additionally, 32% of rural households have a radio, 0.3% owns a telephone[14], 33% of households use a bicycle, as their primary means of transportation and 14% own a plough.[15] Families do not own much capital, whether for farming or for comfort, and the investment in an irrigation pump technology is shown to be a significant financial decision for the majority of farmer-households in Zambia.

3.3 - Hypotheses of Interest

With these program and population characteristics in view, we can formulate several concrete hypotheses. The bottom-line test of impact uses a collection of five primary performance indicators: total family earnings, total crop income, total crop revenues, high-value vegetable revenues and total crop production by weight.[16]

> *(1) Have farmers receiving the IDE treatment experienced greater income growth over the intervention period relative to those who have not?*

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[11] Mud bricks are sun dried and less resistant to weather than baked bricks.
[12] Pole and dagga households are more common in the Eastern and Western provinces.
[13] Biomass is composed of wood, paraffin and cow dung.
[14] This number is expected to be much higher for the 2010 census, because of the increase of affordable cell phones in the region.
[15] Housing and Household Characteristics Analytical Report: 2000 Census of Population and Housing. Published by Zamstats.gov
[16] Total family earnings is one of the income indicators generated by the Mon-Qi Income model which is described in detail in Section 5.1.

For this question, we will utilize the PSM tailored survey dataset and compare the change in performance indicators of farmers in the treatment groups to the change in performance indicators of those in the control groups.[17] In other words, can we distinguish the income difference between those who have chosen to participate in an IDE treatment activity from those who have not? For the primary impact, we will look at the difference in all five of the performance indicators for the whole sample.

Additional treatment effects will be measured using the same dataset, by stratifying the sample, and by limiting the sample population to isolate specific combinations of treatment. Auxiliary treatment effects of interest are listed below:[18]

(2) Full treatment effect for each RPI
(3) Income difference between treated farmer with an irrigation technology and treated farmer that has not adopted an irrigation technology
(4) Income difference between treated farmer with training and pump compared to a treated farmer with just training experience
(5) Full treatment effect for male-HHHs compared to full treatment effect for female-HHHs?

Treatment effect magnitude and significance could be thought of as a drug trial. There is a group of subjects that have received "treatment" and an additional group of subjects that are the "control" group. In fact, many of the impact evaluation methodologies are rooted in the epidemiological literature. Many of the papers that examine the impacts of micro-irrigation simply compare means between the treated and control groups. In the following section, however, I will discuss the difficulties that one faces when trying to determine causal impacts, and more importantly, what analytical steps the present study takes to overcome the obstacles in causal impact evaluation.

[17] Treatment and control group classification is explained in detail in Section 6.3.
[18] Additional impacts are of particular interest to IDE field staff, for continued program development and program consistency.

SECTION 4: THE PROBLEM WITH EVALUATING IMPACTS

Although there is a growing body of randomized impact analyses in the developing world, the majority of economic research relies on ex-post observational data. In observational studies, investigators do not have control over the treatment assignment, especially in a market-driven developmental initiative. Econometric techniques can be used to reduce differences in observed covariates, but there is still a lack of a counterfactual. Obviously, one cannot observe the same individual under two different situations at the same time. Statistical controls for socio-economic factors that may have separate impacts on household income, apart from treatment, must be in place. There could be large differences in covariates between the treatment group and the control group, and these differences could cause biased estimates of treatment effects. According to Caliendo and Kopieng (2008), "every microeconomic valuation study has to overcome the fundamental evaluation problem and address the possible occurrence of selection bias." This fundamental problem has led to the development of quasi-experimental methods, such as propensity-score matching.

Selection bias results from unseen differences between control and treatment groups when treatment is not randomized. If technology were randomly distributed to households, the treatment effect on household income would simply be the average difference between the two groups (Mendola, 2007). More formally, the results in the two treatment groups can be directly compared because the treated/untreated units are likely to be similar. In the present case, however, farmers have made the independent decision to purchase the technology or not, which necessitates some statistical solutions to the problem of systematic selection bias. In other words, there will be differences between the two groups of farmer-households whether there is treatment or not, and if one does not control for these differences one would not be able to answer the underlying question of whether the technology increases farmer incomes, or if farmers with higher incomes are the ones to purchase the technology.

In the present case, we are particularly interested in the treatment effect on the treated household. To understand how a propensity score will be used in estimating this treatment effect, we must build off of a theoretical treatment effect as shown formally in equation 1:

[Equation 1] $$\alpha = E(Y_i^1 - Y_i^0)$$

Where:
α = Treatment effect
E(Y)= expected income
1 = treated
0 = untreated
i = farmer-household

The problem with estimating a causal effect from equation 1 is that one can only observe Y_i^1 or Y_i^0 (Rosenbaum and Rubin, 1983). If the technology were randomly assigned to households, the treatment effect would be the average difference in mean incomes between the treated and untreated households. When treatment is random, all other covariates influencing household income would be randomly distributed between control and treated groups. In a randomized experiment the treatment effect, then, becomes:

[Equation 2] $\alpha = E(Y_i^1 - Y_j^0)$

The treatment effect is the difference between Y_i^1, which represents a randomly assigned member of the treatment group, and Y_j^0, which represents a randomly assigned member of the control group (Rosenbaum and Rubin, 1983).

Since the current intervention was not randomized, a balancing score is needed. A balancing score (*b(x)*) is a function of the observed characteristics such that, the conditional distribution of the observed covariates (*x*) given the balancing score is the same for the treated and control groups. If there were only one or two characteristics that influenced farmer income, the balancing score would simply be the variable x. In our case, however, the dimensionality of the x vector is very high, because there are a number of factors related to human and physical capital that influence income and crop production, and deciding on which dimension to match would be problematic (Dehejia and Wahba, 2002).

For the present study, we will utilize Rosenbaum and Rubin's (1983) methodology to obtain a propensity score by using a standard probit model (0 = untreated and 1=treated). The probit model for treatment selection is shown below:

[Equation 3] $pr(X_i) = P(Z=1|X_i) = F(\beta_1 +\beta_2 X_i)$

Where:
$pr(x_i)$ = propensity score of the ith individual
$P(Z=1|X_I)$ = probability of treatment given the observable covariates (X) from the i^{th} individual

While all observed characteristics (*x*) must be pretreatment measurements for the specific household, the vector of *x* may not include all covariates used to make treatment decisions, as this would violate the common support condition (Rosenbaum and Rubin, 1983). These characteristics are used in the specification to estimate the propensity scores. The chosen specification should satisfy the balancing property. The balancing property ensures that the treatment and control observations are equal with respect to the observable covariate set (Dillon, 2008).[19]

Rosenbaum and Rubin (1983) to demonstrate that the difference between control and treated means, at each value of the balancing score, is an unbiased estimate of the treatment effect for that specific propensity-score value. Once the propensity scores are in place for each household, the treatment effect becomes:

[Equation 4] $$\alpha\ (pr(X)) = E(Y_i^1 \mid pr(X)) - E(Y_j^0 | pr(X))$$

Where:
α (pr(X)) = Average treatment effect given propensity score (X)
$E(Y_i^1 \mid pr(X))$ = Expected income of household i from treatment group (Z=1) with propensity score (X)
$E(Y_j^0|pr(X))$= Expected income of household j from control group (Z=0) with propensity score (X)

Observations are paired, based on a set of observed characteristics relating to human and physical capital. In the specific case of this study, Zambian households from the group of farmers that have used an IDE product or service (treatment group) are matched to statistically similar Zambian households that do not use an IDE product or service

[19] A STATA program, *pscore,* estimates the propensity score, based on a model specification, and tests the balancing properties of the sample, whereby, the sample is split in equally spaced intervals of the propensity score. Propensity scores are then compared between treated and control observations within each interval to ensure that propensity scores do not differ. Additionally, t-tests are performed within each interval to ensure that the means of the covariate set do not differ between treatment and control observations. If the means of one or more characteristic differ, the balancing property is not satisfied and a less parsimonious specification is needed (Becker and Ichino, 2002).

(control group), based on observed information collected in the pre-treatment survey. In an applied study, it is difficult to obtain exact matches on the propensity score between treatment and control groups. A solution to this is to use a matching algorithm that maintains degrees of freedom while still allowing for an unbiased estimate of the treatment effect.

4.2 - Matching Algorithms

The matching estimator compares the targeted outcomes of a treated individual with one (or more) control group individuals. Certain matching algorithms reduce bias by maximizing statistical similarities between treatment and control, while others maximize the number of matches to reduce variance by allowing comparisons between less similar treatment and control individuals (Rosenbaum et al. 1985). Propensity-score matching estimators differ in the way that the neighborhood surrounding each treatment observation is defined (Caliendo and Kopeinig, 2008). Figure 2 was adopted from Caliendo and Kopeinig (2008) and illustrates the most popular matching algorithms, and the subsequent choices that must be made for each of them. Brief descriptions of the popular matching algorithms are provided in the rest of this section.

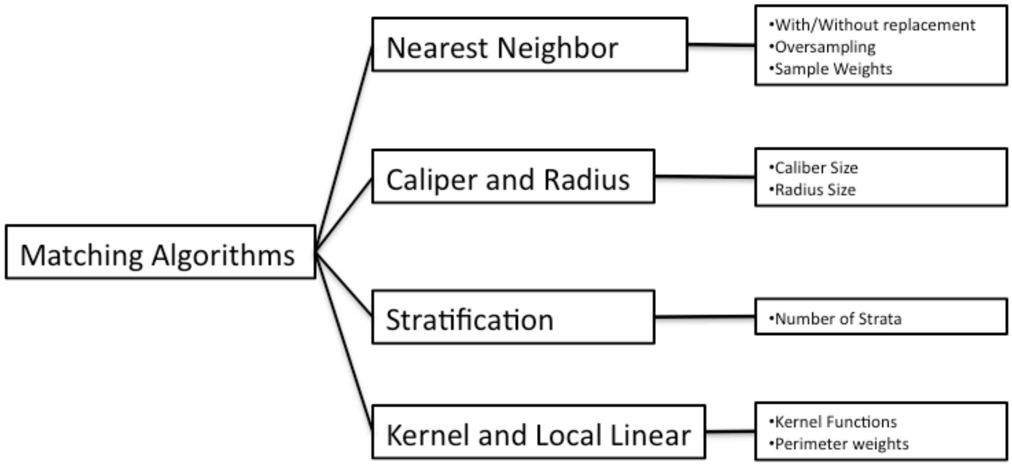

Figure 2: Primary Matching Algorithms

Nearest neighbor matching is the simplest of the matching algorithms. Observations are randomly ordered, and the first treatment observation is matched with the first control group observation having the nearest propensity score. If replacement is used then the control group observation is put back into the sample and may be matched to another treatment group observation if necessary. If no-replacement is used then control and treatment group observations are matched, compared and dropped from the sample, from highest to lowest. If replacement is allowed the quality of matching will increase and resulting treatment effect bias will decrease (Caliendo and Kopeinig, 2008). If the propensity-score distributions are different between treatment and control groups, matching with replacement is the preferred choice, because it would minimize the propensity-score distance between the matched comparison units and the treatment group unit (Dehejia and Wahba, 2002). In addition, matching with replacement allows one to keep additional observations, by oversampling from the limiting group.

The second primary matching algorithm is the caliber/radius method, where a pre-defined propensity-score radius identifies all possible matches. One problem with caliber matching is that the common support area is being enforced, which could reduce the number of possible matches. This, in turn, would increase variance of the treatment effect estimate (Caliendo and Kopeinig, 2008). A slight variation of this is radius matching, where a radius is pre-determined, as in caliper matching, but control group members within the radius can be matched more than once (Dehejia and Wahba, 2002). This reduces the likelihood of bad matching, while still enforcing a common support.

The last, and most commonly reported matching algorithm is Kernel matching. Unlike the aforementioned matching algorithms, Kernel matching utilizes nearly all of the control group participants in creating a counterfactual. Each control group observation is assigned a weight according to how similar or different the propensity score is from the targeted treatment group observation. Formally, the matched observation is identified as "the weighted average of all households in the opposite treatment status within a certain propensity-score distance, with weights inversely proportional to the distance" (Mendola, 2007). As a result, there is less variance in the estimated treatment effects, and observations are seldom dropped from the sample.

In practice, most researchers utilize and present their results from a number of matching algorithms (Becerril et al. 2010; Mendola, 2007; Kassie et al. 2008). When control and treatment groups are significantly different in pre-treatment characteristics, matching with replacement and Kernel based matching are preferred. When the treated and control group households are more similar in pre-treatment characteristics (i.e., common overlap on the propensity-score distribution), no-replacement algorithms result in similar estimated treatment effects, but with lower standard errors (Dehejia and

Wahba, 2002). In the present study, nearest neighbor, caliper and Kernel matching will all be used to test the robustness of the treatment effect results.

4.3 - Applications and potential problems of the propensity-score matching procedure

The propensity-score matching technique has been applied to a number of quasi-experimental causal interventions. It was made first popular in the epidemiological literature, but has since been added to the developmental economics toolbox for estimating intervention impacts using socioeconomic indicators. Becerril et al. (2010) utilized a propensity-score matching approach to estimate the impact of improved maize varieties on rural poverty in Mexico. Similarly, Mendola (2007) used this method to estimate the impacts on poverty reduction of agricultural technology adoption (HYVs) in Bangladesh. Propensity-score matching analyses were used to estimate returns to soil conservation adoption in the northern Ethiopian highlands (Kassie et al. 2008). Another application of this type of model was used by Mocan and Tekin (2006) to study the impacts of Catholic school attendance in the likelihood that teenagers engage in illicit activities, join gangs, attempt suicide or run away from home.

Although matching estimators have become quite popular among evaluators and impact analysts, some recent contributions to the literature have identified potential sources of bias: (1) the failure of the common support condition; (2) the selection on unobservables; (3) the problems with selecting a comprehensive set of covariates not related to treatment or outcome; (4) geographic mismatch – which could be thought of as a stratification problem; (5) the importance of measuring the target indicator – or outcome variable – the same for the treated and control groups (Heckman and Navarro-Lozano, 2004; Smith and Todd, 2003). The current study seeks to reduce all of the aforementioned biases by presenting the total treatment effects and the RPI Area stratified treatment effects to eliminate geographic mismatch; using the same survey instrument and income models for treatment and control groups; using a number of selection models matching algorithms a a sensitivity analysis to estimate treatment effects. One goal of this study is to build on this growing strand of literature, and to introduce propensity-score matching analysis to the rural development and micro-irrigation impact literature streams.

SECTION 5: METHODOLOGIES [20]

5.1 - Sample Design

An end-line survey was used to collect necessary control-group observations and first-year adopting observations. Control-group households are drawn from areas not subject to treatment contamination. Propensity-score matching techniques described in Section 4 were used to ensure a balanced sample. Comparisons between the adjusted control group and matched treatment group will be used to establish an average treatment effect on the treated (ATT). The control group contains 15 percent more farmers than the treatment group. As mentioned in Section 4, the PSM procedure relies on a larger control group sample to ensure appropriate matches can be made to treatment group observations.

Deciding on a sample size is largely a factor of the variance of the target variable within the population (Ashram, 2008). Using previous survey data from the Rolling-Baseline and Follow-Up Survey an estimate of income variance was calculated. The necessary sample size is a function of the baseline means and standard deviation in relation to the expected income increase from the program. The sampling plan for this analysis resulted in the collection of information from 960 rural households using in-person interviews. 448 of these were IDE product/service using customers and 512 non-adopting, control-group households received the same interview. Both control- and

[20] This section relies heavily on a report written by Clifford Zinnes for the IDE impact evaluation, titled: *Impact Evaluation Design for Zambian Irrigation Project.* This report is included in Appendix B, as it provides additional detail on earlier stages of experimental design used for this evaluation.

treatment-group observations were collected using a multi-site cluster randomized trial. Specific methodologies, design effect, effect size, enumeration costs and underlying assumptions of the design are described in detail in Appendix C.

5.2 - Sampling Plan[21]

Whenever a farmer purchases an IDE product or receives an IDE sponsored service they are registered into a Master Client Database. This database served as the treatment-group sample frame for the current evaluation. A clustered randomized sampling method was used to collect treatment observations. 14 individual farmers were selected from each IDE farmer group using simple random sampling without replacement from the IDE Master Client Database. 8 farmer groups were chosen from each RPI area[22] using simple random sampling without replacement, totaling 32 farmer groups. This is summarized in the equation below:

14 farmers • 8 IDE farmer groups • 4 RPI areas = 448 treatment observations

IDE farmer group membership requires either purchasing a micro-irrigation technology, attending a training seminar or a combination of both. Therefore, it was not possible to utilize IDE farmer groups for control-group clustering. The control-group observations were collected using simple random sampling without replacement from farmer associations in a pre-selected and matched control area.[23] In total, 512 control-group households were sampled. Again, this is summarized below:

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[21] Although Clifford Zinnes was the lead for the experimental design and sampling sections of the evaluation, I was providing significant amount of statistical support during the development of the sampling plan.

[22] RPI area 4 and RPI area 5 are combined and referred to as RPI area Choma/Livingstone, because of an insufficient number of farmer groups.

[23] Comparable control group areas were decided using the Control Group Selection Criteria Matrix, which made qualitative comparisons between areas on water availability, market accessibility, infrastructure, weather, soil, topography and NGO presence. This can be found in Appendix C.

16 farmers • 8 unaffiliated farmer associations • 4 Matched Control Areas = 512 Control Observations

Farmers were asked to come to a community meeting area, so that interviews could be conducted quickly and efficiently. Meeting areas were familiar to farmers, as they were the same locations used for farmer-group meetings (i.e., schools, churches, community centers, etc.).

5.3 - Survey Instrument

The survey instrument was designed by IDE for the Rolling-Baseline and Follow-Up surveys conducted in earlier IDE evaluation efforts. Baseline measures required farmers to recall income, crop production and expenditure information from two years earlier. Costumer Characteristics survey work that has been carried out in Zambia since 2006.[24] Slight modifications were made to the existing survey instrument to include questions for PSM specific covariates and IDE participation. Additionally, a Likert scale section on recall accuracy was added to supplement the recall-bias modeling efforts. Simplifications to the crop-production and sales questions were recommended to speed up the interview process. The complete survey instrument can be found in Appendix D. Trained enumerators filled out surveys during the in-person interview, which took about an hour to complete. Surveys were then collected and coded by IDE staff in Zambia.

[24] Rolling Baseline, Follow-Up and Costumer Characteristics surveys were part of an earlier evaluation effort performed by IDE. The data from these earlier rounds was used to calculate interclass correlation coefficients for the sample design and early model development, but was not used in the current analysis.

SECTION 6: MODELS

6.1 - Income Model

IDE is primarily concerned with the target population's income and production related outcomes. Defining a farmer's income is relatively complex. IDE contracted the University of Wageningen to develop a spreadsheet model that calculates various types of farmer income, as well as other farmer financials. This will be referred to as the MonQi model in all subsequent sections. The MonQi model is a household financial model that is based on the registration of inputs and outputs for the primary activities, including: crops, livestock, and off-farm activities. Inflows and outflows are aggregated for each farmer-household over the time period of interest, and gross margins are summed for all farmer activities. The primary performance indicators that will be used for this evaluation will be total family earnings and total crop income. The general equation for total family earnings is given below:[25]

$$NFI = \Sigma LA.GM + \Sigma AA.GM + \Sigma RA.GM + \Sigma SA.GM + \Sigma OAagri.GM - FIXCOST$$

Where :

ΣLA.GM : Sum of gross margins of all LAs (crops)

ΣAA.GM : Sum of gross margins of all AAs (animals)

ΣRA.GM : Sum of gross margins of all RAs (redistribution activities)

ΣSA.GM : Sum of gross margins of all RAs (stocks)

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[25] From the IDE document titled: *Explanation of the main MonQi financial calculation rules*, produced under contract by University of Wageningen

ΣOAagri.GM: Sum of gross margins of all OAs (other activities)

FIXCOST : Fixed costs

Total family earnings has some distinct advantages over the other income indicators produced by the MonQi model, in that it internalizes all labor reallocation effects as the household adjusts their labor composition between on-farm and off-farm activities. Secondary measures of income that are used for preliminary model development and hypothesis testing are total crop income, total crop revenues, high-value vegetable revenue and crop weight. Additional information on the MonQi model and other indicator equations can be found in Appendix E.

6.2 – Recall-Bias Correction Model

Using data from previous survey rounds, a systematic recall bias model was developed. Unfortunately, there were insufficient observations to develop a model that could be used to correct for baseline recall bias. Additional information, as well as potential future improvements on these efforts is discussed in Appendix F. For the purposes of this study no recall-bias corrections were made, and I assume that recall inaccuracies are normally distributed.

SECTION 7: DATA AND DESCRIPTIVE STATISTICS

The data for this study are from a farmer household survey conducted in 2011 by IDE in four major intervention areas, where the fourth RPI area is a combination of two smaller RPI areas, Choma and Livingstone.[26] A total of 901 farmer households were interviewed on agricultural production, technological adoption, and household demographic and socioeconomic information. Of those that were sampled, 820 were usable observations.[27] The current study has 386 control group farmer households and 434 treated farmer households.[28]

Farmers are faced with different geographic, infrastructure and climactic endowments, depending on what part of the country one is located. To capture some of this variation, IDE has requested that the current analysis considers differences between RPI areas, which were discussed in the *Target Population* section. In a similar fashion, there are innate differences between farmer strata. Of the various strata one could consider for the analysis, gender is the most obvious example. Female-HHHs often lack access to the same input channels and market mechanisms that male-HHHs have, and

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[26] Complete sample design and plan are summarized in Section 5 and presented fully in Appendix B.

[27] Farmer observations were dropped if the percentage of irrigated land was greater than 1. This indicator relied on a number of stated land and crop production values and was a useful proxy for unreasonable responses throughout the survey instrument. Additional observations were dropped if the difference-in-difference estimator was more than 5 standard deviations from the mean.

[28] “Treatment” in this case indicates farmer group membership. This was used as the sampling cluster, and does not necessarily indicate treadle pump adoption. Although the primary treatment effect uses farmer group membership as the binary treatment choice, additional treatment effects were calculated for treadle pump adoption, specifically. These can be found in Section 7.3.

often times they face socio-demographic hardships that must be considered when discussing treatment effects. For these reasons, unmatched[29] pre- and post-treatment descriptive statistics are presented and discussed for the five RPI areas and for male- and female-HHHs, in addition to the obvious inclusion of treatment- and control-group descriptive statistics.

7.1 - RPI Area

Although the districts are similar, there were a number of distinct pre-treatment characteristics that must be considered prior to the calculation of an RPI-specific treatment effect. Observation, treatment and gender counts, as well as key socio-demographic means for each RPI district are presented in Table 2.

Table 2: Sample sizes and demographic statistics, by RPI District[⊗]

RPI District	Total Obs.	Treated Obs.	Control Obs.	% Male HHH	Years of Educ.	# of ppl. in Home	Dist. To Mkt (km)
Kabwe	204	118	86	72%	7.1	7.4	23.8
Lusaka	198	104	94	70%	6.8	7.4	26.7
Kafue	208	120	88	61%	6.9	7.5	27.6
Choma/ Livingstone	203	104	99	78%	7.7	7.7	21.4
Total	**853**	444	409	70%[⊗⊗]	7.1	7.5	24.9

[⊗] Age statistics were not presented because there was not much variation in the RPI District means for age of household head.
[⊗⊗] The sample percentage is less than the population mean presented in the 2010 Zambian census. Largely, this is because IDE targets female-HHHs in their intervention efforts, which would lead to a misrepresentative amount of female-HHHs in the treatment group sample.

The Choma/Livingstone district has a slightly higher education level with 7.7 years of formal education. In addition, the mean number of people in the household is slightly higher for Choma/Livingstone, when compared to other RPI Districts. Other

[29] "Unmatched" refers to the current sample before treatment and control observations are paired based on their propensity scores.

obvious differences are that the percent of male-HHHs is slightly higher in the Choma/Livingstone district. This value is exactly what the Zambian Census of Agriculture claims to be the percent of male-HHHs for rural population of Zambia as a whole.

Table 3 shows key crop production statistics for each RPI Area, and illustrates some important pre-treatment production differences between the RPI areas. For instance, the average amounts of cultivated land in the Kafue and Lusaka RPI Areas is much less than in Kabwe and Choma/Livingstone areas. Despite the smaller crop areas, Kafue produces a similar amount of crop weight compared to the other regions, whereas Choma/Livingstone produces significantly less.[30] The *# of different crops* is a proxy used for crop diversification, as it measures the number of different crops a farmer grows on his/her land over the designated crop year. For the total sample, there was very little change in mean number of different crops between pre and post treatment. However, there are significant differences in the mean number of crops grown in each RPI Area. Choma/Livingstone farmers had the highest level of crop diversification and Lusaka farmers had the lowest, with 6.20 and 4.04 different crops grown, respectively. Standard t-tests demonstrate statistically significant increases in crop weight were observed for every RPI District, as well as the whole sample.

[30] This will be explored in greater detail in Table 4.

Table 3: Land & Crop Production Statistics, by RPI Area[⊗]

Production Measure	Total Sample	Kabwe	Lusaka	Kafue	Choma/ Livingstone
Crop Area 2009 (acres)	6.23	7.43	4.34	4.84	8.35
Crop Area 2010 (acres)	6.77	8.23	4.48	5.47	8.84
Irrigated Area 2009 (acres)	0.63	0.57	0.63	0.72	0.59
Irrigated Area 2010 (acres)	0.67	0.63	0.65	0.79	0.61
# of different crops 2009	5.19	5.69	3.96	4.90	6.22
# of different crops 2010	5.18	5.68	3.84	5.11	6.02
Crop Wgt 2009 (kg)	6,029	7,120	6,118	6,100	4,748
Crop Wgt 2010 (kg)	7,050	8,695	6,710	7,273	5,470

[⊗] The treatment sample only includes those farmers that enrolled in an IDE farmer group between 2009 and 2010, therefore, any 2010 measure will also be referred to as "post-treatment."

Although total crop weight is a good measure for agricultural productivity, it is important to look at what types of crops are being grown. IDE trainings promote the growing of vegetables (i.e., eggplant, cauliflower, tomatoes, onions, cabbage and beans) because they are labor intensive and receive a higher price at the market, compared to staple grains (i.e., maize, millet, amaranth). Table 4 shows the percentage share each crop contributes to total crop weight that is sold by farmers for each RPI Area in 2009. The primary crops grown across all five RPI areas are cabbage, groundnut, maize and rape,[31] where the percentage share of total crop weight for each is 4.8, 4.4, 41 and 14.5, respectively. Looking at the crop shares for each RPI Area, however, we see that the RPI Areas are not homogenous in crop production and that there are some important differences between RPI areas. Kafue grows significantly more okra than the other RPI Areas, with an average of 1.41% of total crop weight being high-valueokra. However, Kafue and Choma/Livingstone districts have a higher share of high-valuetomato production, compared to Kabwe and Lusaka. Another primary difference between RPI Areas are that Lusaka and Kabwe have a more diverse profile than Kafue and

[31] Rape is grown for its leaves, which are cooked and consumed like collard greens.

Choma/Livingstone. Choma/Livingstone has smaller share of Maize (37.6%) than the Lusaka region (54.92%). Also, Kabwe has a much larger share (9.94%) of groundnut than any of the other districts, and Choma/Livingstone has a much lower share (8.77%) of rape production than the other areas. Lastly, Lusaka grows significantly more high-valueChinese cabbage (3.4%) than any other RPI Area.

Table 4: 2009 Individual Crop weight Percentages of Total Crop Weight that is Sold, by RPI Area[⊗]

Type of Crop	Total Sample	Kabwe	Lusaka	Kafue	Choma/ Livingstone
Amaranth	0.54	0.2	1.94	0.06	-
Bean	0.86	0.24	2.19	0.65	0.37
Cabbage	4.78	4.19	1.56	6.7	6.55
Cassava	0.19	0.09	0.46	0.11	0.1
Cauliflower	0.05	0.02	0.14	-	0.04
Chili	0.04	-	0.15	-	-
Cotton	0.83	1.52	1.45	0.19	0.21
Cowpea	0.23	0.06	0.46	0.32	0.1
Cucumber	0.1	0.01	0.36	-	0.02
Eggplant	0.14	0.14	0.07	0.16	0.2
Groundnut	4.44	9.04	3.24	2.41	3.12
Impwua	1.3	1.87	0.85	2.24	0.17
Kale	0.03	-	0.08	0.05	-
Maize	41	41.37	50.82	37.22	34.86
Mango	0.06	0.26	-	-	-
Millet	0.09	0.06	-	0.06	0.25
Okra	0.64	0.42	0.57	1.27	0.28
Paprika	0.01	0.02	-	-	-
Rape	14.05	15.13	15.6	16.86	8.43
Sorghum	0.05	0.03	0.04	0.04	0.1
Soybean	0.42	1.34	0.33	-	-
Tomato	6.7	5.56	5.37	8.39	7.39
Watermelon	0.09	0.1	0.25	0.01	-
Chinese Cabbage	1.22	0.74	3.4	0.74	0.07
Green Beans	0.09	0.05	-	0.28	-
Green Peppers	0.27	0.02	0.64	0.03	0.41
Indig. Vegetables	0.58	-	2.36	-	-
Onion (bulb)	0.71	1.17	0.35	1.27	-
Onion	0.46	-	-	-	1.85
Irish Potatoes	0.17	0.18	0.01	0.44	0.01
Spring Onions	0.04	-	-	-	0.15

Sugar Cane	0.02	0.07	-	0.01	-
Sunflower	0.44	0.18	0.24	0.45	0.91
Sweet Potato	2.61	4.42	2.32	1.4	2.33
Swiss Chard	0.11	-	0.43	-	-

⊗ Sold Crop % $_{i,t}$ = Sold Crop Weight$_{i,t}$ / Total Crop Weight$_t$ -- Where: i = individual crop ; t = crop year

∇ Fields that are left blank indicate 2009 sold crop percentages less than .01%.

Lastly, it is appropriate to look at income differences between RPI Areas. Table 5 contains pre- and post-treatment means for total family earnings, off-farm income and crop income. Although these measures are collinear, it is important to look at the differences in incomes, as these are our primary indicator for our treatment effects. Pre and post-treatment total family earnings for the whole sample were 1,719 USD and 2,178 USD, respectively. Notable increases between the two crop years for both off farm income and crop incomes were observed for the whole sample, where the differences were 151 and 335 USD, respectively. At the RPI level, however, there was some variation. Pre treatment family incomes were similar for Kabwe and Lusaka farmers, and were lower than Kafue and Coma/Livingstone. Similarly, Kafue and Choma/Livingstone pre treatment family earnings were not statistically different from one another. Lusaka farmers did not have statistically significant changes in total family earnings or crop income, unlike the other RPI Districts. Kabwe, Kafue and Choma areas all had significant increases in total family income from 2009 to 2010 crop years, where total family earnings changes were 756, 706 and 329 USD, respectively. Accompanying significant increases in crop earnings were observed for the same three RPI areas. This illustrates the increased importance of matching, because the majority of the region experienced increases in total family income and crop earnings, and as a result, treatment effects could be biased upwards in Lusaka if not properly estimated.

Table 5: Grouped Treatment and Control Sample Income Means, by RPI Area

Income Measure	Total Sample	Kabwe	Lusaka	Kafue	Choma/ Livingstone
2009 Family Earnings	1,719	1,501	1,593	1,887	1,888
2010 Family Earnings	2,178	2,257	1,624	2,593	2,217
Diff. Family Earnings	460***	756**	32	706***	329**
2009 Off Farm Income	306	179	382	303	364
2010 Off Farm Income	457	204	463	728	430
Diff. in Off Farm Income	151***	26**	81*	426***	66**
2009 Crop Earnings	1,261	1,157	1,213	1,300	1,370
2010 Crop Earnings	1,596	1,884	1,276	1,639	1,573
Diff. in Crop Earnings	335***	727**	63	339***	202***

All values are in U.S. Dollars using exchange rates from the Bank of Zambia at the time of interview, Where: 1USD = 4740 ZMK.
T-tests were conducted to determine whether the pre and post treatment incomes were equal (* = 10%, ** = 5% & ***=1%)

7.2 – Gender of Head of Household

One of the primary impacts that IDE is concerned with is the impacts they are having on male-HHHs compared to female- headed households. Table 6 contains demographic statistics for male- and female-HHHs. Female-HHHs were older than male-HHHs by about 2 years. Not surprisingly, male-HHHs had completed more years of school (7.6) than female-HHHs (6.6). No statistical differences were observed for the number of people in the home, the distance to market or the dependency ratio.[32]

Table 6: Demographic statistics, by Gender of HHH (HHH)

Demographic Measure	Male HHH	Female HHH	T-Test Sig.
Age	42.13	44.22	**
Education Years	7.37	6.58	***
# of ppl. In home	7.57	7.23	
distance to mkt.	26.69	20.65	
Dependency Ratio	1.51	1.37	

T-tests were conducted to determine whether the male and female means were equal (* = 10%, ** = 5% & ***=1%)

[32] Dependency Ratio = # of ppl. in HH unable to work / # of ppl. in HH able to work
With: Ages 0 – 14 and 50-99 were designated as unable to work; 15-49 were classified as workers.

There were significant differences between male-and female-HHHs with respect to total land area, where male-HHHs cultivated approximately 6.5 acres compared to female-HHH who cultivated about 5.8 acres. Pre and post treatment differences were greater for male-HHHs than for female-HHHs, where male-HHHs increased their cultivated area by about .5 acres compared to the increase in cultivated land for female-HHHs, which was only .1 acre. There were no statistical differences between male-and female-HHHs with respect to crop diversity. Significant differences were observed, however, with regard to total crop weight produced. In 2009 and 2010, female-HHHs produced significantly less than male-HHHs, 5,350 KG and 6,318KG in 2009 and 5,946KG and 7,520KG in 2010, respectively. The specific drivers of this are outside the scope of this project, but some general hypotheses have been briefly discussed in previous sections.

Although the total crop weights and land areas are statistically different between male- and female-HHHs there are very few differences in the specific crop shares between male-and female-HHHs. Table 8 only shows the crops that had significantly different crop shares for male- and female-HHHs. Female-HHHs had higher crop shares of the primary niche vegetables amaranth, groundnut and "indigenous vegetables," 1.36, 5.95 and 1.20 percents, respectively. Male-HHHs grew significantly more Irish potatoes than female headed households, although the actual crop share was quite small at .23 percent.

Table 7: Land & Crop Production Statistics, by Gender HHH

Production Measure	Male HHH	Female HHH	T-Test Results
Crop Area 2009 (acres)	6.42	5.78	*
Crop Area 2010 (acres)	7.09	6.03	***
Irrigated Area 2009 (acres)	0.65	0.58	*
Irrigated Area 2010 (acres)	0.70	0.59	
# of different crops 2009	5.19	5.19	
# of different crops 2010	5.20	5.12	
Crop Wgt 2009 (kg)	6,318	5,350	**
Crop Wgt 2010 (kg)	7,520	5,946	***

T-tests were conducted to determine whether the male and female means were equal (* = 10%, ** = 5% & ***=1%)

Table 8: Pre-treatment Individual Crop weight Percentages of Total Crop Weight that is Sold, by Gender of HHH$^{\otimes}$

Type of Crop$^{\nabla}$	Male HHH	Female HHH	T-Test Result
Amaranth	0.4%	1.36%	*
Groundnut	4.4%	5.95%	*
Indigenous Vegetables	.30%	1.20%	**
Irish Potato	.23%	.001%	**

$^{\otimes}$ Sold Crop % $_{i,t}$ = Sold Crop Weight$_{i,t}$ / Total Crop Weight$_t$ -- Where: i = individual crop ; t = crop year
$^{\nabla}$ Only those crops that had statistically different shares are shown.

Table 9: Income Means, by Gender of HHH

Income Measure	Male HHH	Female HHH	T-Test Result
2009 Family Earnings	1,823.67	1,537.96	
2010 Family Earnings	2,312.34	1,977.38	
Diff. Family Earnings	488.67	439.42	
2009 Off Farm Income	297.30	346.78	
2010 Off Farm Income	425.65	549.54	
Diff. in Off Farm Income	128.35	202.75	
2009 Crop Earnings	1,352.03	1,097.51	**
2010 Crop Earnings	1,735.93	1,357.43	**
Diff. in Crop Earnings	383.90	259.92	

All values are in U.S. Dollars using exchange rates from the Bank of Zambia at the time of interview, Where: 1USD = 4740 ZMK.
T-tests were conducted to determine whether the male- and female-HHH incomes and pre/post differences were equal (* = 10%, ** = 5% & ***=1%)

Income differences between male-and female-HHHs are particularly interesting. Somewhat surprisingly, there are no significant differences between pre or post treatment total family earnings, or between pre-and post-off-farm incomes. Although female-HHHs had a slightly lower mean for the whole sample, the difference was not statistically significant. Crop earnings were a different story. Pre treatment crop earnings were significantly lower for female-HHHs at a 5% level of significance, where female-HHHs earned 1,097USD and male-HHHs earned 1,352USD. Post treatment means were similar, in that female-HHHs earned significantly less than male-HHHs, with 1,357USD and 1,735USD, respectively. This is not too surprising, given the social and market difficulties that female-HHHs face in the agricultural sector, often times paying more for inputs and receiving less for outputs. This was also evident in the statistical difference in crop production mentioned before. What is surprising, however, is that the crop earnings from 2009 to 2010 increases were not significantly different for male- and female-HHHs. Although we are not looking at matched treatment and control groups at this point, this would indicate that the factors driving the increase in crop earnings affected female-HHHs equally as much as they affected male-HHHs.

7.3 - Unmatched Treatment and Control Groups

It is important that pre treatment comparisons of income-related characteristics are made between treatment and control group members. If there are drastic differences between treatment and control group samples, quasi-experimental methods, like PSM, will not overcome the problems of sample selection bias that was previously discussed. Therefore, demographic, crop production, land and income differences are presented for two reasons: First, to provide pre treatment (i.e., baseline) information to the reader. Second, to provide some initial descriptive statistics so that the reductions in bias from matching become evident in the subsequent sections.

For sampling purposes, the "treatment" group was comprised of any farmer who had become a member of an IDE farmer group. For the sake of the present evaluation, however, we look at a number of “treatments.” As previously discussed, IDE farmers could receive/invest in a number of different treatments. For the rest of the paper, we will look at five primary “treatments” and three primary “controls.” The differences in these treatment and control sub-samples are presented in Table 11. This is done for two reasons: first, it allows us to calculate the specific treatment effects of a multitude of treatment combinations, which will allow us to test a number of hypotheses. Second, it will provide IDE with a much more thorough and nuanced evaluation that can be used for further program development and expansion.

Table 10: Treatment and Control Group Combinations

		Was hardware purchased over evaluation period?				
	Source	*Maybe*	*No*	*Yes*	*Yes, IDE technology*	*Any pump or drip*
Type of Training	*Potentially*	C0	C1			
	None					
	IDE	T0	C2, T4	T1	T3	T2
	Any					
	Non-IDE					

It is important to note that any combination of cells within this matrix could be tested, if we had the appropriate sample sizes. As more and more limitations are enforced, observations are quickly lost, which is what the limiting factor was for the present analysis. Nonetheless, five different treatment combinations have been included and three different control groups have been created to calculate the treatment effects presented in the results section. The sub-sample notations presented in Table 10 and 11 will be used throughout the rest of the paper. Descriptive statistics are presented for two different combinations of treatment and control, as they are the highest priority for IDE. The first is T_0 and C_0, and the second set is T_3 and C_1. Additional information on sample size and brief descriptions of each sub-sample is given in Table 11.

Table 11: Treatment and Control Group Observation Counts and Descriptions.

Sample	# of Obs.	Description
Control		
C_0	370	Any non-IDE farmers that were sampled based on the sample design stipulations. This sample includes non-IDE farmers who may or may not have irrigation technologies. This may also include farmers who have received non-IDE training or alternative extension services from another organization.
C_1	342	Non-IDE farmers that do not have any irrigation technology, where possible irrigation technologies include: treadle pump, rope and washer pump, drip irrigation, motorized pump or micro-sprinkler.
C_2	289	IDE farmer group members who have not invested in an irrigation technology. This is used to test the incremental impact of technology adoption for farmers who have received training.
Treatment		
T_0	424	Any IDE-farmer group members based on the sample design stipulations. This sample includes IDE farmers who may or may not have invested in an irrigation technology. This is the largest treatment sample.
T_1	135	Any IDE-farmer group members that have also invested in at least one irrigation technology, including: treadle pump, rope and washer pump, drip irrigation, motorized pump or micro-sprinkler.
T_3	127	Any IDE-farmer group members that have invested in at least one IDE irrigation technology, including: treadle pump, rope and washer pump or drip irrigation.
T_2	134	Any IDE-farmer group members that have invested in at least one pump technology, including: treadle pump, rope and washer, motorized pump and/or drip irrigation.
T_4	289	Any IDE-farmer group member that has NOT invested in any irrigation technologies. This is used to test the incremental impact of IDE training. This is the same sample as C_2, but it is used as a treatment sample instead of a control sample.

There were no significant differences between T_0 and C_0 with respect to age of household head, education of household head, total number of people in the household or the average distance to the nearest market. This would suggest that age, education and absolute subsistence pressure (i.e., total consumption need for the family) are not correlated with the decision to participate in IDE activities or adopt a micro-irrigation technology. Significant differences were observed, however, when looking at the gender distribution between T_0 and C_0 groups. C_0 had approximately 76% males and T_0 had only 65% male population. Again, this is not too surprising as we would expect to see a higher percentage of female headed households in the treatment group because IDE targets female HHH in their intervention and marketing efforts. Another important difference is that T_0 has significantly higher dependency ratios (1.54) than C_0 (1.38). This indicates that T_0 has less relative labor in the household, compared to C_0. Farmers could possibly be supplementing their labor with pump technologies or more efficient farming practices.

Although there were few demographic differences between T_0 and C_0 group samples, there are significant pre treatment land and crop production differences; these are presented in Table 12.

Table 12: Land & Crop Production Statistics, by T_0 and C_0 Samples

Production Measure	C_0	T_0	T-Test Sig.
Crop Area 2009 (acres)	6.40	6.08	
Crop Area 2010 (acres)	7.12	6.47	**
Irrigated Area 2009 (acres)	0.56	0.69	**
Irrigated Area 2010 (acres)	0.60	0.73	**
# of different crops 2009	4.89	5.45	**
# of different crops 2010	4.86	5.46	**
Crop Wgt 2009 (kg)	5,316.0	6,456.4	**
Crop Wgt 2010 (kg)	5,992.9	7,460.4	***

T-tests were conducted to determine whether the T_0 and C_0 means were equal (* = 10%, ** = 5% & ***=1%)

T_0 and C_0 group farmers did not have significantly different 2009 crop area estimates. In 2010, however, T_0 farmers had a significantly lower mean crop area. T_0 farmers had higher irrigated crop area means for both the 2009 and 2010 crop years. Similarly, T_0 members had a more diverse crop portfolio compared to C_0 members. Although this finding would not be surprising for the post treatment (2010) crop year, it is a little surprising to see in the pre treatment crop year. In addition, pre treatment crop weights were significantly higher for T_0 members than C_0 members, where crops weights were 6,4560KG and 5,316KG, respectively. More importantly, T_0 crop weights increased by 15.5% over the period, and C_0 crop weights only increased by 12.7%. It is particularly interesting that T_0 group members cultivated less land than C_0, but had higher yields (more intense production). This may be explained by IDE program participation and/or irrigation technology adoption.

Table 13: Pre-treatment Individual Crop Weight Percentages of Total Crop Weight that is Sold, by T_0 and C_0 ⊗

Type of Crop∇	C_0	T_0	T-Test Results
Cabbage	2.93%	6.41%	***
Impwua	0.63%	1.88%	***
Tomato	5.27%	7.96%	***
Chinese Cabbage	1.68%	0.82%	**
Onion	0.05%	0.81%	***

⊗ Sold Crop $\%_{i,t}$ = Sold Crop $\text{Weight}_{i,t}$ / Total Crop Weight_t -- Where: i = individual crop ; t = crop year
∇ Only those crops that had statistically different shares are shown.

Using the same methods as before, individual crop shares were compared to see if there were any significant differences between T_0 and C_0 with regard to what is actually being grown. Table 13 shows that T_0 group members were growing significantly higher shares of high-value, labor-intensive, vegetables before treatment began. 6.4% of the total crop weight grown by treatment group members was cabbage, compared to only 2.9% by a C_0 farmer. Similarly, T_0 farmers produced larger shares of tomatoes than C_0 farmers, where tomato crop shares were 7.96% and 5.2%, respectively. Other high-value crops that had statistically higher shares among T_0 households include: onion, Chinese cabbage and impwua. Although these shares were smaller in magnitude, compared to cabbage and tomatoes, they illustrate some important differences in pre-treatment crop mix between T_0 and C_0 farmer households. Exploring this in detail is outside the scope of the current project, but it begs the question: do farmers invest in pump technologies and trainings because they recognize that changing farming practices will increase their incomes? Or, do they do so because they have already begun growing high-value, labor-intensive crops, and need additional technological support? This table would suggest that treatment group farmer households have made the decision to grow tomatoes and cabbage prior to joining an IDE farmer group.

Income comparisons for T_0 and C_0 samples are presented in Table 14. T_0 and C_0 family earnings were statistically different for pre and post treatment at 10%. 2009 and 2010 total family earning differences were not statistically different for T_0 and C_0. Of particular interest is the fact that C_o off-farm income increased by 104% but T_0 off-farm income only increased by 17%. This could be explained by the fact that treatment group members are less likely to substitute away from crop production, because they have either invested money into a pump technology or time into farmer group trainings and services. Therefore, the control group farmer-households would more easily substitute into off-farm income activities than treatment group farmer-households. Pre-treatment crop earnings were significantly higher for the T_0 sample (1,378USD) than the C_0 sample (1,074USD). T_0 farmers had significantly higher increases in crop earnings between 2009 and 2010, which is were IDE expects to see the majority of their impacts take place. The two groups had almost identical relative increases in overall production by weight, but farmers in the control group had larger relative increases in crop income per kg produced (15% for controls and 4% for treatment). Another interesting observation is that treatment group members earned more per acre, but control group members increased acreage more than treatment members over the period of interest. These farming practice decisions may dilute any potential treatment effects, as they are different means to the same end. Control group members seem to be increasing their scale of productivity, whereas treatment members are increasing the efficiency of production.

Table 14: Income means and differences, by T_0 and C_0

Income Measure	C_0	T_0	Ttest Sig.
2009 Family Earnings	$1,553	$1,847	*
2010 Family Earnings	$1,941	$2,217	*
Diff. Family Earnings	$388	$370	
2009 Off Farm Income	$250	$349	
2010 Off Farm Income	$512	$410	***
Diff. in Off Farm Income	$262	$60	***
2009 Crop Earnings	$1,074	$1,378	***
2010 Crop Earnings	$1,218	$1,684	***
Diff. in Crop Earnings	$143	$307	***

All values are in U.S. Dollars using exchange rates from the Bank of Zambia at the time of interview, Where: 1 USD = 4740 ZMK.
T-tests were conducted to determine whether the control and treatment incomes and pre/post differences were equal (* = 10%, ** = 5% & ***=1%)

Because of the spectrum of treatment opportunities that was mentioned in the previous section, treatment effects were calculated looking at various levels of treatment. One of the primary effects IDE is interested in was the impact of an IDE farmer who has adopted a pump technology over the evaluation period compared to a non-IDE farmer who has not adopted any irrigation technologies. This could be thought of as the "whole" treatment effect, in that the individuals who received the most treatment (i.e., IDE training/services and investment in at least one irrigation technology) are compared to control group farmers who have the least amount of treatment spillover (i.e., no IDE training and no irrigation technologies). Comparisons of income measures of IDE farmers who have adopted an IDE irrigation technology (T_3) and control group farmers who have not adopted any irrigation technology (C_1) are presented in Table 15.

Table 15: Sample income means and differences, by T_3 and C_1

Income Measure	C_1	T_3	T-Test Sig.
2009 Family Earnings	1,504.23	2,315.18	***
2010 Family Earnings	1,900.47	2,716.05	***
Diff. Family Earnings	396.24	400.86	
2009 Off Farm Income	256.72	468.77	***
2010 Off Farm Income	545.88	499.48	
Diff. in Off Farm Income	289.16	30.71	***
2009 Crop Earnings	1,029.67	1,655.37	***
2010 Crop Earnings	1,182.09	2,015.19	***
Diff. in Crop Earnings	152.42	359.82	***

All values are in U.S. Dollars using exchange rates from the Bank of Zambia at the time of interview, Where: 1 USD = 4740 ZMK.
T-tests were conducted to determine whether the control and treatment incomes and pre/post differences were equal (* = 10%, ** = 5% & ***=1%)

Similar results are found for T_3 and C_1 as with T_0 and C_0. Namely, pre and post total family earnings are significantly different from one another, but the differences between pre and post intervention total family earnings are not statistically different. This would suggest that there is no significant treatment effect on total family income if we were to look at an unmatched sample. There is evidence of a positive treatment effect on total crop earnings. Although T_3 farmers had higher baseline and end line measures, they also demonstrated a significantly greater change in crop earnings over the period, where T_3 and C_1 crop income changes were 359USD and 152USD, respectively. There is also evidence of a negative treatment effect on off-farm income, as C_1 farmers (289USD) had a significantly higher change in off-farm income than T_3 farmers (31USD).

These findings suggest that IDE participation and/or adoption of a micro-irrigation technology may have a role in increasing family incomes, and particularly, increasing crop earnings. However, many conflicting activities are taking place, and it has been shown that many additional characteristics correlate with total family earnings and crop earnings, namely: RPI area and gender. The treatment effects on total family earnings seem to rely on the relative magnitudes of positive and negative effects on crop income and foregone off-farm income gains, respectively. The fact that participation and/or adoption is endogenous further supports the fact that simple comparisons between treatment and control groups have no causal interpretation, and that further analysis must be performed to make causal inferences.

SECTION 8: RESULTS[33]

Difference-in-differences (DID) matching estimators for five primary outcome indicators are estimated by comparing the mean changes between treatment and control groups over two periods, including: total family earnings, total crop income, total crop revenue, high-value vegetable revenue and crop weight. Using the DID matching estimators as the outcome indicator in a propensity-score matching framework controls for events that took place over the intervention period that are not measured in the pre-treatment covariate set, while simultaneously controlling for self selection bias by matching. The primary assumption of the model, however, is that changes occurring over the intervention period have identical influence on treatment and control outcomes.[34] Stratifying the samples according to specific characteristics that would influence the propensity to adopt and the outcome indicator of interest can reduce the magnitude of this assumption. For these reasons, whole treatment effects are presented for six evaluations of interest, gender specific treatment effects are calculated for two primary evaluations and RPI Area treatment effects are presented for two evaluations. The evaluations that were performed are presented in Table 16.

[33] Sampling weights are applied for the estimation of all treatment effects in this section.
[34] The term that is most commonly used for this assumption is unconfoundedness, which is also a common assumption of multi-variate regression based analyses (Imbens et al. 2009).

Table 16: Evaluations, by strata

Evaluation	Primary Question
Whole Treatment	
T_0 vs. C_0	What is the impact of any involvement with IDE?
T_1 vs. C_1	What is the impact of involvement with IDE and any irrigation technology?
T_3 vs. C_1	What is the impact of involvement with IDE and any IDE technology?
T_2 vs. C_1	What is the impact of involvement with IDE and any pump technology or drip system?
T_3 vs. C_2	What is the incremental impact of adopting an IDE technology if you are already involved with IDE?
T_4 vs. C_1	What is the impact of being in an IDE farmer group?
Stratified by Gender	
T_3 vs. C_1	What is the impact of involvement with IDE and any IDE technology for men? Women?
T_4 vs. C_1	What is the impact of being in an IDE farmer group for men? Women?
T_0 vs. C_0	What is the impact of any involvement with IDE for men? Women?
Stratified by RPI Area	
T_3 vs. $C_1^{\otimes}$	What is the impact of involvement with IDE and any IDE technology for each RPI Area?
T_4 vs. C_1	What is the impact of being in an IDE farmer group in each RPI Area?
T_0 vs. C_0	What is the impact of any involvement with IDE for each RPI Area?

$^{\otimes}$ This evaluation was not completed for Lusaka because there were an insufficient number of treatment group members.

8.1 - Selection Model[35]

As explained in the Section 4, each sample requires a binary selection model to obtain the individual propensity scores for each observation. Household, socio-economic, crop production and income variables are used as controls in the probit model for treatment classification. A number of specifications were used, depending on the specific sample size and balancing properties. Household and socio-economic characteristics

[35] Additional selection model results for RPI Area and gender treatment effects, as well as subsequent balancing tests, are included in Appendix G.

include: household size, dependency ratio, household assets,[36] gender of household head, age of household head, education level of household head, pre-treatment household income and distance of household to nearest major market. Crop production characteristics include: number of different crops grown, vegetable producer dummy variable and livestock dummy variable.[37] The primary income characteristic that was used was pre-treatment household cash income.[38] Table 17 presents the results of the selection models used for the whole treatment evaluations given the covariate set.

Table 17: Selection model results, by evaluation$^{\otimes}$

VARIABLES	T_0 vs. C_0	T_1 vs. C_1	T_3 vs. C_1	T_2 vs. C_1	T_3 vs. C_2	T_4 vs. C_1
Gender of HHH	-0.347**	-0.270*	-0.214	-0.260*	0.063	-0.329**
	(-0.107)	(-0.155)	(-0.158)	(-0.156)	(-0.154)	(-0.118)
Age of HHH	0.004	0.010**	0.010**	0.010**	0.003	0.005
	(-0.004)	-(0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.004)
Dist. To Market	-0.002	0.000	0.000	0.000	-0.008**	-0.007**
	(-0.001)	(-0.001)	(-0.001)	(-0.001)	(-0.003)	(-0.003)
Education of HHH	-0.008	0.001	-0.001	0.002	0.01	-0.018
	(-0.016)	(-0.021)	(-0.021)	(-0.021)	(-0.023)	(-0.018)
# of Different Crops Grown	0.001	-0.006	-0.01	-0.007	0.01	0.011
	(-0.019)	(-0.028)	(-0.028)	(-0.028)	(-0.027)	(-0.022)
# of Assets	0.014	0.095***	0.092***	0.093***	0.135***	-0.009
	(-0.018)	(-0.026)	(-0.027)	(-0.026)	(-0.029)	(-0.021)
Total # of ppl in HH	-0.02	-0.039*	-0.036*	-0.039*	-0.033	-0.008
	(-0.014)	(-0.022)	(-0.022)	(-0.022)	(-0.022)	(-0.015)
Vegetable Producer (2009)	0.391***	0.623***	0.626***	0.623***	0.219	0.327**
	(-0.112)	(-0.164)	(-0.165)	(-0.164)	(-0.169)	(-0.124)
Livestock Dummy (2009)	-0.058	-0.232*	-0.184	-0.236*	-0.144	0.065
	(-0.095)	(-0.136)	(-0.138)	(-0.136)	(-0.142)	(-0.108)
Willingness to try new technology (Dummy)	0.02	-0.048	-0.131	-0.049	-0.142	0.044
	(-0.076)	(-0.106)	(-0.128)	(-0.106)	(-0.107)	(-0.088)
% Irrigated Crop Land(09)	-0.183	-0.056	-0.132	-0.061	-0.228	-0.123

[36] A continual variable measuring how many assets the household owns, or has partial ownership in, was used as a simple household asset indicator. The potential set of assets includes technological assets (i.e., cell phone, television, radio), agricultural assets (i.e. watering cans, poly-pipe, ox-plough, wheelbarrow, vegetable dryer), transportation assets (i.e., bicycle, motor bike, car) and structural assets (i.e., iron sheet roofing).

[37] Vegetable and livestock dummies equal 1 if the household earns more than 50USD per year from high-value vegetable production and if the household earns any revenues from livestock production, respectively.

[38] Household net cash income exhibited the lowest variance out of the pre-treatment household income indicators, and was therefore the easiest to use for selection model development.

	(-0.246)	(-0.377)	(-0.388)	(-0.377)	(-0.423)	(-0.272)
Regional Sale of Crops(09)	-0.112	-0.194	-0.148	-0.198	-0.157	-0.058
	(-0.106)	(-0.146)	(-0.149)	(-0.146)	(-0.157)	(-0.12)
HH Net Cash income (09)	0.001**	0.001**	0.001**	0.001**	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.053	-1.273**	-1.090**	-1.265**	-1.217**	-0.106
	(-0.349)	(-0.486)	(-0.516)	(-0.486)	(-0.52)	(-0.404)
Observations	744	452	445	451	388	593

⊗ All of the selection models presented in this paper result in balanced samples, according to the *pscore*, *pstest* and *psmatch* routines conducted in STATA
Note: Standard Errors are in parentheses and * = 10%, ** = 5% & ***=1% levels of significance.

It is important to reiterate that this is not an exercise in technology-adoption modeling explicitly. This is not a causal model for technology adoption or IDE farmer group participation, as it does not include every observable household covariate that could influence treatment classification. Instead it is a selection model that includes covariates as part of a propensity-score specification to ensure that a balanced comparison group is constructed where observable characteristics are distributed evenly across propensity-score intervals, as described by Smith and Todd (2005).

Despite its limitations, the selection model can shed some light on the significance of observable covariates in predicting treatment classification. Significant covariates that predict the decision to adopt irrigation technologies or to participate in IDE farmer groups are somewhat robust across the various evaluations. The gender of the HHH is significant for all evaluations except for those using the T_3 treatment group. The coefficients on gender of HHH are negative and significant for the majority of evaluations, which lend further support to the notion that females are targeted by IDE intervention efforts, and are therefore more likely to be members of a treatment group. It is not clear why gender would be insignificant for the evaluations including the T_3 group, this may be explained by the lower number of observations within that evaluation sample. The age of HHH is positive and significant for three of the six evaluation specifications, each of which is specifically looking at the IDE farmer group members that have also adopted an irrigation technology. This indicates that older heads of household are more likely to become involved in IDE farmer group and adopt an irrigation technology. In two of the evaluation specifications, the distance to the nearest market is a significant predictor of treatment classification. Those households that are further from an active market are less likely to be members of the T_3 or T_4 treatment groups. This is line with a priori expectations, in that those who are further from a market are less likely to be influenced by market-driven programs like IDE's.

The number of household assets is also positive and significant for four of the six evaluations, primarily those evaluations that are specifically considering technology adoption in the treatment classification. This may be indicative of an overall willingness to invest in household assets. Those farmer-households that made more than 50USD from high-value vegetable production were more likely to be involved in any treatment group, including those that specifically looked at technology adoption. This suggests that those farmers who were already growing and selling high-value vegetables were more likely to become involved with an IDE farmer group and adopt irrigation technologies. For two of the evaluations (T_1 vs. C_1 and T2 vs. C_1) households that have revenues from livestock were less likely to become members of IDE farmer groups and adopt any irrigation technologies. This is not surprising, especially when income is being controlled for, as farmers are limited in their investment abilities. A farmer-household that is focused on raising livestock would be less likely to adopt irrigation technologies that would allow them to grow high-value vegetables. The last covariate that was significant in predicting treatment classification is household cash income. (i.e., farmers that had a higher income were more likely to be members of any treatment group).

8.2 - Whole-sample Treatment Effects

The treatment effects for each of the evaluations are estimated using three different methods: nearest neighbor matching (NNM), caliper based matching (CBM)[39] and Kernel-based matching (KBM).[40] Results for the whole-sample treatment effects are shown in Tables 18 and 19. I will first briefly discuss the results from each individual evaluation, and then I will discuss the results for each of the performance indicators across the various evaluations.

Table 18: Whole-sample treatment effects for evaluations 1-3

Performance Indicator	T_0 vs. C_0			T_1 vs. C_1			T_3 vs. C_1		
	KBM	**NNM**	**CBM**	**KBM**	**NNM**	**CBM**	**KBM**	**NNM**	**CBM**
Total Family Earnings Diff.									
Treatment Effect	-\$43	**-\$163**	**-\$177**	-\$112	\$161	\$207	-\$116	\$144	\$102
p-value	0.373	0.041	0.027	0.318	0.428	0.324	0.293	0.574	0.706
Total Crop Income Diff.									
Treatment Effect	**\$204**	**\$130**	**\$119**	**\$318**	**\$499**	**\$534**	**\$300**	**\$262**	\$211
p-value	0.000	0.002	0.005	0.000	0.000	0.000	0.000	0.083	0.176
Total Crop Revenue Diff.									
Treatment Effect	**\$174**	**\$94**	**\$86**	**\$251**	**\$324**	**\$347**	**\$230**	\$170	\$113
p-value	0.000	0.028	0.041	0.002	0.002	0.001	0.005	0.257	0.467
High-value vegetable Rev.									
Treatment Effect	**\$40**	\$33	\$30	\$83	\$94	\$103	**\$78**	**\$129**	\$72
p-value	0.079	0.250	0.300	0.109	0.136	0.101	0.090	0.023	0.171
Crop Weight Difference (kg)									
Treatment Effect	**396**	213	199	-35	**590**	**696**	76	308	247
p-value	0.005	0.194	0.226	0.446	0.067	0.038	0.752	0.458	0.573

[39] The caliper radius used for the estimation of all results was (0.05).
[40] Matching with replacement is performed for both the NNM and CBM methods. This was done because there are a limited number of observations to be used for matching. Although this reduces bias, it can cause problems when there are control units similar to the treated units. In this case, bias may increase, but the precision of the estimates could be improved.

For the first evaluation (T_0 vs. C_0), which is the comparison of any IDE farmer group member to any non-IDE farmer group member regardless of technology adoption status, there was a negative significant effect on total family earnings between 163-177USD. Conversely, there were positive significant effects across all three matching estimators for crop income between 119-204USD. Not surprisingly, there were positive significant results for crop revenues as well, however, it remains unclear as to why the impacts on crop revenues would be lower in magnitude than the impacts on crop income. One potential explanation for this finding is that IDE activities reduce the costs of production/inputs to their farmers, rather than increasing the revenues received from the sale of goods. For the KBM estimates there were positive significant results in high-value vegetable revenues and crop weights. These effects were not robust across matching estimators and should be treated as being relatively weak.

The second evaluation (T_1 vs. C_1), narrows the treatment and control groups by comparing IDE farmers who have adopted any irrigation technology with non-IDE farmers that have not adopted any irrigation technology. Now that the focus is on a more sophisticated form of treatment one would expect to see the magnitudes and significance of the treatment effects to rise, and this is indeed what was found. There were no robust or significant effects on total family earnings, but there were positive significant effects across all three matching estimators on total crop income (318-499USD) and total crop revenues (251-347USD). There were additional positive effects on crop production of 590-696kg of additional crop production between the two crop years for the treatment group.

The third evaluation (T_3 vs. C_1) looks at the impact of IDE farmers that have adopted an IDE pump/drip technology compared to non-IDE farmers that do not have any irrigation technologies. The primary difference for this evaluation is that those farmers who own a motorized pump are removed from the treatment sample. One would expect that the magnitudes would fall slightly because the irrigation technologies that are considered as part of treatment are more manually driven. This was indeed the case, where positive significant effects were found for total crop income between 262-300USD. Although the effects on crop revenues were not robust, positive significant effects on high-value vegetable production were evident for the NNM and CBM estimators.

Table 19: Whole-sample treatment effects for evaluation 4-6

Performance Indicator	T_2 vs. C_1			T_3 vs. C_2			T_4 vs. C_1		
	KBM	NNM	CBM	KBM	NNM	CBM	KBM	NNM	CBM
Total Family Earnings Diff.									
Treatment Effect	-$107	-$81	-$85	-$55	$43	$36	-$13	$108	$100
p-value	0.341	0.684	0.684	0.536	0.969	0.873	0.821	0.205	0.242
Total Crop Income Diff.									
Treatment Effect	**$335**	**$341**	**$335**	-$37	$0	$59	**$151**	**$178**	**$176**
p-value	0.000	0.030	0.042	0.584	0.998	0.622	0.000	0.001	0.001
Total Crop Revenue Diff.									
Treatment Effect	**$269**	$142	$123	-$96	-$99	-$27	**$145**	**$170**	**$167**
p-value	0.001	0.292	0.376	0.182	0.415	0.818	0.001	0.001	0.002
High-value vegetable Rev.									
Treatment Effect	**$105**	**$163**	**$145**	-$20	$19	$13	**$52**	**$64**	**$62**
p-value	0.040	0.015	0.016	0.614	0.727	0.802	0.077	0.058	0.064
Crop Weight Difference (kg)									
Treatment Effect	238	-159	-145	**-550**	**-736**	-600	**449**	**473**	**458**
p-value	0.300	0.721	0.757	0.033	0.055	0.131	0.010	0.016	0.020

Note: treatment effects in bold are significant at the 10% level.

In the fourth evaluation (T2 vs. C_1) the treatment group contains IDE farmers that have adopted any pump or drip technology, but does not include those that have a micro-sprinkler. Positive significant impacts on crop income were found for all three matching estimators, between 335-341USD. Additional positive robust effects for the high-value vegetable revenues were found in all three cases (105-145USD). No significant results were found for total family earnings or crop weight measures.

The fifth evaluation (T_3 vs. C_2), seeks to determine the incremental impact of IDE technology adoption for an IDE farmer. This evaluation suffers from a limited sample size, and as such, the standard errors were quite large. Nonetheless, negative significant treatment effects were found for crop weights for the KBM and NNM estimators, where IDE farmers that have adopted an IDE technology actually produced between 550-736kg less over the intervention period than IDE farmers that have not adopted any technologies. Additional discussion on this will be found later.

The sixth evaluation (T_4 vs. C_1) explores the effect of IDE farmer group enrollment, by comparing IDE farmer group members that have not adopted any irrigation technologies with non-IDE farmers that have not adopted any irrigation technologies. Positive significant treatment effects were observed for all performance measures except total family earnings. The magnitudes of the crop income and crop revenue effects were smaller than what was found in the other evaluations, but this is to be expected considering the intensity of "treatment" is lower (i.e., IDE farmer group enrollment).

Overall, positive significant impacts were observed for crop income and crop revenues at the 1 and 5 percent levels across evaluation. The crop income and crop revenue treatment effects were significant and robust across matching estimators and evaluation type, and their magnitudes were dependent on the evaluation type. These findings indicate that both the enrollment in an IDE farmer group alone and the combination of IDE farmer group enrollment and irrigation technology adoption have positive treatment effects on crop incomes and crop revenues. This is evidence that the type of irrigation technology (i.e., manually operated or motorized) can have difference impacts on crop income and revenues. The overall impacts on total family earnings were negative and significant in one evaluation, but remained insignificant for all subsequent evaluations. The adoption of technologies and the enrollment in an IDE farm groups had a positive impact on high-value crop revenues, but the significance and magnitude of the effects were dependent on the evaluation and the specific matching algorithm used. For the most part, there was a positive impact on crop production. There were negative impacts on crop production for the incremental impact of technology adoption, however. The reasons for this are unclear, but further discussion will be provided in the discussion section.

8.3 - RPI Area Treatment Effects[41]

Stratifying the sample by RPI Area reveals some fairly large differences in the significance and magnitude of IDE impacts across the four RPI areas. NNM and CBM were used to estimate the treatment effects for RPI Area.[42] The smaller sample sizes limited the number and type of evaluations that could be estimated. For this reason, only

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[41] Selection model results and subsequent balancing tests for the RPI Area analysis can be found in Appendix G.

[42] Kernel based matching can be problematic when performed on small samples like those used in the RPI area estimates (Caliendo et al. 2008). Therefore, CBM and NNM were used.

two evaluations were conducted for each RPI area: T_0 vs. C_0 and T_4 vs. C_1. Treatment effects for the T_0 vs. C_0 evaluation are reported in Table 20.

Table 20: T_0 vs. C_0, by RPI Area

	Kabwe		Lusaka		Kafue		Choma/Livingstone	
Performance Indicator	**NNM**	**CBM**	**NNM**	**CBM**	**NNM**	**CBM**	**NNM**	**CBM**
Total Family Earnings Diff.								
Treatment Effect	**$673**	**$489**	-$126	-$90	**-$1,020**	**-$1,088**	**$361**	**$449**
p-value	0.000	0.005	0.431	0.582	0.000	0.000	0.026	0.009
Total Crop income Diff.								
Treatment Effect	**$548**	**$557**	-$152	-$104	-$102	$84	**$282**	**$303**
p-value	0.000	0.000	0.280	0.463	0.217	0.286	0.017	0.013
Total Crop Revenue Diff.								
Treatment Effect	**$479**	**$511**	-$255	-$195	-$134	$81	**$299**	**$324**
p-value	0.001	0.001	0.108	0.205	0.132	0.323	0.014	0.010
High-valueVeg. Revenue								
Treatment Effect	$27	**$94**	**-$376**	**-$352**	**$227**	**$216**	**$173**	**$175**
p-value	0.418	0.009	0.010	0.016	0.001	0.003	0.028	0.030
Crop Weight Diff. (kg)								
Treatment Effect	661	**861**	-170	131	-266	271	472	**569**
p-value	0.106	0.096	0.748	0.804	0.309	0.276	0.107	0.061

Note: Treatment effects in bold are significant at 10%

Involvement in an IDE farm group, whether a technology was adopted or not, had significant positive impacts on total family earnings for household within Kabwe and the Choma/Livingstone RPI Areas, where the treatment effects were slightly larger in Kabwe (489-673USD) compared to Choma/Livingstone (361-449USD). Negative effects on total family earnings for both estimators were found in Kafue. There were no significant impacts on total family earnings in the Lusaka RPI area. Positive significant effects on total crop income were found in Kabwe and Choma/Livingstone areas, while there were no significant effects in Kafue or Lusaka. Similarly, there were positive effects on crop revenues in Kabwe and Choma/Livingstone, but not in Kafue or Lusaka. The effects on high-value vegetable revenues is mixed, where positive effects were found in Kabwe, Kafue and Choma/Livingstone, but negative effects were observed for Lusaka. The reasons for this are unclear, but suggest the presence of some programmatic, geographic or climactic differences between the four RPI Areas. Additional treatment effects from the IDE farmer group enrollment evaluation (T_4 vs. C_1) are presented in Table 21.

Table 21: T_4 vs. C_1, by RPI Area

	Kabwe		Lusaka		Kafue		Choma/Livingstone	
Performance Indicator	**NNM**	**CBM**	**NNM**	**CBM**	**NNM**	**CBM**	**NNM**	**CBM**
Total Family Earnings Diff.								
Treatment Effect	$39	$58	$273	-$153	**-$326**	**-$471**	$74	$141
p-value	0.766	0.681	0.137	0.393	**0.075**	**0.019**	0.577	0.313
Total Crop income Diff.								
Treatment Effect	**$282**	**$324**	-$91	-$60	$22	$9	$60	$83
p-value	**0.015**	**0.007**	0.404	0.594	0.795	0.911	0.431	0.307
Total Crop Revenue Diff.								
Treatment Effect	**$218**	**$277**	-$148	-$120	$11	-$17	$120	$148
p-value	**0.083**	**0.033**	0.199	0.312	0.901	0.837	0.150	0.094
High-valueVeg. Revenue								
Treatment Effect	**$114**	**$119**	-$112	-$103	**$159**	**$204**	**$92**	**$111**
p-value	**0.047**	**0.051**	0.233	0.291	**0.006**	**0.001**	**0.089**	**0.055**
Crop Weight Diff. (kg)								
Treatment Effect	661	**861**	-170	131	-266	271	472	**569**
p-value	0.106	0.096	0.748	0.804	0.309	0.276	0.107	0.061

Note: Treatment effects in bold are significant at 10%

As with the previous RPI area evaluation, there is variation in the treatment effects between RPI areas. Statistically significant increases in four of the five performance indicators were found for farmer households in Kabwe that are enrolled in an IDE farmer group and do not have an irrigation technology, when compared to non-IDE farmer households that do no have an irrigation technology. IDE farm group enrollment does not have any significant effect on total family earnings in Kabwe, Lusaka or Choma/Livingstone. Negative significant impacts between 326-471USD were found in Kafue, however. The only RPI area to have significant effects on total crop incomes and total crop revenues was Kabwe. The magnitudes of these effects are similar to those found for the whole-sample treatment effects of IDE farmer-group enrollment, between 282-324USD and 218-277USD for crop incomes and crop revenues, respectively. Kabwe, Kafue and Choma/Livingstone had positive treatment effects for high-value vegetable revenue, with Kafue having the largest effects (159-204USD), Kabwe having lower effects (114-119USD) and Choma/Livingstone having the lowest effects significant effects (92-111USD). Lastly, Kabwe and Choma/Livingston had significantly positive effects on crop production from IDE farmer group enrollment. These were only significant for the CBM estimators in both cases, however.

Overall, positive and significant treatment effects on crop incomes and revenues were observed for Kabwe at the 1, 5 and 10 percent levels. Additional evidence for positive impacts on high-value vegetable revenues was found in both evaluations, but these were dependent on the matching estimator used. There were no significant effects across both evaluations in Lusaka. There were negative significant effects on high-value vegetable revenues in the first evaluation. Negative significant impacts on total family earnings were found in the Kafue area, in both evaluations. Although the magnitudes of the total family earnings impacts were larger, positive significant impacts on high-value vegetable revenues were found in both evaluations for Kafue. The Choma/Livingstone area had positive significant effects on total family earnings, crop income, crop revenues and high-value vegetable revenues in the first evaluation. The only effect to be significant in the second evaluation, however, was on high-value vegetable revenues. Sample size limitations made the RPI Area evaluations potentially problematic, and this seems to be particularly true for the Lusaka and Choma/Livingstone areas.

8.4 - Gender-specific Treatment Effects[43]

For reasons previously discussed in Section 7.2, it is reasonable to believe that IDE intervention efforts would have different impacts on men than women. Treatment effects were estimated separately for men and women for three evaluations: T_0 vs. C_0 , T_4 vs. C_1 and T_3 vs. C_1. NNM and CBM estimators were used to ensure robustness of gender treatment effects. Gender-specific treatment effects for the three evaluations of interest are presented in Tables 22, 23 and 24.

Table 22: T_0 vs. C_0, by Gender of HHH

Performance Indicator		Male		Female	
		NNM	CBM	NNM	CBM
Total Family Earnings Diff.					
	Treatment Effect	**-$180**	**-$180**	-$97	-$86
	p-value	0.048	0.049	0.462	0.527
Total Crop income Diff.					
	Treatment Effect	**$127**	**$122**	**$248**	**$230**
	p-value	0.020	0.026	0.001	0.001
Total Crop Revenue Diff.					
	Treatment Effect	**$101**	**$104**	**$266**	**$242**
	p-value	0.062	0.057	0.000	0.001
High-value vegetable Rev.					
	Treatment Effect	$60	**$66**	**-$49**	-$34
	p-value	0.118	0.083	0.091	0.187
Crop Weight Difference (kg)					
	Treatment Effect	334	339	**812**	**650**
	p-value	0.147	0.140	0.004	0.019

Note: Treatment effects in bold are significant at 10%

When looking at the effects from any involvement with IDE (T_0 vs. C_0) in Table 22, statistically significant positive effects on total crop income and total crop revenues were found for male- and female-HHH, but the effects for women were nearly twice as large than the male-HHH effects. Total crop income effects for male-HHH were 122-127USD, whereas the effects for female-HHH were 230-248USD. Negative impacts on high-value

[43] Selection model results and subsequent balancing tests for the gender analysis can be found in Appendix G.

vegetable revenues were found for female-HHH, but this is only the case for one of the matching estimators. Male-HHHs, on the other hand, were impacted positively by IDE interventions, but this too was only significant in one of the matching estimators. IDE efforts had positive impacts on female-HHH on crop production, but no significant impacts for male-HHH with respect to crop production.

Table 23: T_3 vs. C_1, by Gender of HHH

Performance Indicator		Male		Female	
		NNM	CBM	NNM	CBM
Total Family Earnings Diff.					
	Treatment Effect	**-$247**	-$117	-$117	$4
	p-value	0.034	0.476	0.476	0.990
Total Crop income Diff.					
	Treatment Effect	**$219**	**$269**	**$269**	**$308**
	p-value	0.004	0.016	0.016	0.051
Total Crop Revenue Diff.					
	Treatment Effect	**$168**	**$227**	**$227**	**$248**
	p-value	0.029	0.050	0.050	0.095
High-value vegetable Rev.					
	Treatment Effect	$31	-$17	-$17	$35
	p-value	0.519	0.773	0.773	0.588
Crop Weight Difference (kg)					
	Treatment Effect	-73	-189	-189	$598
	p-value	0.780	0.637	0.637	0.266

Note: Treatment effects in bold are significant at 10%

The impacts for male-HHH and female-HHH are nearly the same, when looking at the difference between IDE farmer group members who have adopted an IDE pump technology and non-IDE farmers that do not have an irrigation technology (T_3 vs. C_1). The effects for male-HHH on crop income and crop revenues were between 219-269USD and 168-227USD, respectively. The impacts on female-HHH with respect to crop income (269-308USD) and crop revenues (227-248USD) are slightly larger. There were no significant effects on high-value vegetable production or crop production for male-HHH or for female-HHH.

Table 24: T_4 vs. C_1, by Gender of HHH

Performance Indicator		Male		Female	
		NNM	CBM	NNM	CBM
Total Family Earnings Diff.					
	Treatment Effect	**$223**	**$278**	**$261**	-$114
	p-value	0.004	0.011	0.016	0.266
Total Crop income Diff.					
	Treatment Effect	**$210**	**$156**	**$149**	**$159**
	p-value	0.000	0.035	0.045	0.009
Total Crop Revenue Diff.					
	Treatment Effect	**$210**	**$146**	**$139**	**$159**
	p-value	0.001	0.059	0.075	0.008
High-value vegetable Rev.					
	Treatment Effect	**$83**	$58	$72	**$39**
	p-value	0.055	0.215	0.128	0.019
Crop Weight Difference (kg)					
	Treatment Effect	**674**	279	299	**615**
	p-value	0.004	0.371	0.342	0.013

Note: Treatment effects in bold are significant at 10%

IDE farmer group enrollment, when not coupled with the adoption of an IDE technology, has a greater benefit for male-HHH than for female-HHH. Male-HHH that are enrolled in an IDE farmer group increased their total crop income between 156-210USD more than control group male-HHH. The same treatment effect for female-HHH was between 149-159USD. Lastly, crop weight and total family income impacts were similar between male and female-HHH.

The stratification of sample households by gender shows that the impacts of IDE involvement and irrigation technology adoption are different for male-HHH and female-HHH. In particular, female-HHHs have larger positive impacts than men when irrigation technologies are coupled with trainings. Impacts on Male-HHHs are larger when households choose not to invest in an irrigation technology and solely enroll in and IDE farm group.

SECTION 9: DISCUSSION

The primary research question that was addressed in this study was: *Have farmers receiving the IDE treatment experiences greater income growth over the intervention period relative to those who have not?* The answer to this question is, it depends. According to the PSM estimation method, there is substantial evidence that IDE intervention activities have had positive and significant impacts on crop incomes and crop revenues. The magnitude of these impacts changes, when different irrigation technologies are included in the treatment, where the greatest impacts on crop incomes and revenues were seen in the evaluation containing the motorized pump and micro-sprinkler technologies. This result might be expected given the added benefits of pump technologies that do not rely on manual power. Involvement in an IDE farmer group, when coupled with an irrigation technology, has been shown to increase total crop incomes between 260-300USD. The impacts from IDE farmer-group enrollment alone are positive and significant as well, but are lower in magnitude. This is indicative of the relative value of technology adoption when coupled with agricultural trainings and services.

Additional evidence suggests that female-HHHs that are involved with IDE could benefit greatly from the adoption of an irrigation technology. Female-HHHs had lower baseline total-family earnings and crop-income levels, but the treatment effects from IDE farmer-group enrollment and irrigation-technology adoption are about 20% higher than the effects for male-HHHs. Both male- and female-HHHs benefit from the enrollment in a farmer group, but the male-HHHs benefited more than female-HHH by simply joining a farmer group. This would suggest that irrigation technologies play a particularly important role for female-HHHs, and may in fact, offset some of the social obstructions that face female-headed farmer households in Zambia.

The relationship between irrigation technology adoption and income impacts becomes more complex when specific geographic areas are considered. Treatment effects were subject to additional bias because of limited sample sizes. Farmers living in Kabwe that received agricultural training and services by being involved in an IDE farmer group increased their crop incomes by about 550USD more than matched control group households over the intervention period. Very few of the results from the Lusaka region were significant and robust across matching estimators. A cursory analysis of the summary statistics from the Lusaka region, support the results found in the more complex matching estimation. For reasons that remain unclear, total family earnings were negative and significant in the Kafue area in both of the evaluations. There were, however, positive impacts on household crop income and revenues in Kafue. The proximity to large market outlets may be a reason why such treatment effects on crop income and crop revenues were observed for the Choma/Livingston Area.[44]

The impacts on total family earnings remain less clear than the impacts on crop income. Impacts were not robust across matching estimators and relied heavily on the specific evaluation and strata. A potential explanation could be found in a more detailed examination of the specific income deflator that was used to calculate the nominal

[44] A causal attribution equation is necessary to make this statement with certainty. This is a possible extension of the present study that is under consideration with IDE and myself.

performance indicators. The deflator of nominal variables (i.e., CPI deflator) could be improved beyond the basic CPI adjustment that was performed. As a result, the attributed impacts of IDE interventions, as currently measured, could be biased. Although this is a theoretical possibility, it does require some additional investigation into the sensitivity of income-specific impact on the specific choice of nominal deflator. As an example, the physical quantity performance measure (i.e., Crop Weight) demonstrates more consistent and positive impacts, whereas the total family earnings indicators tend to "bounce around" more than the physical measures. Secondly, the present study utilizes an income model that was developed prior to the current evaluation and little documentation was provided on the specific mechanics of the MonQi model. It remains unclear how the MonQi model specifically expenses the irrigation technology purchases. This could be investigated by using the alternative available measures of household income. Thirdly, It is possible the hardware was purchased sufficiently late in the evaluation period so that the costs could not be recovered in time.

One of the more problematic limitations of the present study is that the baseline measures relied on recalled information. Farmer-households were required to recall agricultural production and expenditure information from nearly two years prior to the evaluation. For these reasons, performance indicators had very high variances, which made hypothesis testing problematic. A rudimentary systematic recall bias correction model was developed, but a lack of observations limited the application of this model to correct for recall-bias in the current sample. A more thorough explanation of this model and the methodologies used can be found in Appendix E.

An additional limitation of this study is that the treatment sample frame was limited to first-year adopters. There is a lot of evidence to suggest that agricultural benefits from technology adoption take place over a longer time horizon (Feder and Umali, 1993; Feder et al. 1985, Foster and Rosenzweig, 1995; McWilliams and Zilberman, 1996). Continuing data collection and re-estimating the treatment effects after two or three years, would allow for the estimation of time-specific treatment effects. This would also provide the evaluators with a much more accurate baseline measure. Understanding the temporal nature of agricultural technology adoption would also benefit further program development and irrigation technology information campaigns in the field.

There is some disagreement in the literature as to how the complex sampling design weights should be incorporated into a PSM framework. For the present study they have been incorporated into the treated individuals and the subsequent synthetic control group observations. An alternative solution would be to leave the sampling weights out, but to bootstrap all of the treatment effects.[45] Although this would increase the accuracy of the standard errors on the matched estimation, the resulting decrease in accuracy by failing to include intra-class correlations from the complex survey design seem too great to be ignored.

The limitations of the study have been discussed with IDE, and potential future steps have been discussed. Potential funding for the development of a multivariate attribution model is being considered. This would allow for a more sophisticated measure

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[45] This method was conducted initially, but a convincing paper written by Heckman and Todd (2008) led to the methodology that was used to correct the standard errors of the treatment effects.

of the random effects from geographic and socio-economic variation, beyond the pre-treatment measures that are included in the selection model and the stratification techniques employed in the present study. Nonetheless, the consistent nature of the impacts on household crop income and crop revenues are statistically robust and supported by previous survey based research carried out by IDE, as well as the existing micro-irrigation research by Adiote et al. (2007), Mangsoni (2008) and Enterprise Works.

SECTION 10: CONCLUSION

The causal relationship between irrigation technology adoption and household income and crop production is very complex. The present study utilizes a PSM framework to estimate the causal treatment effects of agricultural training and services, as well as irrigation technology adoption, on household income, crop income, crop revenues, high-value vegetable revenues and total crop production.

The causal relationship between the enrollment in agricultural trainings and services and the subsequent adoption of irrigation technologies, and household income and crop production is explored by creating a matched control group, thereby controlling for self-selection bias and other observable traits that would influence both; the decision to participate in treatment and the performance indicators of interest. Five distinct evaluations were conducted for the whole sample, which estimate the total treatment effect of trainings plus irrigation technology adoption, as well as the incremental impacts of farmer group enrollment, and of irrigation technology adoption for a farmer who has already been involved with a farmer group. Additional effects were estimated for four distinct regions of Zambia, where significant differences in treatment effects were found between regions. Gender effects were calculated, where treatment effects were larger for women when irrigation technologies were adopted. This suggests the potential for irrigation technologies to offset the difficulties faced by female-headed farmer-households in Zambia.

These results are interpreted as evidence that irrigation technology adoption and agricultural training and farmer group enrollment can have direct positive impacts on household crop income and crop revenues, for both male- and female-HHHs, depending on the geographic region of Zambia. Future rural development efforts should consider the importance of supplemental irrigation technology investment for improving rural incomes, and the incremental impact of technology adoption in general, should become a standard component of market driven developmental initiatives. The limitations of the present study, as well as the general lack of applied literature on the impacts of micro-irrigation provide reason enough that additional research must be conducted on the causal impacts of irrigation technology adoption on household income and crop production.

SECTION 11: REFERENCES

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APPENDIX A: GIS MAP OF ZAMBIA RPI AREAS

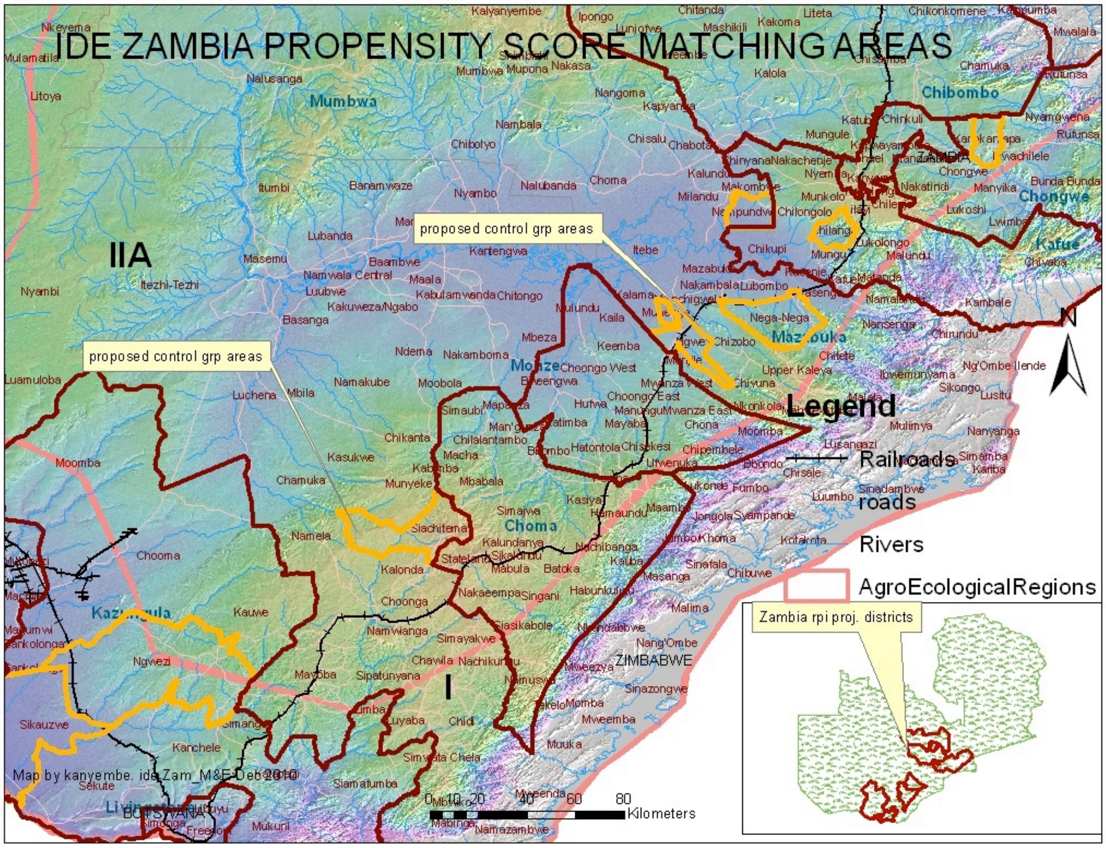

Figure A-1: RPI Intervention Area Map, Zambia

APPENDIX B: SAMPLING PLAN

IDE Zambia Rural Prosperity Initiative Impact Evaluation

Summary of Proposed Sampling Plan

Lead: Clifford F. Zinnes

Statistical Support: Christopher Nicoletti

24 February 2011 (Revised 7 March 2011)

After considering literally hundreds of different experimental designs and their sampling properties, enumeration costs, and parameter sensitivity implications, I have converged on the sampling *qua* experimental design contained herein. This memo outlines its general design, sampling instructions to construct the treatment and control observations, properties of the sample, assumptions underlying the design, caveats to keep in mind, and suggested follow up.

1. General design

- *Experimental Design (Simulated)*:[1] Multi-site cluster-randomized trial
- *Blocking*: IDE famer groups
- *Total sample size*: 963 farmers
- *Stratification*: (i) By RPI Area, where RPI Area 4 and RPI Area 5 are combined and called RPI Area 4' and (ii) by block
- *Objective indicator*: Family net crop income (calculated from MON-Q model by IDE)

2. Treatment group

- Size of treatment group: 448 farmers
- *Number of IDE farmer groups*: 32 groups, 8 groups from each RPI area
- *Number of farmers per IDE farmer group*: 14 farmers
- *Method of selecting IDE farmer groups*: simple (non-proportional) random sampling without replacement
- *Method of selecting IDE farmers*: simple random sampling without replacement from the membership list of a selected IDE farmer group.

3. Control group

- *Size of control group*: 515 farmers

[1] I say "simulated" because the experimental design should have been implemented prior to the intervention.

- *Method of selecting control farmers*: simple random sampling from a farmer association in a control area matched to the IDE farmer group's respective treatment area.
- *Number of farmers per control association*: 14 farmers

4. Discussion

a. For this design one should think that IDE farmer groups (blocks) are randomly selected from each RPI area and that the farmers within them are then randomly split between those receiving the IDE treatment and those remaining untreated. However, since this experiment is being run retrospectively, we are not able to select the latter from the IDE farmer groups. Hence, the untreated farmers should be selected from a different area that has been identified as similar to the area containing the respective IDE farmer group. The former may be called a "control area" and the latter a "treatment area".

b. Since we are not able to disentangle the salutary effect of being a member of an IDE farmer group from that of receiving IDE training and equipment, we must "balance" this characteristic difference between treatment and control farmer by requiring that untreated farmers be selected from an existing association found in (or mostly in) the control areas that matched the treatment area containing the respective IDE farmer group.

c. The choice of design was made based on predictions made by statistical optimal design algorithms by Spybrook *et al.* (2009) for the parameters assumptions described in Section 6.[2]

d. I simulated perturbations in the parameter values upon which the experimental design was based (Section 6) and found that the estimated design properties (Section 5) are quite sensitive to these values. As such, the final design chosen for the evaluation has been modified to contain two more farmer groups from that which was recommended by the statistical optimal design algorithms (32 instead of 30). This was done to create a bit of insurance to compensate for possible errors in the estimation of the parameters set by the assumptions (Section 6). The additional cost (or risk premium) of this insurance is approximately $1,600.

e. The control group contains 15-percent more farmers than the treatment group. This is to ensure an adequate variety of farmer characteristics from which to choose during the PSM matching exercise. This will require that *two* more famers be sampled from each control site than from each

[2] Spybrook, Raudenbush, Congdon, and Martínez (2009), "Optimal Design for Longitudinal and Multilevel Research", *mimeo*.

IDE farmer group. However, it is not mandatory that such a procedure be followed to collect these 67 additional observations as long as said farmers are members of a farmer organization and are located in a recognized, matched, control area corresponding to the respective IDE farmer group treatment area.

f. It is possible that there be two obstacles to implementing this sampling plan. First, one RPI has an IDE farmer group (Muchenje B) with less than 14 members. This group may simply be dropped prior to sampling selection. Second, neither RPI Area 4 nor RPI Area 5 has at least eight farmer groups. That is why these two areas have been merged for the sake of sampling (see Section 1).

5. Estimated design properties

- *Design effect*: 2.35
- *Effect size (absolute)*: 681 thousand Kwachas
- *Effect size (percent of income)*: 7 percent
- *Enumeration cost*: $26,000
- *Exchange rate:* 4,900 Kwachas per U.S. dollar

6. Assumptions underlying design

- R^2 = 0.20
- *Variance of MDES*: 0.1
- Percent of variance explained by blocking variable (IDE farmer group): 30 percent
- *Between-farmer standard deviation*: 8 million Kwachas (2010)
- *Average farmer net crop income*: 9.6 million Kwachas (2010)
- Cost model (to be sent separately) for enumeration is based on the parameters shown in Table B-1.

Table B-1: Parameter values used in the estimation of the enumeration cost function

Cost item	*Amount*
Lunch	$ 10.50
Hourly wage	$ 5.63
Fixed cost per day per enumerator	$ 21.75
Enumerator salary/day	$ 45.00
Cost per trip (vehicle and 8 hours of supervisor time, standard wage)	$ 228.75
Interviews/day/enumerator	4
Cost of vehicle travel:	$ 75.00
Hours per trip:	2
Enumerators per visit	4
Hours per interview:	2

7. Caveats

a. The ICCs were based on simulations of RBS (first-year adopter) from IDE survey data enumerated in 2007, 2008, and 2009, in which farmer group identification was available for 477 of 549 treated farmers.

b. Inferences about control-group-household standard errors were proxied by CCS survey data for 2008 and 2009. These are of untested and therefore uncertain relevance since the above design calls for using farmers from other areas than those from which the CCS were drawn.

8. Follow up

a. IDE should randomly draw the necessary number of IDE farmer groups from the Master List.

b. IDE should randomly select the required number of farmers from the Master List corresponding to the IDE farmer groups drawn in the previous step.

c. IDE should identify at least one control area that corresponds to each of the treatment areas containing a selected IDE farmer group.

d. IDE should acquire or consider assembling a list of farmer cooperatives or similar organizations since only farmers who are members of such organizations should be interviewed for the evaluation.

e. I would urge IDE to draft its own sampling plan report that details how it drew the specific farmers and groups. I would then review that report before it is put into practice.

f. In addition to revisiting my own as well as Sudip's list of instrument modifications, I will modify the survey instrument so that it contains a sorting section at the beginning to assist enumerators in rejecting respondents who do not meet the organizational requirement.

g. Enumerators should be trained in understanding the interview protocols and procedures that should be followed. These will likely be stricter than those applied in previous rounds. I will draft a list of my most serious concerns in that regard with regard to the evaluation's needs.

APPENDIX C: CONTROL GROUP SELECTION CRITERIA MATRIX

Control group selection criteria matrix (by RPI and treatment area)

Area type	*Group name*	*Water*	*Markets*	*Roads*	*Weather*	*Soil*	*Topography*	*IDE service awareness*
	Livingstone RPI							
T1	Luyaba (Mandia area, Swekute ward)	2	1	2	1	1.5	2	2.5
C1	Simonga Sekute ward	2	1	2	1	1.5	2	1
T2	Luyando-Mandia (Mania area, Sekute ward)	2	1	2	1	1.5	2	2.5
C2	Ngwezi (Sekute ward)	2	1	2	1	1.5	2	0
T3	Mubwato (Simango ward)	2	1	2	1	1.5	2	2.5
C3	Myana Dam (Kabuyu)	2	1	2	1	1.5	2	1
T4	Lusumpuko (Katombora area, Sekute ward)	2.5	1	2	1	2	2	2
C4	Sikauzwe-Mambova (Sekute ward)	2.5	1	2	1	2	2.5	1
AC-a	Kauwe (Kalomo District)	1.5	1	2	1	1.5	2.5	0
AC-b	Chali Dam (West of Zimba)	2	1	2	1	1.5	1.5	0
AC-c	Siamoya Dam (near Kabuyu)	2	1	2	1	1.5	2	0
AC-d	Minyemu Nyemu	1.5	1	2	1	1.5	2	0
	Chomo RPI							

T1	Mpande (Musaya ward)	2	1	2.5	2	2	1.5	2.5
C1	Neganega (Neganega ward)	2	1	2.5	2	2	1.5	0
T2	Mahili (Musaya ward)	2	1	2.5	2	2	1.5	2.5
C2	Mugoto (Neganega ward)	2	1	2.5	2	2	1.5	0
T3	Shikaunzwe (Malundu ward)	2	1	2	2	2	1.5	2.5
C3	Bomora (Bomora area, Chilanga)	2	1	2	2	2	2	1
AC-a	Nampundwe	2	1	2	2	2	1.5	0
				Kafue RPI				
T1	Katole (Mungule ward)	3	1	3	2	2	3	2.5
C1	Nampundwe	3	1	3	2	2	3	0.5
T2	Mankoloto Garderners	3	1	3	2	2	3	2.5
C2	Chiota (Kanakatapa)	3	1	3	2	2	3	0

Area type	*Group name*	*Water*	*Markets*	*Roads*	*Weather*	*Soil*	*Topography*	*IDE service awareness*
				Lusaka RPI				
T1	Katole (Mungule ward)	3	1	3	2	2	3	2.5
C1	Nampundwe	3	1	3	2	2	3	0.5
T2	Mankoloto garderners	3	1	3	2	2	3	2.5

C2	chiota- kanakatapa	3	1	3	2	2	3	0
				Kabwe RPI				
T1	Chishinka Coope -kampumba ward	3	2	2	3	3	2	2.5
C1	Yongwe (Youth Club)	3	2	2	3	3	2	1
T2	Kakwelesa	3	2	2	3	3	2	2.5
C2	Nchembwe (Youth Group)	3	2	2	3	3	2	1

Notes:

1. Characteristics of treatment and control groups:

    Water availability 1 to 3. 3=Abundant, 1= less abundant

    Market availability 1 to 3: 3=Three main markets, 1=only one market

    Distance to main market: 1=very far, 2=far, 3=within easy reach

    Weather: 1=less favorable 2=favorable 3=very favorable

    Soil quality: 1= poor, 2= good, 3= excellent

    Topography: 1=hilly, 2=less hilly, 3=more or less flat

    Awareness of IDE Services: 3=more aware, 2= aware, 1=less aware

2. Area types: “T”=Treatment area “C”=Control area, “AC”=Alternate control area

APPENDIX D: SURVEY INSTRUMENT

1a Farm identification and interview

Household code	ZM _ __ __ __ __ __
Name household head (see also 2a)	
Date of interview	Date : __ / __ / ____
Name enumerator	
Name person(s) interviewed	(Male/Female/Both)
"Past year" refers to period "Before adoption" refers to period	1/nov/2008 - 31/oct/2009 ➔ **2009*** 1/nov/2009 – 31/oct/2010 ➔ **2010*** * indicates **agricultural year** as opposed to calendar year
Classifications Religion : ○ 1) Christian ○ 2) Muslim ○ 3) Other Tribe : ○ 1) Bemba ○ 5) Luvale ○ 2) Cewa ○ 6) Lozi ○ 3) Kaonde ○ 7) Tonga ○ 4) Lunda ○ 8) Others	**Location identifiers** Province : District : Ward : Village : RPI area : Coordinates : _° __'__.__" S _° __'__.__" E Distance to the nearest market : (km) (where you sell most of your produce, in value)
To be done by supervisor Survey type: **Treatment** | **Control**	[ ] **unreliable 2009* income data** explanation: signature M&E supervisor:

1b Membership farmer organizations

Are you or someone in your household a registered member of any farmers' organizations or IDE farmer group?

Farmer organization	2009*	2010*
i. Farmers Group	○ 1) No, no member in household ○ 2) Yes, male or female IDE group member ○ 3) Yes, non-IDE male member only ○ 4) Yes, non-IDE female member only ○ 5) Yes, male *and* female non-IDE members	○ 1) No, no member in household ○ 2) Yes, male or female IDE group member ○ 3) Yes, non-IDE male member only ○ 4) Yes, non-IDE female member only ○ 5) Yes, male *and* female non-IDE members
ii. Cooperative	○ 1) No, no member in household ○ 2) Yes, male member only ○ 3) Yes, female member only ○ 4) Yes, both male and female members	○ 1) No, no member in household ○ 2) Yes, male member only ○ 3) Yes, female member only ○ 4) Yes, both male and female members

#	**Position**	**Full name**	**Gender(M/F)**	**Year of birth**	**Relation to HHH**	**Education** **no. of years (level ①)**
1	*Main Partici-pant in the RPI Program*				(a) Self (b) Spouse (c) Other	
3	*Household head if not main Program participant*				XXXXXXXXXXXXXX XXXXXXXXXXXXXX	

1.c END THE INTERVIEW?

***(A) IF* survey type *IS "C"* AND *THE ANSWER TO 1.b.i IS (2) FOR* EITHER *YEAR THEN* <u>*END INTERVIEW*</u>.**

(B) ***IF*** **survey type** ***IS "C"*** **AND** ***THE ANSWER TO TO 1.b i*** **AND** ***ii IS (1) FOR*** **BOTH** ***YEARS THEN <u>END INTERVIEW</u>.***

(C) ***IF*** **survey type** ***IS "T"*** **AND** ***THE ANSWER TO 1.b.i*** **IS** ***(2) FOR 2009 THEN <u>END INTERVIEW</u>.***

(D) ***IF*** **survey type** ***IS "T"*** **AND** ***THE ANSWER TO 1.b.i IS*** **NOT** ***(2) FOR 2010 THEN <u>END INTERVIEW</u>.***

(E) ***NO, RESPONDENT QUALIFIES FOR INTERVIEW***

2 Household

2a Household heads

Note: in case of polygamy select first wife only.

2b Household composition

	No. of men	No. of women	Total
> 50 years			
15- 49 years			
5- 14 years			
< 5 years			
Check total>>			

① **Table 2a: Education levels**

- Illiterate (0 years)
- Informal (adult literacy) (1 year)
- Primary (grade 1-7)
- Lower secondary (grade 8-9)
- Senior Secondary (grade 10-12)
- Tertiary (13-17)

3 Land by source of irrigation

3a		Measure	2009*	20010*
	Area of total land farmed regardless of water source during each year:			

3b						2009*	2010*
#	**Land primarily irrigated by:**	**Ownership of land** (see list)	**Availability (reliability) of water** (no. months)	**Land under own control?**	**Measure**	**Area**	**Area**
1	Rain	(P) (C) (R)		Yes No			
2	River	(P) (C) (R)		Yes No			
3	Pond	(P) (C) (R)		Yes No			
4	Well	(P) (C) (R)		Yes No			
5	Bore hole	(P) (C) (R)		Yes No			
6	Lake/dam	(P) (C) (R)		Yes No			
7	Harvested rain water	(P) (C) (R)		Yes No			
8	Spring/dambo	(P) (C) (R)		Yes No			
9	…	(P) (C) (R)		Yes No			
10	…	(P) (C) (R)		Yes No			
					Total >>	①	②
		(P) Privately owned (C) Customary ownership (R) Rented/ borrowed	Months per year (max 12)		Area Measure as reported by farmer, e.g. lima, acre, hectare, m^2, $yard^2$ Same for both years.		

Guiding questions form 3

1) What was the **total size of your land** in 2008* and in 2009* (fill out the Totals for both years at ① and ②)
2) How much of that total land **can not be irrigated?** (enter information on line #1 rainfed)
3) Do you use a **single source of water** for irrigation?

a. **YES >>**

What is the **source of water** for the irrigated land (complete the information on the appropriate line) (go to 4)

b. **NO >>**

Are the different water sources used to irrigate the same piece of land?

i. **YES >>**

enter information for the main (most reliable) source of water on the appropriate line, ignore the other source. (go to 4)

ii. **NO >>**

enter the information for both (or more) sources on the appropriate lines. Take care that you are describing separate (not overlapping) tracks of land. (go to 4)

4) Check that the land recorded in the 2009* and 2010* columns is equal to the total amount of land from question 1). If not; try to find out why.

IF TOTALS IN QUESTION 3b DO NOT EQUAL TOTAL IN QUESTION 3a, DISCUSS BOTH SETS OF ANSWERS AND ADJUST UNTIL THE RESPONDENT IS COMFORTABLE WITH BOTH AND THEY ARE CONSISTENT.

4 Equipment & assets used

	2009*		2010*	
Equipment type	Owned by household? (Yes, In part, No)	Number of items	Owned by household? (Yes, In part, No)	Number of items
Treadle pump: I Mosi-o-tunya	Y IP N		Y IP N	
Treadle pump: II Indian adves	Y IP N		Y IP N	
Treadle pump: III Indian plastic	Y IP N		Y IP N	
Treadle pump: IV Saro Kick start	Y IP N		Y IP N	
Treadle pump: V Mufl'ra MGS	Y IP N		Y IP N	
Treadle pump: River pump	Y IP N		Y IP N	
Treadle pump: Other	Y IP N		Y IP N	
Electrical pump	Y IP N		Y IP N	
Motorised fuel pump	Y IP N		Y IP N	
Rope and washer pump (owned!)	Y IP N		Y IP N	
Drip kit	Y IP N		Y IP N	
Watering can	Y IP N		Y IP N	
20L-Bucket	Y IP N		Y IP N	
Polypipes (metres)	Y IP N		Y IP N	
Drum	Y IP N		Y IP N	
Ox-plough	Y IP N		Y IP N	
Ox-cart	Y IP N		Y IP N	
Wheelbarrow	Y IP N		Y IP N	
Knapsack sprayer	Y IP N		Y IP N	
Handmill	Y IP N		Y IP N	
Solar vegetable dryer	Y IP N		Y IP N	
Maize Sheller	Y IP N		Y IP N	
Yenga press	Y IP N		Y IP N	
Bicycle	Y IP N		Y IP N	
Motor bike	Y IP N		Y IP N	

Car / pickup	Y IP N		Y IP N	
Radio	Y IP N		Y IP N	
TV set	Y IP N		Y IP N	
Cellphone	Y IP N		Y IP N	
Iron sheet roof (in sq. metres)	Y IP N		Y IP N	

Notes:

- *Include only items that are owned by the household (in part or whole).*
- *When an equipment is communally owned then the household owns a fraction of the equipment (for example: a pump owned by 4 other households results in 1/5 partial ownership)*
- *The list was trimmed by removing everything of less than 50.000 ZMK (~10 USD) that was not for irrigation, processing or luxury (i.e most basic generic farm tools were removed).*

5a Technology/service adoption and use *[AQ 5a]*

	If A = No then skip to the next T/S		*B: Adoption facilitated by*					
	Technologies/Services	**A: Year first used or 0 if no longer in use by the end 2010*?)** Yes No	IDE/WI	Other NGO *(not allied to IDE)*	*farmers' organisation*	*government agencies/local authorities/extension services*	*neighbours or family*	*others (e.g. traders, traditional practice)*
Market linkages	Market information	O O	☐	☐	☐	☐	☐	☐
	Marketing cooperatives	O O	☐	☐	☐	☐	☐	☐
	Contract farming	O O	☐	☐	☐	☐	☐	☐
	Market outlet-regional/Lusaka	O O	☐	☐	☐	☐	☐	☐
Agricultural practices	Use of compost	O O	☐	☐	☐	☐	☐	☐
	Pesticides	O O	☐	☐	☐	☐	☐	☐
	Organic pesticides	O O	☐	☐	☐	☐	☐	☐
	Cultural control/IPM	O O	☐	☐	☐	☐	☐	☐
	Staggered production	O O	☐	☐	☐	☐	☐	☐
	Inorganic fertilisers	O O	☐	☐	☐	☐	☐	☐
	Use of manure	O O	☐	☐	☐	☐	☐	☐
	Intercropping	O O	☐	☐	☐	☐	☐	☐
Impr. Seeds	Improved seeds	O O	☐	☐	☐	☐	☐	☐
Irrigation	Treadle pump	O O	☐	☐	☐	☐	☐	☐
	Drip kit	O O	☐	☐	☐	☐	☐	☐
	Micro-sprinkler	O O	☐	☐	☐	☐	☐	☐
	Motorized pump	O O	☐	☐	☐	☐	☐	☐
	Rope and washer pump	O O	☐	☐	☐	☐	☐	☐
	Water tank/container	O O	☐	☐	☐	☐	☐	☐
	Water reservoir/pond	O O	☐	☐	☐	☐	☐	☐

	If A = No then skip to the next T/S		***B: Adoption facilitated by***					
	Technologies/Services	**A: Year first used or 0 if no longer in use by the end** 2010*?)Yes No	IDE/WI	Other NGO *(not allied to IDE)*	*farmers' organisation*	*government agencies/local authorities/extension services*	*neighbours or family*	*others (e.g. traders, traditional practice)*
Business support services	Credit services (group saving)	O O	☐	☐	☐	☐	☐	☐
	Training in irrigation practices	O O	☐	☐	☐	☐	☐	☐
	Training in crop production practices	O O	☐	☐	☐	☐	☐	☐
	Marketing training	O O	☐	☐	☐	☐	☐	☐

*Fill out questions B only **IF** questions A is answered "yes"*

Checklist for "Introduction by others than IDE" :1) other NGOs (not allied to IDE)	*2) farmers' organisation*	*3) government agencies/local authorities/extension services*
4) neighbours or family	*5) others (e.g. traders, traditional practice)*	

- *Relate to the information in tables 3,4 (presence of certain irrigation technologies and equipment) to skip the non-relevant items in this table.*

6. Demonstration farms

Has IDE or any other organization set up a demonstration farm on your farm land or in your village?

1 – Neither

2 – On my farm

3 – In my village

7 Crop production

(7a) Cropping pattern and (6c) crop production for human consumption and sales

	← 2009* →							← 2010* →						
	Area planted		**Harvest**		**Sales**			**Area planted**		**Harvest**		**Sales**		
Crop	Units	Amount	**Units**	**Amount**	**Average price per unit sold**	**Sales (% *or* quantity)**		**Unit**	Amount	**Units**	**Amount**	**Average price per unit**	**% sold**	
Irrigated crops						Pct.	Qty						Pct.	Qty
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
Non-irrigated crops						Pct.	Qty						Pct.	Qty
		z				%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
						%							%	
Note to data-entry → 7a		7a		7c	7c	7c			7a		7c	7c		7c

•	As reported by farmer, e.g. lima, acre, hectare, m^2, $yard^2$ Same for both years.			Enter either the amount or harvest share sold	To be reported in same unit as same crop (line) in previous year			Enter either the amount or harvest share sold

Checklist crops:

Amaranth Bananas Beans (dry) Carrots	Cassava Cauliflower Chillies Chinese cabbage Cotton	Cowpeas Egg plant Garlic Green beans Green pepper	Groundnuts Guava Impwua (African egg plant) Irish potatoes	Kale Mangoes Millet Okra Orange	Paprika Pumpkin Sorghum Soybean	Sugarcane Sweet potatoes Swiss chard Water melon

7b Crop Inputs (purchased)

Product/service	**2009***	**2010***	
	Total value (ZMK)	**Total value (ZMK)**	*Notes and comments*
Labour and services *(e.g., hired labour)*			
Land rent			
Rental of machinery, vehicles and tools ,			
Seed & seedlings (local)			
Seed & seedlings (improved)			
Fertilizers *(Urea, AN, CAN, NPK, etc)*			
Organic fertilizers *(only if purchased!)* *(manure, compost, green manure)*			
Pesticides *(herbicides, acaricides, fungicides, etc)*			
Biological pesticides *(only if purchased!)*			
Fuel/Electricity			
Other inputs *(not listed above)* *(wires, plastics, sticks)*			[NOTE ITEM(S) IF ROW USED:]
Inputs • Consider only inputs that are purchased or otherwise obtained from outside the farm • Enter the total value (total price) of a certain input for all crops combined for the two agricultural years			

7c Payment of inputs

For the items, below, where you are the owner or only user of the item, do you believe you paid the full market price for it or was it part of the price paid for by another non-profit organization (not IDE), a friend or family member, the government, a community organization, or a donor?

Item	*Don't own/use*	*Price subsidized by*					
		NGO	Friend/family	Government	Community organization	IDE	Other donor
a) Fertilizer							
b) Seed							
c) Irrigation pump							
d) Other irrigation equipment							
e) Pesticide							

7d Market outlets and 9 Livestock production: ***9a Number of livestock and changes in numbers***

	2009*	**Purchased (+)**		**Sold (-)**		**Born (+)**	**Died (-)**	**Consumed (-)**	**Other in (+)**	**Other out (-)**	**2009 (end)**
Type	No.	No.	Total value	No.	Total value	No.	No.	No.	No.	No.	No.
Cattle											
Sheep/goats											
Pigs											
Donkeys											
Poultry											
	2009 (end)*	**Purchased**		**Sold**		**Born**	**Died**	**Consumed**	**Other in**	**Other out**	**2010 (end)**
Type	No.	No.	Total value	No.	Total value	No.	No.	No.	No.	No.	No.
Cattle											
Sheep/goats											
Pigs											
Donkeys											
Poultry											

9b Livestock Inputs (purchased)

	2009*	**2010***
Product/service name	**Total value**	**Total value**
Animal feed		
Supplements (minerals)		

Veterinary services		
Bull service		
Shepherd		
Others		

9c Livestock production and service (for home consumption and sales)

	2009*				**2010***			
Product name	**Quantity Measure**		**Price per measure**	**% sold**	**Quantity Measure**		**Price per measure**	**% sold**
Manure (sold!)				100%				100%
Milk				%				%
Milk products				%				%
Eggs				%				%
Wool				100%				100%
Skins/hides				100%				100%
Traction/transport				100%				100%
Others				100%				100%

10 Other sources of income (over 12 month period)

	2009*		2010*	
Type of activity	Gross earnings per year	Costs incurred to generate earnings	Gross earnings per year	Costs incurred to generate earnings
Wage labour				
• in local agriculture				
• As agricultural service providers (extension, input supplier, processor, etc.)*				
• in local non-agricultural sectors				
Non-wage income				
• Petty trader*				
• Agro-processing*				
• Rent received (*land, capital, social allowances, aid, etc.*)				
• Migration remittances (within or outside country)				

11 Social Provisioning (past year) 2010* compared to (previous year) 2009*

To what extent were you able to provide your family with the following expenditures/services this year (2010*) compared to the previous year (2009*)?

Expenditure/social provision	0) n.a.①	1) much worse	2) worse	3) same as before	4) better	5) much better
Amount of calories (*bread, rice, grains, potatoes, millet, etc.*)		○	○	○	○	○
Amount of protein *(meat, chicken, pork, fish)*		○	○	○	○	○
Housing and clothing		○	○	○	○	○
Health care and sanitation (*clean water*)	○	○	○	○	○	○
Children's education expenses		○	○	○	○	○
Productive tools/equipment, agricultural inputs, land		○	○	○	○	○
Social obligations, entertainment and luxury items		○	○	○	○	○
Savings		○	○	○	○	○

① Use "n.a." = "Does Not Apply" when no children.

12 IDE collaboration [*SKIP IF survey type = C*]

Have you ever been any of the following?

a) An IDE group leader (Y/N)

b) An IDE promoter (Y/N)

c) IDE group committee member (Y/N)

13 Value chain relationships *[AQ 11]*

	1. disagree	2. Indifferent / don't know	3. agree
The economic situation is getting better in our country	○	○	○
In the future, my children will have opportunity to make money with farming	○	○	○
I like to try new crops on my farm	○	○	○
I like to try new equipment on my farm	○	○	○
My buyers can usually be trusted (offer me a fair price)	○	○	○
When I produce a better quality, I usually get a better price	○	○	○
My input providers can usually be trusted	○	○	○
The law protects me against those who cheat me	○	○	○
I prefer to sell my horticultural products privately than together in an organized way with other farmers	○	○	○
I have traveled outside of Zambia	○	○	○

14 Farmer advice

a. I know it is hard to have to recall all the way back to 2009. How accurate do you feel your responses are?

1 - Very poor 2 – Poor 3 – Fair 4 – Good 5 - Very good

b. For which type of information would you say your answers would turn out to be more accurate, the quantity or the value information (e.g., information about the quantities produced or the value of sales and costs associated with production)?

1 - Quantity information 2 - Sales and cost information

c. Which kinds of questions do you think other farmers in your group or association would find to be most sensitive such that they might even be inclined to either exaggerate or minimize their answers?

Income and wages:1 Very likely 2 Possibly 3 Not very likely

Quantities produced or planted: 1 Very likely 2 Possibly 3 Not very likely

Value of sales:1 Very likely 2 Possibly 3 Not very likely

…..AND THEN END INTERVIEW. Thank the farmer for participating in the interview.

Data entry: Name: Date: Signature:	**Supervisor:** Name: Date: Signature:

APPENDIX E: EXPLANATION OF THE MAIN MONQI FINANCIAL CALCULATION RULES

Introduction
MonQI implements a household financial model that is based on the registration of inputs and outputs (flows) for the different activities (crops, livestock, household) in the household. The financial model uses the lowest level information (the flows, inputs/outputs) and classifies and aggregates that information to the intermediate level (the activities) and the highest level, the farm/household.

Assumptions

The following assumptions are relevant for the implementation of the calculation rules:

Input and output flows

- Only activities (LA, AA, RA, OA, HA and SA) have input and output flows. No flows can be recorded directly on the other units (AE, LU)
- Each flow has a value but internal flows (between on-farm activities) do not have a cash value. Only external flows (those crossing the farm boundary) have a cash value.
- The value of a flow is calculated as:
    - Flow Value = Quantity (of measure) x Price per Measure
- If no Price per Measure is provided (as often with internal flows) then the following is used:
    - Flow Value = Quantity (kg) x Price per Kg (from BGDB)

Food in stock and home consumption

- All food produced and not sold is going to stock (SA)
- Food that is not sold from stock is assumed being consumed by the household (HA).
- Therefore flows recorded to/from HA only concern "Services" and not food stuffs.

Permanent labor

Whether permanent hired labour is a fixed cost or a variable cost, depends on how fixed the labour is available in the household. Labor is considered permanent if it is present all year round, not seasonal, can not be attributed to any particular crop or animal activity. The salary paid to this laborer is registered in Form 50-I ('Services obtained') and this person is / is not registered in Form 2 ('Household members')

'Other Activities' (OA) that are considered agriculture

OAs are classified as either ‘agricultural’ or ‘non-agricultural’. This determines whether the income from these activities is added to either the NFI (Net Farm Income) or the OFI (Off Farm Income).

Value and Cash
A clear distinction is made between those indicators based on cash money (money actually being received or paid) and those based on value (the value of a product, regardless of sales or purchases). Value indicators are an expression of the value of a certain service or good, which may not be the same as the price (cash) value.

Cash maintained at a bank account is not included. For most smallholder farmers in the (sub)tropics, bank accounts are not common methods to safe money.

Gross Margin (GM)
Gross Margin is an indicator of profitability and takes into account the intrinsic value of all inputs and intrinsic value of all outputs. The gross margin indicator is calculated at the level of each activity.

GM = GV – VC

Where:

GV: Gross Value: the value of an output of a farm activity over some accounting period (e.g. a month or a year), regardless of that fact that that output was sold or not

VC: Variable Costs: the value of all inputs (family labour optional). Variable Costs are the same as variable expenses , which are specific to a particular activity and that vary more or less in direct proportion the scale of that enterprise. The variable cost is regardless of the fact that the input was purchased or from an internal source.

Gross Margin for Livestock (GM_AA)
The GM of livestock includes terms to account for herd development (HD), i.e. the change in asset value due to the increase or decrease in the number of animals. Herd development is calculated using *the average price per head* from the BGDB and is included in GV_HD (in case of increase) or VC_HD (in case of decrease).

GV_HD = (positive)ValueChange + ValueSales + ValuePurposeOut

Where:

ValueChange:	$ValueAnimals_{t+1}$ – $ValueAnimal_t$
ValueSales:	Value (price) of animals sold
ValuePurposeOut:	Value of animals that were disposed on purpose (home consumption and gifts, excluding sales, deaths and losses)

VC_HD = (negative)ValueChange +ValuePurchases + ValuePurposeIn

Where:

ValueChange:	$ValueAnimals_{t+1}$ – $ValueAnimal_t$
ValuePurchases:	Value (price) of animals purchased
ValuePurposeIn:	Value of animals that are obtained on purpose (gifts obtained, excluding purchases and births)

Increase/decrease of animal numbers that are not marked as "on purpose" (such as animals born, died and lost) influence the income through the value of herd development only. In case of trade(sales/purchases) the changing number of animals is counted as herd development against the average price per head while the income from sales or costs due to purchase count against it at a market rate. A purchase can thus result in negative income if the price paid per head was more than average (the opposite, an increase in income is also possible).

Other changes of animal numbers, those that are on purpose, are counted against the average price from the BGDB and thus result in no net income change.

Net Cash Flow (NCF)
Cash indicators are an expression of the amount of money being spent or earned and are based on the CASH variable of a flow. They are expressed as Net Cash Flows which is an indicator of cash flows involved. The indicator is measured at activity level.

NCF = CR – CE

Where:

CR: Cash Receipts : the money received from selling outputs

CE : Cash Expenses : the money spent on buying inputs

Breakdown of GM and NCF
GV, VC, CR and CE can be subdivided into several categories, depending on the type of activity, as listed in Annex 1. This table also lists the names of the variables as presented in the export tables. Note that the detailed breakdown is only available for LA and AA.

A flow is placed into a certain category based on the 'product type' of its product.

Aggregation to AE (farm/household) level
Farm level income indicators are based on an aggregation of the Activity level results. Here again the distinction between VALUE and CASH indicators is made.

Net Farm Income (NFI)
Net farm income is based on the GMs of the farming activities. For OA (Other Activities) only those activities marked as 'agriculture' are included.

NFI = ΣLA.GM + ΣAA.GM + ΣRA.GM + ΣSA.GM[3] + ΣOAagri.GM – FIXCOST

Where :

ΣLA.GM : Sum of gross margins of all LAs (crops)

ΣAA.GM : Sum of gross margins of all AAs (animals)

ΣRA.GM : Sum of gross margins of all RAs (redistribution activities)

ΣSA.GM : Sum of gross margins of all RAs (stocks)

ΣOAagri.GM: Sum of gross margins of all OAs (other activities)

FIXCOST : Fixed costs

IDE-RPI project
- SA.GM is excluded from the NFI
- RA.GM and OA.GM are not relevant because not registered.

[3] SA.GM is optionally part of NFI. The assumption that, what remains in storage is assumed to be consumed, implies that this is an opportunity costs because it is not sold. This opportunity costs is lower than the real cost because no overhead is included for sales and transport.

Fixed Costs (FIXCOST)
Fixed costs refer to the costs associated with a product, that are fixed over a number of units. Thus regardless of the number of units produced and sold, the fixed costs remain the same. Examples of fixed costs are rent of land, rent on equipment, digging and maintaining wells, preparing and maintaining terraces (land preparation) and the costs for permanent labor.

FIXCOST = D + LR + PL

Where:

D = depreciation of assets or costs for maintenaince (currently not implemented)

LR = rent on land (registered in 50-I: services obtained)

PL = costs for permanent labor (registered in 50-I: services obtained)

Farm Net Cash Flow (FARMNCF)
Farm Net Cash Flow is based on the NCFs of the farming activities. For OA (Other Activities) only those activities marked as 'agriculture' are included.

FARMNCF = ΣLA.NCF + ΣAA.NCF + ΣRA.NCF + ΣOAagri.NCF + ΣSA.NCF

Where :

ΣLA.GM : Sum of net cash flows of all LAs (crops)

ΣAA.GM : Sum of net cash flows of all AAs (animals)

ΣRA.GM : Sum of net cash flows of all RAs (redistribution activities)[2]

ΣOAagri.GM: Sum of net cash flows of all OAs (other activities)[2]

ΣSA.GM : Sum of net cash flows of all SAs (stocks)

[2] not registered and not taken into account in IDE-RPI set up

Family Earnings (FAMEARN)
Family earnings are defined as the income from agriculture (NFI) plus that of off farm income

FAMEARN = NFI + OFI_TOT

Where :

OFI_TOT : Off Farm Income total

Household Net Cash Flow (HHNCF)
Household Net Cash Flow is defined as the net cash flow from agriculture (FARMNCF) plus that of off farm labour.

HHNCF = FARMNCF + OFI_TOT - OEC

Where :

OFI_TOT : Off Farm Income total

OEC : Other (agricultural) external costs (land rent and permanent labor)

Total Off Farm Income (OFI_TOT)
Total off farm income is calculated as the sum of off farm income earned from ‘Services provided’ (Form 50-O) and that of non-agricultural Other Activities (OA, Forms 40, 40-I and 40-O).

OFI_TOT = OFI_SERV + OFI_OA

Where:

OFI_SERV : off farm income earned from ‘Services provided’

OFI_OA : off farm income earned from non-agricultural Other Activities

OFI_SERV = ΣHA.CR

OFI_OA = ΣOAofffarm.NCF

Where:

ΣHA.CR: Sum of the cash receipts for the household recorded in Form 50-O

ΣOAofffarm.NCF: Sum of the NCFs for the OA (Other Activities) marked as non-agricultural)

Note: Land rent received (a service provided) is treated as any other off farm income.

Table E-1: Breakdown of GM and NCF per activity type

GM = Gross Margin, VC = Variable Cost, GV = Gross Value

NCF = Net Cash Flow, CE = Cash Expenses, CR = Cash Receipts

Activity*	Indicator	Variable name	Description	Remarks
LA			**Land use activity**	
	GM	GM	Gross Margin	
		GV	Gross Value	Sum of the detailed GVs
		VC	Variable Costs	Sum of the detailed VCs
		GV_HP	GV Harv. Prod	Harvested products
		GV_CR	GV Crop Residue	
		GV_OT	GV Others	
		VC_MF	VC Min. Fert	Mineral fertilizers
		VC_OF	VC Org Fert	Organic fertilizers
		VC_SE	VC Seed	
		VC_PE	VC Pesticide	
		VC_HL	VC Hired labor	
		VC_FL	VC Family labor	Can optionally be included
		VC_TR	VC Traction	
		VC_OT	VC Others	
	NCF	NCF	Net Cash Flow	
		CR	Cash Receipts	
		CE	Cash Expenses	
		CR_HP	CR Harv Prod	Harvested products
		CR_CR	CR Crop Residue	

		CR_OT	CR Others	
		CE_MF	CE Min Fert	Mineral fertilizers
		CE_OF	CE Org Fert	Organic fertilizers
		CE_SE	CE Seed	
		CE_PE	CE Pesticide	
		CE_HL	CE Hired Labor	
		CE_TR	CE Traction	
		CE_OT	CE Other	
AA			**Animal Activity**	
	GM	GM	Gross Margin	
		GV	Gross Value	
		VC	Variable Costs	
		GV_MI	GV Milk	
		GV_MN	GV Manure	(currently not part of model)[4]
		GV_TR	GV Traction	
		GV_HD	GV Herd Development	See: Gross Margin for Livestock
		GV_OT	GV Other	
		VC_MF	VC Min. Feeds	Mineral feeds
		VC_OF	VC Org Feeds	Organic feeds
		VC_GR	VC Grazing	(currently not part of model)[5]
		VC_VS	VC Veterinary services	
		VC_HL	VC Hired labor	

[4] Manure represents ‘animal droppings’ as calculated by the grazing model. This is not yet implemented in MonQI

[5] Grazing represents ‘grazing uptake’ as calculated by the grazing model. This is not yet implemented in MonQI

	VC_FL	VC Family labor	
	VC_HD	VC Herd Development	See: Gross Margin for Livestock
	VC_OT	VC Others	
NCF	NCF	Net Cash Flow	
	CR	Cash Receipts	
	CE	Cash Expenses	
	CR_MK	CR Milk	
	CR_TR	CR Traction	
	CR_HG	CR Herdgrowth	
	CR_OT	CR Other	
	CE_MF	CE Min. Feeds	Mineral feeds
	CE_OF	CE Org Feeds	Organic feeds
	CE_VS	CE Veterinary services	
	CE_HL	CE Hired labor	
	CE_HG	CE Herdgrowth	
	CE_OT	CE Others	
RA		**Redistribution activity**	
GM	GM	Gross Margin	
	GV	Gross Value	
	VC	Variable Costs	
	GV_OT	GV Other	
	VC_OT	VC Others	
NCF	NCF	Net Cash Flow	
	CR	Cash Receipts	
	CE	Cash Expenses	
	CR_OT	CR Other	

		CE_OT	CE Others
OA			**Other activity**
	GM	GM	Gross Margin
		GV	Gross Value
		VC	Variable Costs
		GV_OT	GV Other
		VC_OT	VC Others
	NCF	NCF	Net Cash Flow
		CR	Cash Receipts
		CE	Cash Expenses
		CR_OT	CR Other
		CE_OT	CE Others
SA			**Storage activity**
	GM	GM	Gross Margin
		GV	Gross Value
		VC	Variable Costs
		GV_OT	GV Other
		VC_OT	VC Others
	NCF	NCF	Net Cash Flow
		CR	Cash Receipts
		CE	Cash Expenses
		CR_OT	CR Other
		CE_OT	CE Others
HA			**Human/household activity**
	GM	GM	Gross Margin
		GV	Gross Value

	VC	Variable Costs
	GV_OT	GV Other
	VC_OT	VC Others
NCF	NCF	Net Cash Flow
	CR	Cash Receipts
	CE	Cash Expenses
	CR_OT	CR Other
	CE_OT	CE Others

* Refers to the MonQI export table with the same name

APPENDIX F: SYSTEMATIC RECALL BIAS EFFORTS

Literature Review

The act of income and/or crop production recollection may generate recall biases, where reported earnings and production are subject to random errors as well potential systematic recall bias. There is little research on the effect of these systematic biases on impact analyses, with most of the economic research coming from the labor economics literature. Recall bias has often been classified as a distinct form of differential misclassification bias, and may in fact bias results away from or towards the null hypothesis (Coughlin, 1990). It is important however to distinguish between recall bias and recall inaccuracies. Although the majority of the literature on recall bias is epidemiological in nature, there are some valuable insights that will help to better understand the specific case at hand, and whether or not there is evidence of systematic and correctable recall biases.

For the present study, farmers were asked to recall information over a nearly twenty-month period. Despite being an obvious consideration, Baumgarten et al. (1983) found that the time interval since exposure was a significant factor in subjects' ability to recall work history. In a similar study, subjects were asked to report their specific weight during different times on their life, the correlation between reported weight and elapsed time was .89 (Corwin et al. 1971). Many of the studies explicitly studying recall accuracy used relatively simple recall tasks. In our case, farmers are being asked to recall very specific aspects of production (i.e. crop expenditures, production inputs, livestock births and deaths, percentage of market outputs and their value, amount of total production for household consumption, etc.) The complexity of the recall task has been shown to influence the accuracy of recall for a number of different exposures (Stewart et al. 1987). Although informative, there is no variance in the complexity of the recall task between observations in the present study, save for the two-year recall observations, which are made more difficult by the time of the recall period and not by the complexity of the questions. Personal characteristics such as age, socioeconomic status and education have also been shown to influence the accuracy of recall in drug usage and other health related information (Schlesselman 1982; Paganini-Hill, et al. 1982). Stewart et al. (1987) also demonstrated the existence of a U-shaped age effect for subject recall accuracy. Specifically, the accuracy rate for subjects 65-69 years of age was 53% regarding their work history compared to an accuracy rate of 60% for subjects that were less than 65 years old.

Another important factor to consider is the social desirability of the targeted recall information. The accuracy of self-reported events or information may tend to be distorted in a socially-desirable direction (Rossi et al. 1983). A number of additional studies have identified differential biases in recall accuracy between control and treated groups. Motivation for program participation of treatment group participants, and less sensitization to relevant question material for control group respondents, may contribute to differential recall bias as well (Raphael 1987). This is important in the current study, because developmental assistance is often offered to those who are most vocal about its need. IDE clientele have an incentive to either: overstate the benefits of the technology on the target indicators, so that further technical and educational assistance will be offered. Or, understate the benefits of adoption/participation on income with the belief that more assistance will be offered to compensate for the insignificant effects of their efforts.

Because there is a lack of variance in the recall task between observations, and because the social motivation issues are exogenous and random, we will primarily utilize demographic and socioeconomic covariates in the present study. Although there are a large number of additional covariates that surely influence a farmer's recall accuracy, we are limited to the observable covariates that were measured in the previous survey efforts and therefore, will rely heavily on social and demographic covariates.

Description of the sample

For the existing data, there are 835 farmer households with 1 year of data, 171 farmer households with 2 years of data and 49 farmer households that have three years of data. There are 835 first-year farmer households, 155 of which are untargeted households.[6] According to the IDE methodology report, there were no untargeted households that were involved in any follow-up survey activities. To confirm this was the case and that the coding was correct, count commands were utilized to ensure that there were no Consumer Characteristics Survey respondents that had more than one year of data collected. Essentially, there are three years worth of responses for 49 households, two years of responses for 171 households and one year of responses for 753 households.

You can see comparisons of one and two year back recalled incomes across years below in Table F-1 through Table F-3. Note that all first-year households in Table F-1 are also included as first-year households in Table F-2 and in Table F-3 (and, likewise, all second-year households in Table F-2 are included as second-year households in Table F-1). Still, while these figures have been deflated and while one cannot reject the hypothesis that same-year households' earnings change over time, the fact that *t*-year means increase over time for all *t* underscores the possibility that the IDE program may have drawn from different household populations over time as facilitators moved through the countryside from one year to the next.

Table F-1: Comparison of treated farmer-households that have completed three consecutive survey-rounds, Net Farm Income (two-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First-Year	47	4,846,859	6,773,347	-2,492,813	37,700,000
Second-Year	49	5,650,152	9,843,996	-13,100,000	48,600,000
Third-Year	48	6,727,733	5,083,907	-3,206	20,200,000

Table F-2: Comparison of treated farmer-households that have completed Two consecutive survey-rounds, Net Farm Income (two-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First-Year	163	5,205,921	6,796,804	-9,716,308	43,300,000
Second-Year	162	6,187,403	7,713,605	-13,100,000	48,600,000

6 To avoid possible confusion we use the term, "untargeted" rather than "control" because our evaluation design does not use these households as part of the control group. First, their proximity to the treatment group made contamination rather likely and, second, we found *de facto* statistical differences between them and those households in the treatment group.

Table F-3: Farmer-households that have completed one survey round, Net Farm Income (two-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First-Year	753	6,040,634	7,391,299	-16,800,000	67,100,000

You can see comparisons of post-survey incomes across years in Table F-4 through Table F-6.

Table F-4: Comparison of three-year, farmer-household, CPI-adjusted Net Farm Income (one-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First Year	47	5,961,999	5,817,977	-1,020,506	30,200,000
Second Year	49	8,577,209	9,587,248	-907,253	50,400,000
Third Year	48	7,860,701	4,552,003	1,100,679	16,500,000

Table F-5: Comparison of two-year, farmer-household, CPI-adjusted Net Farm Income (one-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First Year	163	6,568,310	7,867,717	-8,668,377	44,100,000
Second Year	162	8,010,561	8,857,028	-1,961,144	50,400,000

Table F-6: Comparison of first-year, farmer-household, CPI-adjusted Net Farm Income (one-year recall)

Variable	Obs	Mean	Std. Dev.	Min	Max
First Year	753	7,309,965	8,620,907	-8,668,377	72,200,000

Paull (2002) refers to the sections in his data where different survey rounds contain pieces of information for the same time period as “overlaps”. Specifically, there is data that is collected with a recall period of a few months, and additional data collected for the *same* period but a year later (and, hence, with a recall period of a few months plus one year). Comparing the former survey data, which should be more accurate, with the latter survey data provides Paull enough information to determine whether there is systematic recall bias in his reported income and production indicators. We are faced with the same issue with the IDE Zambia data, and will use a similar methodology.

To begin looking at the potential recall bias, for t=(2008,2009) we calculated the difference $y(t\text{-}2|t\text{-}1)$ - $y(t\text{-}2|t)$, where y is CPI-adjusted income for the year to the left of the “|” taken (collected) in the year to the right of the “|”. This concept is illustrated in Figure 1.

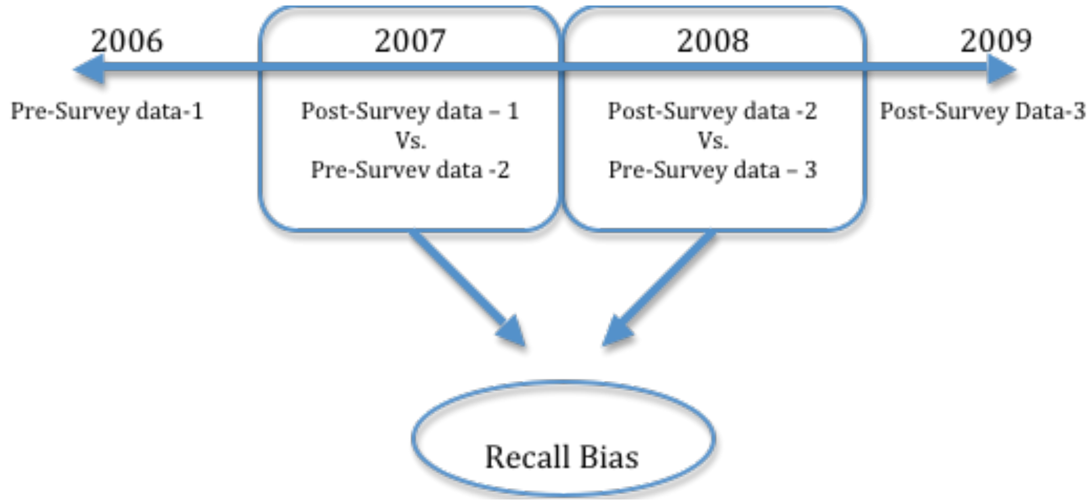

Figure F-1: Relationship between recall periods

It is important to note that we have a fairly limited sample, because there are only 160 and 49 farmer households that were surveyed for two and three years in a row, respectfully. This, in total, lends 208 observed differences between "current" and recalled data for the following summaries and modeling efforts.[7] The following equation presents this mathematically:

$$CPI\ Adj.\ NFI\ Diff.\ \#1 = y(t\text{-}2|t\text{-}1) - y(t\text{-}2|t)$$

Where:
y = CPI-adjusted income for the year to the left of the "|" taken (collected) in the year to the right of the "|".

The following differences for CPI-adjusted net family incomes are summarized Table F-7

Table F-7: Differences between "current" and recalled CPI-adjusted Net Family income

Variable	Obs	Mean	Std. Dev.	Min	Max
CPI Adj. NFI Diff. #1	160	228,399	8,147,845	-35,400,000	27,600,000
CPI Adj. NFI Diff. #2	48	1,717,172	8,743,283	-18,600,000	43,200,000

Variable Comparisons

Theoretically, the magnitude of recall bias should be similar, after the units are controlled for. This is supported by the epidemiological literature mentioned in the literature review of this section. To examine this, recall inaccuracies from one area indicator (total farm

[7] Obvious, both periods involve recalled data, only that one requires an additional year of recollecttion.

area) and three income indicators (household cash income, net family income and off farm income) were CPI-adjusted and compared in Table F-8 below:

Table F-8: Recall differences of four key variables exhibiting overlap

Variable	Obs	Mean	Std. Dev.	Min	Max
NFI Diff. 1	160	228,399	8,147,845	-35,400,000	27,600,000
Total Area Diff. 1	160	4,345	22,510	-75,000	74,600
OFI Diff. 1	160	-32,698	3,114,285	-13,500,000	13,800,000
Net Cash Inc. Diff. 1	160	-809,626	8,525,271	-42,200,000	21,000,000
NFI Diff. 2	48	1,717,172	8,743,283	-18,600,000	43,200,000
Total Area Diff. 2	48	5,044	23,663	-40,000	75,000
OFI Diff. 2	48	456,975	2,465,590	-9,548,319	11,200,000
Net Cash Inc. Diff. 2	48	1,927,072	8,694,803	-8,484,229	50,300,000

Notes: The four variables (appropriately CPI adjusted) are: Net Farm Income, Off-Farm Income, Total Farm Area and Net Cash Income of the Family from All Sources)
Differences are calculated by subtracting earlier crop years from later crop years.

Normalized differences

The differences in Table F-8 were then normalized by dividing each observed difference by the sample mean for the respective variable, as shown in Table F-9. The specific equation is shown below:

$$Norm.\ Diff.\ of\ y_i = [\ y_i(t\text{-}2|t\text{-}1) - y_i(t\text{-}2|t)\ ]\ /\ mean(y(t\text{-}2|t\text{-}1))$$

Where:
i = farmer household
y = income

Normalizing the differences allows for easier comparison between variables. The specific mean that was used for normalization was calculated from the first-year sample, because it had the highest number of observations. Using the normalized differences, we can compare indicators and see how the accuracy of recalled responses compares to the variable mean. This will be beneficial when specific indicators are used in the calculation of average treatment effects for the treated.

Table F-9: Normalized differences of four key indicators

Variable	Obs	Mean	Std. Dev.	Min	Max
Norm NFI Diff. 1	160	0.008	0.298	-1.297	1.012
Norm Total Area Diff. 1	160	0.171	0.888	-2.960	2.944
Norm OFI Diff. 1	160	-0.027	3.709	-14.874	15.605
Norm Net Cash Inc. Diff. 1	160	0.084	1.624	-6.313	5.059
Norm NFI Diff. 2	48	0.063	0.320	-0.683	1.581
Norm Total Area Diff. 2	48	0.199	0.934	-1.579	2.960
Norm OFI Diff. 2	48	0.483	2.592	-9.001	10.982
Norm Net Cash Inc. Diff. 2	48	0.493	1.679	-2.916	8.612

Notes: See Table.

A t-test comparison of sample means for the four indicators found that the only significant difference between any of the normalized indicators was *between NFI Diff 1* and *Total Area Diff 1,* with 0.02 level of significance. This is an important finding because it supports the hypothesis that recall inaccuracy is relatively consistent, regardless of income or area estimates.

Percent Differences

Percent differences were also calculated for each of the four primary indicators. The percent differences were calculated by dividing each observed difference by the individuals stated income in period t, as shown in the equation below.

$$\%\ diff.\ of\ y_i = [\ y_i(t\text{-}2|t\text{-}1) - y_i(t\text{-}2|t)\ ]\ /\ y_i(t\text{-}2|t\text{-}1)$$

Where:
i = farmer household
y = income

Using the percent differences allows for easier comparison between observations and specific income indicators. By using the percent difference the income level of each farmer is controlled for, and the specific units of measure for the indicator cancels out. This will allow for comparisons between indicators (i.e. income and stated area), and they can be used interchangeably to test for systematic recall bias. Descriptive statistics for the percent differences of the fours primary indicators, for first year recall bias and second year percent difference recall inaccuracies are shown in Table F-10.

Table F-10: Percent differences of four key indicators

Variable	Obs	Mean	Std. Dev.	Min	Max
% NFI Diff. 1	160	-1.254	9.393	-104.392	21.933
% Total Area Diff. 1	160	-0.218	1.396	-9	1
% OFI Diff. 1	72	-0.364	4.971	-30.206	1
% Net Cash Inc. Diff. 1	160	-5.66	49.859	-584.974	35.656
% NFI Diff. 2	48	-0.032	3.201	-12.226	13.29
% Total Area Diff. 2	48	-0.39	1.765	-10	0.864
% OFI Diff. 2	32	-0.596	3.434	-13.79	1
% Net Cash Inc. Diff. 2	48	0.4	3.969	-8.855	23.632

Notes: Off farm income has fewer observations because the first year income, which is used as the denominator for the percent difference equation, was stated as zero for these households.

Similar to the normalized differences, t-test comparison of means revealed no statistically significant difference between indicators, area or income, when units and individual incomes/land area are controlled for. This lends further support for the notion that recall inaccuracy is consistent, whether income or land area estimates are used.

To better understand how specific household characteristics relate with to recall inaccuracies, individual t-test were conducted testing whether the recall inaccuracies from the four primary indicators were significantly different from zero for the farmer-household covariates of interest. Results from this series of hypothesis tests are in Table F-11. There were no clear relationships between socio-demographic characteristics and recall inaccuracies as you move between indicators. For example, Farmers from the lowest and highest quartile had recall inaccuracies significantly different from zero, but for area inaccuracies only the middle quartile had recall inaccuracies that were different from zero. Similarly, lower income farmers had recall inaccuracies different from zero for area and off farm income estimates, but highly educated households had recall inaccuracies different from zero when the household net cash flow indicator is used. To complicate matter even more, when the net farm income indicator is used, only the household in the second income quartile demonstrated significant recall inaccuracy.

Table F-11: Stratum t-test results: Are recall inaccuracies sig. diff. from zero for households with different characteristics?

Characteristic	NFI Diff.	AREA Diff.	OFI Diff.	HHNCF Diff.
Male	0.08	0.06		
Female⊗				
Tonga Dummy		0.01		
Other Ethnicity *	0.04	0.03	0.01	
Low Education		0.04		
Med. Education	0.08		0.09	
High Education				
Age (0-30)			0.04	
Age (30-55)		0.01		
Age (30-55)			0.01	
NFI 1st Quartile		0.01	0.08	
NFI 2nd Quartile	0.02			
NFI 3rd Quartile				
NFI 4th Quartile				0.03
Area 1st Quartile		0	0.04	
Area 2nd Quartile				
Area 3rd Quartile			0.03	
Area 4th Quartile	0.04	0		

Notes: Cell values represent significance level of the mean hypothesis test equaling zero for the specific indicator and the specific characteristic. (*) There were insufficient observations to isolate other ethnicities other than Tongalese. (⊗) There are only fifteen female observations in the present sample; therefore these results should be taken with that in mind.

By looking at Table F-11, it is obvious that there are no clear and obvious household characteristics that relate to general recall inaccuracy. Moving forward we will have to choose a single indicator to base our modeling and corrective efforts on.

Modeling recall bias

Some preliminary models were developed to explain the variance identified in the samples' recall bias. Appropriate survey weights were used in the linear models to ensure accurate standard errors throughout. Although they are not included in this appendix, the most striking result from these preliminary efforts are that no single covariate was significant in explaining recall inaccuracy. Additional efforts will be made with this unique data set to further explore systematic recall bias among smallholder farmers.

APPENDIX G: SELECTION MODEL RESULTS, BALANCING TESTS AND PROPENSITY SCORE DISTRIBUTIONS

Table G-1: Selection Model Results, by RPI Area and Evaluation

VARIABLES	Kabwe T2 vs. C1	Kafue T2 vs. C1	C/L* T2 vs. C1	Kabwe T4 vs. C1	Lusaka T4 vs. C1	Kafue T4 vs. C1	C/L T4 vs. C1	Kabwe T0 vs. C0	Lusaka T0 vs. C0	Kafue T0 vs. C0	C/L T0 vs. C0
agehhh	0.020*	0.019*	0.01	0.008	-0.013	0.015*	0.009	0.011	-0.01	0.017**	0.008
	(-0.011)	(-0.01)	(-0.012)	(-0.009)	(-0.009)	(-0.009)	(-0.01)	(0.008)	(-0.009)	(-0.007)	(-0.008)
distmrkt	-0.018**	0.001	0.002			-0.023**					
	(-0.007)	(-0.002	(-0.007)			(-0.008)					
eduhhhyr	0.053	-0.035	-0.009	0.077**	-0.059	-0.022	-0.021	0.075**	-0.052	-0.037	-0.015
	(-0.042)	(-0.04)	(-0.05)	(-0.039)	(-0.037)	(-0.039)	(-0.042)	(-0.032)	(-0.036)	(-0.03)	(-0.036)
Num_of_Assets_09	-0.042	0.056	0.128**	-0.042	0.205***	-0.129**	-0.123**	-0.045	0.188***	-0.015	-0.055
	(-0.063)	(0.056)	(-0.057)	(-0.053)	(-0.048)	(-0.048)	(-0.048)	(-0.046)	(-0.044)	(-0.038)	(-0.036)
totnohhm	0.038	-0.036	-0.089**	-0.025	0.073**	0.027	-0.036		0.070*	0.007	-0.04
	(-0.049)	(-0.047)	(-0.044)	(-0.041)	(-0.036)	(-0.029)	(-0.029)		(-0.036)	(-0.027)	(-0.026)
VegetableProducer_2009	0.598*	0.444	0.423	1.000***	0.127	0.216	0.670**	0.684**	0.044	0.294	0.607**
	(-0.324)	(-0.301)	(-0.319)	(-0.292)	(-0.23)	(-0.272)	(-0.255)	(-0.236)	(-0.224)	(-0.229)	(-0.217)
LivestockDummy_2009	-0.172	-0.559**	0.421	0.212	-0.012		0.24	0.152	-0.074	-0.354*	0.253
	(-0.301)	(-0.275)	(-0.308)	(-0.252)	(-0.214)		(-0.232)	(-0.207)	(-0.207)	(-0.198)	(-0.196)
VCR04	-0.214			-0.127	-0.009		0.282	-0.141	-0.008	-0.032	0.012
	(-0.233)			(-0.107)	(-0.211)		(-0.302)	(-0.104)	(-0.211)	(-0.166)	(-0.148)
Perc_IrrCropLand_09	-1.477	0.348	1.656	-3.905**	-0.659	0.087	2.575**	-2.169**	-0.832*	-0.099	2.359**
	(-1.022)	(-0.722)	(-1.109)	(-1.255)	(-0.464)	(-0.583)	(-0.858)	(-0.81)	(-0.435)	(-0.516)	(-0.73)
RegionalSell_dum_09	-0.237	-0.749**	0.611*	0.199	0.335	-0.473*	0.053	0.103	0.255	-0.566**	0.153
	(-0.312)	(-0.287)	(-0.322)	(-0.279)	(-0.272)	(-0.264)	(-0.244)	(-0.224)	(-0.264)	(-0.218)	(-0.209)
P09_HHNCF	0.000**	0.001***	0	0	0	0.000*	0	0.000*	0	0.000**	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0	(0)	(0)	(0)	(0)
gndrhhhid				-1.094***	-0.434*	0.477*	-0.362	-0.957***	-0.517**	0.304	-0.256
				(-0.28)	(-0.24)	(-0.253)	(-0.282)	(-0.241)	(-0.235)	(-0.211)	(-0.237)
Num_of_Crops_09						-0.073				-0.089	
						(-0.068)				(-0.057)	
Males								-0.059			
								(-0.076)			

Females								-0.079			
								(-0.092)			
Children								0.004			
								(-0.044)			
Constant	-0.779	-1.525**	-2.275**	0.307	-0.861	0.37	-0.83	0.446	-0.722	0.069	-0.283
	(-1.112)	(-0.739)	(-0.821)	(-0.806)	(-0.884)	(-0.653)	(-1.051)	(-0.72)	(-0.876)	(-0.721)	(-0.673)
Observations	108	134	120	145	170	145	152	199	180	198	194

* C/L stands for Choma/Livingstone ; Standard errors in parentheses ; *** p<0.001, ** p<0.05 , * p<0.10

Table G-2: Selection Model Results, by Gender and Evaluation

VARIABLES	Male T2 vs. C1	Female T2 vs. C1	Male T4 vs. C1	Female T4 vs. C1	Male T0 vs. C0	Female T0 vs. C0
agehhh	0.007	0.036**	0.005	0.007	0.002	0.008
	(-0.006)	(-0.015)	(-0.005)	(-0.008)	(-0.004)	(-0.008)
distmrkt	0.001	-0.012	-0.009**	0.001	-0.002*	-0.004
	(-0.001)	(-0.009)	(-0.003)	(-0.002)	(-0.001)	(-0.005)
eduhhhyr	0.016	-0.059	-0.014	-0.003	0	-0.038
	(-0.024)	(-0.05)	(-0.021)	(-0.036)	(-0.018)	(-0.035)
Num_of_Assets_09	0.074**	0.174**	-0.022	0.031	0.015	0.037
	(-0.03)	(-0.065)	(-0.024)	(-0.041)	(-0.022)	(-0.038)
Num_of_Crops_09					-0.034	0.094**
					(-0.023)	(-0.04)
totnohhm	-0.04	0.035	-0.026	0.046	-0.044**	0.029
	(-0.025)	(-0.05)	(-0.019)	(-0.028)	(-0.018)	(-0.028)
Dep_Ratio					0.090**	0.018
					(-0.034)	(-0.045)
VegetableProducer_2009	0.556**	1.091***	0.375**	0.251	0.492***	0.097
	(-0.181)	(-0.318)	(-0.134)	(-0.21)	(-0.135)	(-0.211)
LivestockDummy_2009	-0.319**	0.272	0.08	0.196	-0.118	
	(-0.158)	(-0.305)	(-0.128)	(-0.194)	(-0.114)	
VCR04	-0.144	-0.144	-0.017	0.035	0.011	-0.013

	(-0.127)	(-0.374)	(-0.081)	(-0.3)	(-0.079)	(-0.269)
Perc_IrrCropLand_09	0.108	-1.964	-0.362	0.321	-0.393	0.23
	(-0.409)	(-1.217)	(-0.325)	(-0.515)	(-0.294)	(-0.51)
RegionalSell_dum_09	-0.152	-0.182	-0.023	-0.13	-0.107	-0.142
	(-0.171)	(-0.313)	(-0.143)	(-0.213)	(-0.127)	(-0.198)
P09_HHNCF	0	0.000*	0	0	0.000**	0
	(0)	(0)	(0)	(0)	(0)	(0)
Constant	-1.026*	-3.093**	0.024	-1.027	-0.009	-0.729
	(-0.536)	(-1.465)	(-0.428)	(-1.041)	(-0.396)	(-0.963)
Observations	341	119	432	183	526	218

* C/L stands for Choma/Livingstone ; Standard errors in parentheses ; *** p<0.001, ** p<0.05 , * p<0.10

Table G-3: Whole Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.6533	.76486	-24.7		-3.46	0.001
	Matched	.66158	.66978	-1.8	92.6	-0.24	0.808
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	43.16	42.487	5	49.8	0.71	0.479
distmrkt	Unmatched	23.39	27.003	-7.3		-1.02	0.308
	Matched	21.949	21.914	0.1	99	0.02	0.986
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	7.0687	7.1066	-1.2	-10.8	-0.17	0.865
Num_of_Cr~09	Unmatched	5.4545	4.8867	20.3		2.78	0.006
	Matched	5.4758	5.4893	-0.5	97.6	-0.07	0.948
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	6.8702	6.9312	-2.2	85.2	-0.29	0.769
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.4453	7.2882	4.4	-35.3	0.64	0.521
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.63104	.62397	1.4	95.8	0.20	0.838
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.54707	.55303	-1.2	5.2	-0.17	0.867
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	3.0153	3.0022	1.8	65.8	0.28	0.781
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.15928	.15704	1.1	-14	0.17	0.865
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.67939	.71002	-6.7	53.4	-0.93	0.352
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1604.4	1609	-0.2	99	-0.03	0.975

Figure G-2: Propensity Score Distribution, by T_0 and C_0

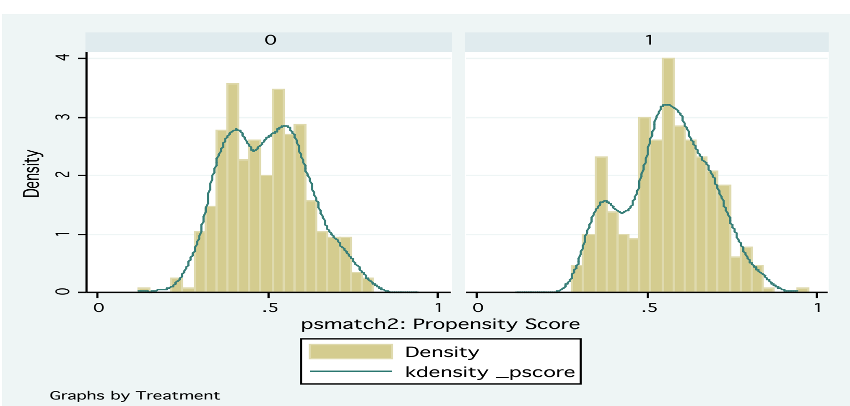

Table G-4: Whole Sample Selection Model Balancing Test Results, by T_1 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.7037	.75439	-11.4		-1.14	0.257
	Matched	.69291	.71203	-4.3	62.3	-0.33	0.741
agehhh	Unmatched	43.689	41.333	16.9		1.68	0.093
	Matched	43.354	43.139	1.5	90.9	0.12	0.902
distmrkt	Unmatched	28.847	27.42	2.7		0.27	0.784
	Matched	29.358	30.781	-2.7	0.3	-0.18	0.854
eduhhhyr	Unmatched	7.6567	7.1754	14.4		1.43	0.153
	Matched	7.5512	7.2838	8	44.4	0.65	0.517
Num_of_Cr~09	Unmatched	5.7752	4.7872	35.6		3.48	0.001
	Matched	5.748	5.8032	-2	94.4	-0.15	0.879
Num_of_As~09	Unmatched	7.9398	6.2143	61.3		5.99	0.000
	Matched	8.0315	8.0223	0.3	99.5	0.03	0.980
totnohhm	Unmatched	7.4478	7.3012	4.4		0.42	0.675
	Matched	7.4016	7.3353	2	54.8	0.17	0.869
VegetableP~9	Unmatched	.72593	.41813	65.3		6.29	0.000
	Matched	.73228	.73639	-0.9	98.7	-0.07	0.941
Livesto~2009	Unmatched	.48889	.54094	-10.4		-1.02	0.306
	Matched	.49606	.4801	3.2	69.3	0.25	0.801
VCR04	Unmatched	3.0149	3.0323	-2.3		-0.23	0.815
	Matched	3.0157	2.9766	5.2	-125.7	0.47	0.637
Perc_IrrC~09	Unmatched	.15834	.14967	4.7		0.43	0.664
	Matched	.16705	.16581	0.7	85.7	0.06	0.955
RegionalS~09	Unmatched	.62222	.73684	-24.7		-2.48	0.013
	Matched	.6378	.6813	-9.4	62	-0.73	0.467
P09_HHNCF	Unmatched	2039.6	1076.6	53		5.62	0.000
	Matched	2091.9	2105.8	-0.8	98.6	-0.05	0.962

Figure G-4: Propensity Score Distribution, by T_1 and C_1

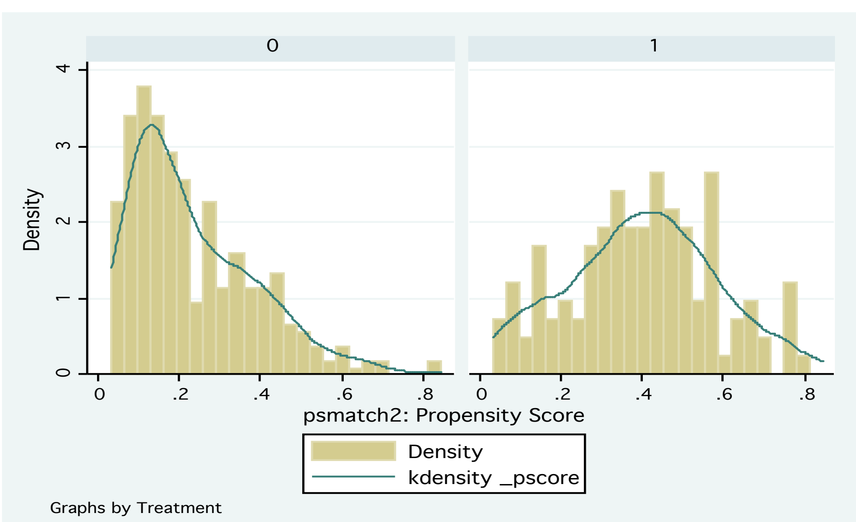

Table G-5: Whole Sample Selection Model Balancing Test Results, by T_2 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.71654	.75439	-8.6		-0.83	0.405
	Matched	.70588	.72944	-5.3	37.8	-0.40	0.688
agehhh	Unmatched	43.669	41.333	16.6		1.62	0.106
	Matched	43.261	43.533	-1.9	88.4	-0.15	0.881
distmrkt	Unmatched	29.853	27.42	4.6		0.45	0.651
	Matched	30.534	33.345	-5.3	-15.5	-0.33	0.744
eduhhhyr	Unmatched	7.5635	7.1754	11.6		1.13	0.259
	Matched	7.4454	7.2579	5.6	51.7	0.44	0.660
Num_of_Cr~09	Unmatched	5.719	4.7872	33.5		3.20	0.001
	Matched	5.7059	5.612	3.4	89.9	0.26	0.799
Num_of_As~09	Unmatched	7.8889	6.2143	59.5		5.70	0.000
	Matched	7.9664	7.9197	1.7	97.2	0.13	0.899
totnohhm	Unmatched	7.4762	7.3012	5.3		0.49	0.626
	Matched	7.4202	7.3749	1.4	74.1	0.11	0.914
VegetableP~9	Unmatched	.71654	.41813	63		5.94	0.000
	Matched	.72269	.72696	-0.9	98.6	-0.07	0.942
Livesto~2009	Unmatched	.51181	.54094	-5.8		-0.56	0.575
	Matched	.52101	.51643	0.9	84.3	0.07	0.944
VCR04	Unmatched	2.9683	3.0323	-9.6		-0.91	0.364
	Matched	2.9664	2.9717	-0.8	91.7	-0.08	0.940
Perc_IrrC~09	Unmatched	.15446	.14967	2.6		0.23	0.814
	Matched	.16286	.1637	-0.5	82.5	-0.04	0.970
RegionalS~09	Unmatched	.64567	.73684	-19.8		-1.94	0.053
	Matched	.66387	.69652	-7.1	64.2	-0.54	0.591
P09_HHNCF	Unmatched	2008.7	1076.6	51.5		5.35	0.000
	Matched	2001.1	1963.7	2.1	96	0.13	0.894

Figure G-3: Propensity Score Distribution, by T_2 and C_1

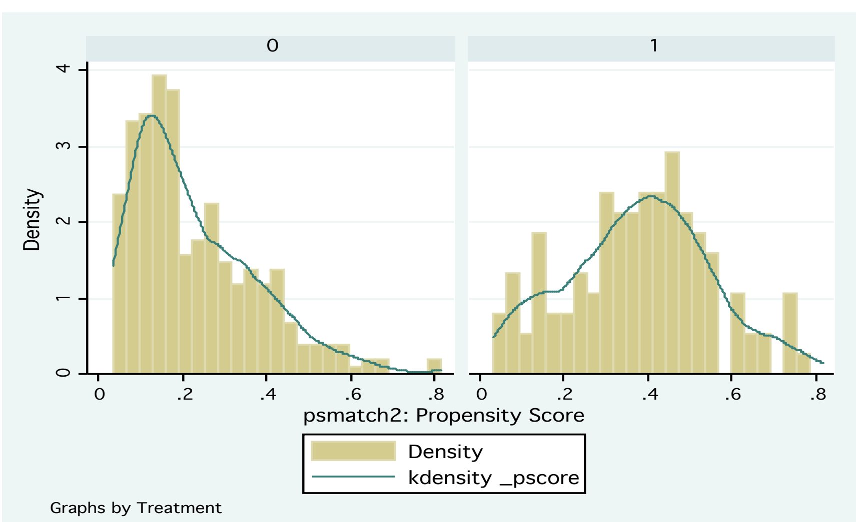

Table G-6: Whole Sample Selection Model Balancing Test Results, by T_3 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.70896	.75439	-10.2		-1.02	0.310
	Matched	.69841	.71327	-3.3	67.3	-0.26	0.797
agehhh	Unmatched	43.716	41.333	17.1		1.69	0.091
	Matched	43.381	43.148	1.7	90.2	0.13	0.894
distmrkt	Unmatched	29.064	27.42	3.1		0.31	0.753
	Matched	29.591	31.34	-3.3	-6.4	-0.22	0.824
eduhhhyr	Unmatched	7.6617	7.1754	14.5		1.44	0.150
	Matched	7.5556	7.2688	8.6	41	0.69	0.490
Num_of_Cr~09	Unmatched	5.7578	4.7872	35		3.41	0.001
	Matched	5.7302	5.801	-2.6	92.7	-0.20	0.846
Num_of_As~09	Unmatched	7.9015	6.2143	60.2		5.86	0.000
	Matched	7.9921	7.9939	-0.1	99.9	-0.00	0.996
totnohhm	Unmatched	7.4436	7.3012	4.3		0.41	0.685
	Matched	7.3968	7.3431	1.6	62.3	0.13	0.894
VegetableP~9	Unmatched	.72388	.41813	64.8		6.23	0.000
	Matched	.73016	.73462	-0.9	98.5	-0.08	0.937
Livesto~2009	Unmatched	.48507	.54094	-11.2		-1.10	0.273
	Matched	.49206	.47573	3.3	70.8	0.26	0.797
VCR04	Unmatched	3.015	3.0323	-2.3		-0.23	0.817
	Matched	3.0159	2.9774	5.1	-123.5	0.46	0.645
Perc_IrrC~09	Unmatched	.15786	.14967	4.4		0.41	0.683
	Matched	.16661	.16502	0.9	80.6	0.07	0.942
RegionalS~09	Unmatched	.6194	.73684	-25.3		-2.54	0.012
	Matched	.63492	.6838	-10.5	58.4	-0.81	0.416
P09_HHNCF	Unmatched	2018.5	1076.6	51.9		5.49	0.000
	Matched	2070.1	2072.2	-0.1	99.8	-0.01	0.994

Figure G- 4: Propensity Score Distribution, by T_3 and C_1

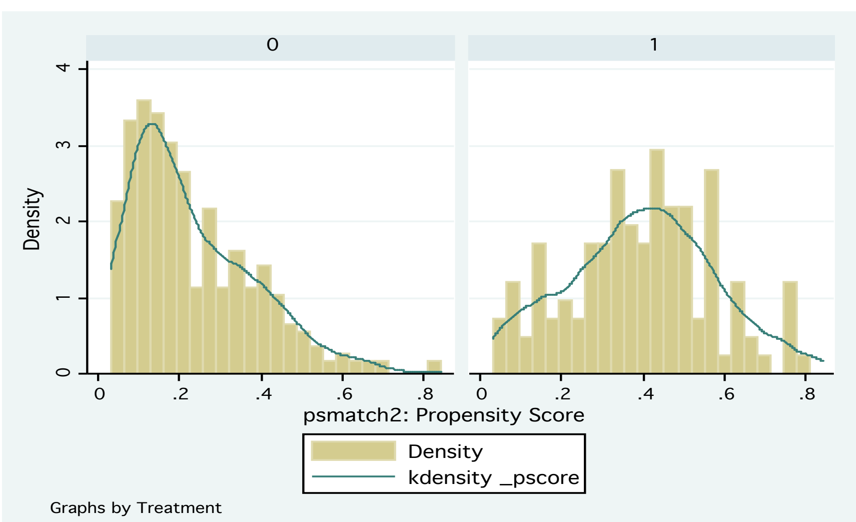

Table G-7: Whole Sample Selection Model Balancing Test Results, by T_2 and C_2

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.71654	.62976	18.5		1.72	0.087
	Matched	.69565	.70357	-1.7	90.9	-0.13	0.897
agehhh	Unmatched	43.669	42.872	5.7		0.55	0.586
	Matched	43.513	44.852	-9.6	-67.9	-0.72	0.474
distmrkt	Unmatched	29.853	20.86	17		1.63	0.103
	Matched	20.674	23.485	-5.3	68.7	-1.13	0.258
eduhhhyr	Unmatched	7.5635	6.9343	19.6		1.89	0.059
	Matched	7.4609	7.0331	13.3	32	0.95	0.345
Num_of_Cr~09	Unmatched	5.719	5.3058	14.4		1.32	0.186
	Matched	5.7565	5.6394	4.1	71.7	0.31	0.757
Num_of_As~09	Unmatched	7.8889	6.2972	59.7		5.73	0.000
	Matched	7.9043	7.7351	6.4	89.4	0.49	0.628
totnohhm	Unmatched	7.4762	7.4844	-0.2		-0.02	0.983
	Matched	7.4435	7.1905	7.2	-2971	0.61	0.540
VegetableP~9	Unmatched	.71654	.56055	32.8		3.03	0.003
	Matched	.71304	.69126	4.6	86	0.36	0.720
Livesto~2009	Unmatched	.51181	.57785	-13.3		-1.25	0.213
	Matched	.52174	.5419	-4	69.5	-0.30	0.761
VCR04	Unmatched	2.9683	2.9965	-4.2		-0.38	0.701
	Matched	2.9652	2.977	-1.7	58.1	-0.14	0.888
Perc_IrrC~09	Unmatched	.15446	.14827	3.7		0.34	0.737
	Matched	.15898	.15646	1.5	59.1	0.12	0.908
RegionalS~09	Unmatched	.64567	.6955	-10.6		-1.00	0.317
	Matched	.65217	.67591	-5	52.4	-0.38	0.705
P09_HHNCF	Unmatched	2008.7	1379.7	31.3		2.98	0.003
	Matched	2027.2	1945	4.1	86.9	0.27	0.786

Figure G-5: Propensity Score Distribution, by T_2 and C_2

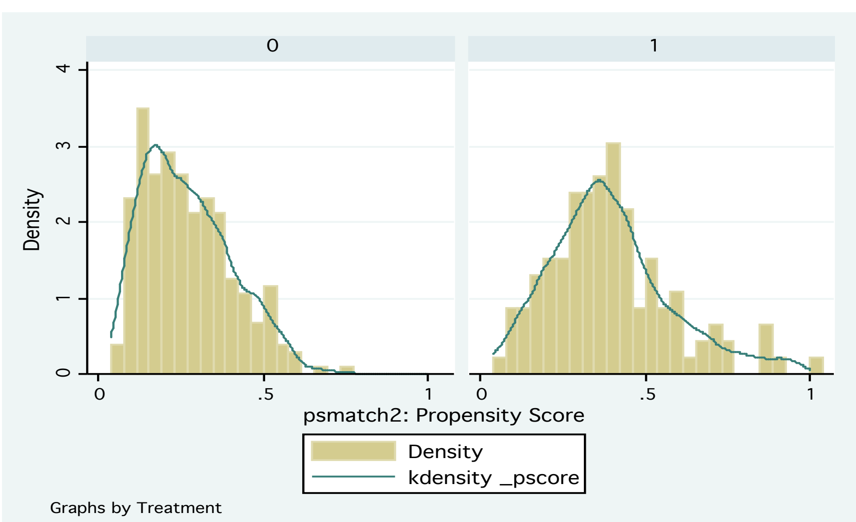

Table G-8: Whole Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.62976	.75439	-27.2		-3.42	0.001
	Matched	.64419	.6286	3.4	87.5	0.37	0.709
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	43.109	43.045	0.5	95.9	0.05	0.956
distmrkt	Unmatched	20.86	27.42	-13.3		-1.66	0.098
	Matched	18.343	18.987	-1.3	90.2	-0.41	0.685
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	6.8577	6.8334	0.8	90	0.09	0.928
Num_of_Cr~09	Unmatched	5.3058	4.7872	18.7		2.30	0.022
	Matched	5.367	5.2426	4.5	76	0.51	0.609
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	6.3146	6.3841	-2.6	16.2	-0.30	0.766
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	7.4757	7.2239	6.8	-37.4	0.81	0.420
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.58427	.57251	2.4	91.7	0.27	0.784
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.57303	.56639	1.3	82	0.15	0.877
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	3.015	3.0131	0.3	94.8	0.03	0.973
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.15553	.15704	-0.8	-8	-0.09	0.927
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.69663	.72677	-6.7	27.1	-0.77	0.443
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1397.1	1357.4	2.3	86.9	0.25	0.803

Figure G-6: Propensity Score Distribution, by T_4 and C_1

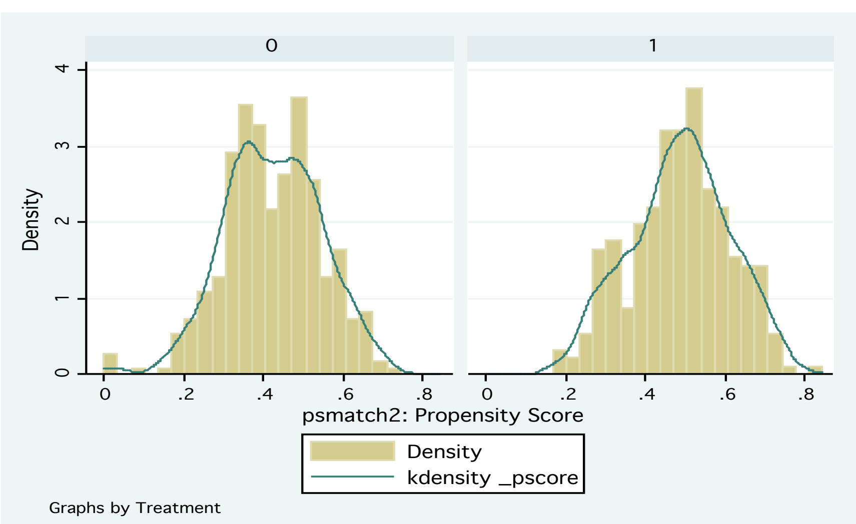

Table G-9: Kabwe Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	**Sample**	**Treated**	**Control**	**%bias**	**bias**	**t**	**p>t**
gndrhhhid	Unmatched	.62976	.75439	-27.2		-3.42	0.001
	Matched	.58228	.60832	-5.7	79.1	-0.33	0.741
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	44.481	43.834	4.8	57.9	0.30	0.766
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	7.1899	7.3268	-4.4	43.2	-0.27	0.785
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	6.5823	6.7279	-5.5	-75.6	-0.38	0.701
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	6.9367	6.5794	9.6	-95	0.86	0.393
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.58228	.58838	-1.2	95.7	-0.08	0.938
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.73418	.67282	12.3	-66.2	0.84	0.402
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	3.038	2.8197	31.6	-509.8	1.79	0.075
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.07375	.08991	-8.2	-1058.1	-1.05	0.296
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.70886	.81053	-22.5	-145.9	-1.50	0.136
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1253.7	1341.3	-5.1	71.1	-0.39	0.699

Figure G-7: Kabwe Propensity Score Distribution, by T_4 and C_1

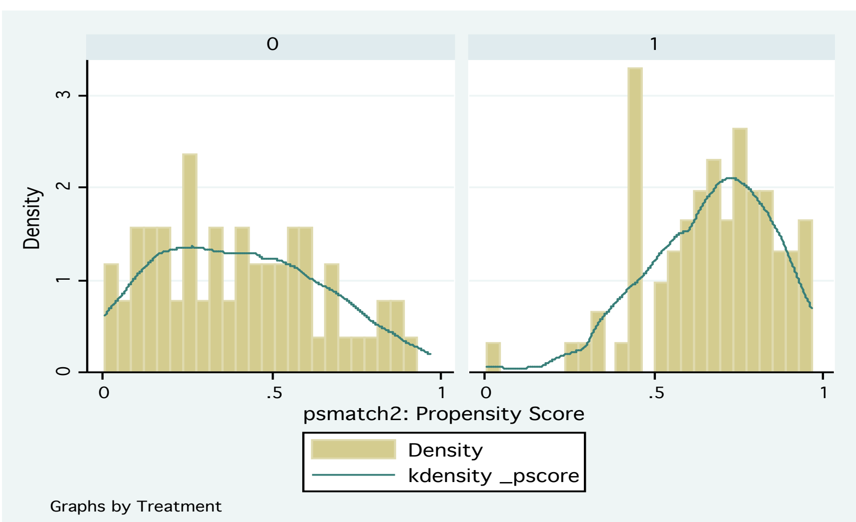

Table G-10: Lusaka Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.62976	.75439	-27.2		-3.42	0.001
	Matched	.70833	.68054	6.1	77.7	0.36	0.721
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	43.389	44.216	-6.1	46.3	-0.38	0.703
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	7.0139	7.1258	-3.6	53.6	-0.21	0.832
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	7.3056	7.2862	0.7	76.7	0.05	0.960
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	7.5278	7.6152	-2.4	52.3	-0.17	0.866
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.43056	.39467	7.2	74.8	0.43	0.666
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.54167	.59178	-10.1	-35.7	-0.60	0.549
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	3.0139	2.9871	3.9	25.1	0.30	0.768
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.179	.17603	1.5	-112.9	0.08	0.934
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.81944	.79883	4.6	50.1	0.31	0.756
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1644.4	1549.9	5.5	68.8	0.27	0.788

Figure G-8: Lusaka Propensity Score Distribution, by T_4 and C_1

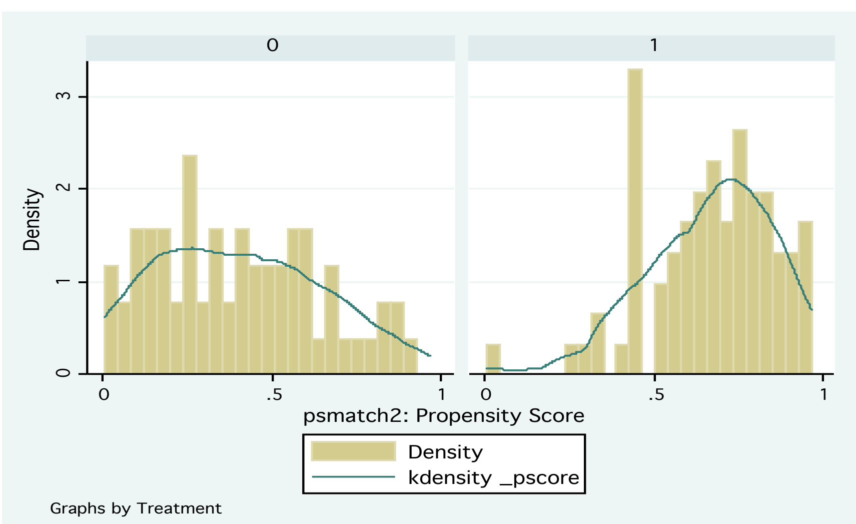

Table G-11: Kafue Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.62976	.75439	-27.2		-3.42	0.001
	Matched	.5614	.48181	17.4	36.1	0.85	0.399
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	42.14	43.41	-9.4	17.5	-0.48	0.635
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	6.3509	6.7817	-13.9	-78.6	-0.68	0.496
distmrkt	Unmatched	20.86	27.42	-13.3		-1.66	0.098
	Matched	13.781	12.359	2.9	78.3	0.54	0.588
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	5.7193	5.6682	1.9	38.3	0.10	0.918
Num_of_Cr~09	Unmatched	5.3058	4.7872	18.7		2.30	0.022
	Matched	4.8421	4.7937	1.7	90.7	0.13	0.899
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	8.0702	8.3435	-7.4	-49.1	-0.28	0.780
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.63158	.63891	-1.5	94.9	-0.08	0.936
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.19915	.19299	3.1	-341.6	0.16	0.872
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.61404	.61671	-0.6	93.5	-0.03	0.977
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1051	864.98	10.8	38.6	0.99	0.323

Figure G-9: Kafue Propensity Score Distribution, by T_4 and C_1

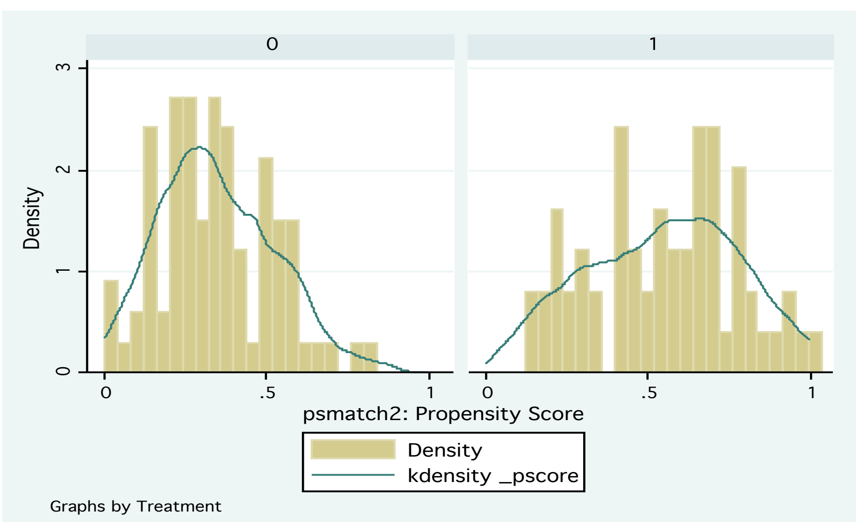

Table G-12: Choma/Livingstone Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.62976	.75439	-27.2		-3.42	0.001
	Matched	.73684	.73893	-0.5	98.3	-0.03	0.980
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	40.281	40.352	-0.5	95.4	-0.03	0.977
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	7.193	6.6901	16.2	-108.5	0.86	0.391
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	5	5.1894	-7.1	-128.4	-0.38	0.704
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	7.2982	7.3767	-2.1	57.2	-0.11	0.915
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.59649	.66705	-14.2	50.5	-0.78	0.439
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.59649	.58384	2.5	65.7	0.14	0.892
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	2.9298	2.9494	-2.8	45.3	-0.38	0.704
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.13371	.11784	8.1	-1038.4	0.54	0.587
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.63158	.62821	0.7	91.9	0.04	0.971
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1164.9	1109.3	3.2	81.7	0.16	0.873

Figure G-12: Choma/Livingstone Propensity Score Distribution, by T_4 and C_1

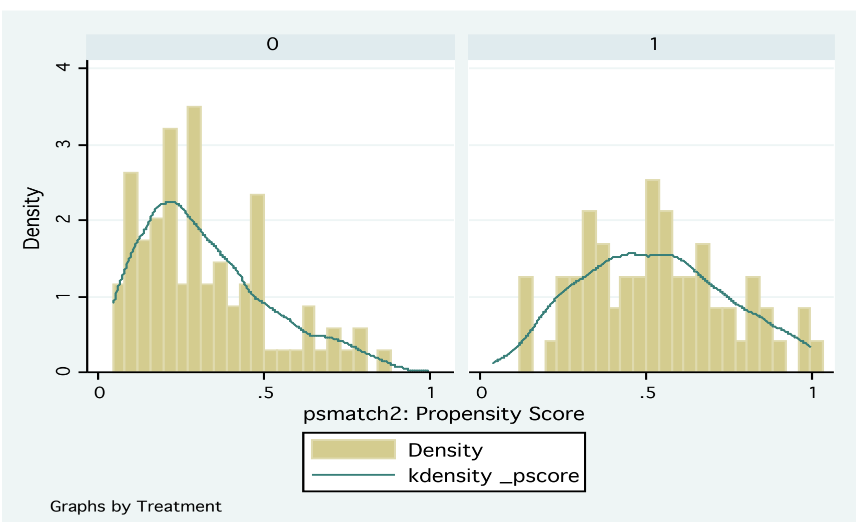

Table G-13: Kabwe Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.6533	.76486	-24.7		-3.46	0.001
	Matched	.61983	.68934	-15.4	37.7	-1.13	0.258
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	44.86	44.978	-0.9	91.2	-0.07	0.945
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	7.3967	8.026	-19.7	-1741.2	-1.49	0.137
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	6.6942	6.7535	-2.1	85.6	-0.19	0.853
Males	Unmatched	2.1392	2.073	4.4		0.62	0.536
	Matched	2.0496	1.8491	13.4	-202.9	1.17	0.243
Females	Unmatched	2.0825	1.9838	6.8		0.96	0.336
	Matched	1.9835	1.8581	8.7	-26.9	0.89	0.373
Children	Unmatched	3.2335	3.3	-2.6		-0.37	0.714
	Matched	3.2231	3.4431	-8.6	-230.8	-0.70	0.484
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.60331	.62194	-3.8	88.9	-0.30	0.768
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.71074	.71333	-0.5	58.9	-0.04	0.965
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	3.0083	2.976	4.4	15.5	0.41	0.679
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.09208	.10076	-4.4	-340.4	-0.63	0.533
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.70248	.70361	-0.2	98.3	-0.02	0.985
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1388.9	1365.4	1.3	94.8	0.13	0.893

Figure G-13: Kabwe Propensity Score Distribution, by T_0 and C_0

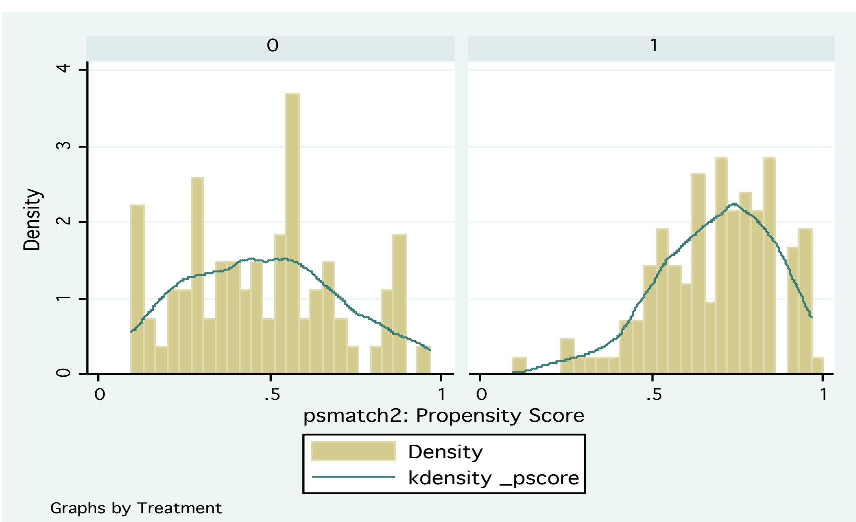

Table G-14: Lusaka Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.6533	.76486	-24.7		-3.46	0.001
	Matched	.67949	.72142	-9.3	62.4	-0.57	0.570
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	43.513	42.904	4.5	54.6	0.30	0.764
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	7.0128	6.9841	0.9	16.1	0.06	0.953
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	7.5128	7.7146	-7.2	51	-0.48	0.630
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.7308	7.453	7.8	-139.4	0.57	0.568
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.46154	.44271	3.8	88.7	0.23	0.815
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.55128	.60876	-11.5	-814.5	-0.72	0.470
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	3.0128	2.9847	3.8	26.4	0.34	0.737
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.18857	.20408	-7.9	-687	-0.42	0.675
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.82051	.81489	1.2	91.4	0.09	0.928
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1758.4	1485.4	14.9	39.8	0.85	0.399

Figure G-10: Lusaka Propensity Score Distribution, by T_0 and C_0

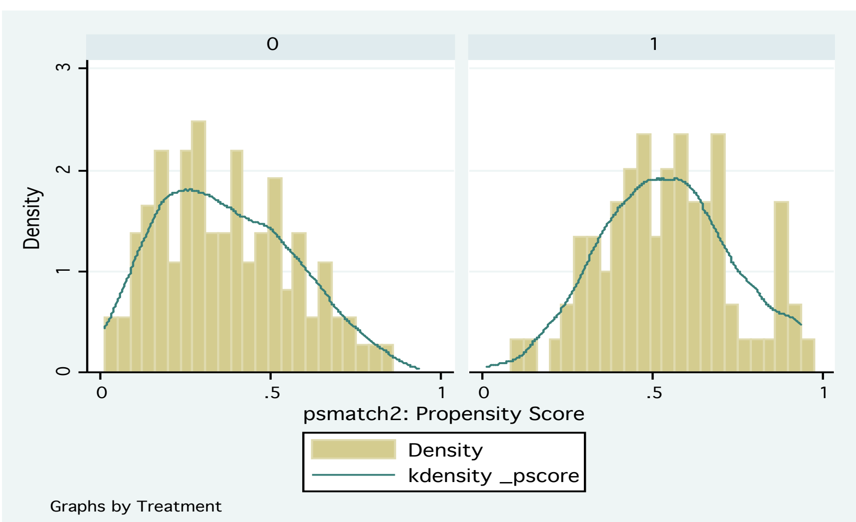

Table G-15: Kafue Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.6533	.76486	-24.7		-3.46	0.001
	Matched	.61856	.58986	6.4	74.3	0.41	0.685
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	41.711	40.525	8.7	11.6	0.58	0.563
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	6.3918	6.3327	1.9	-72.8	0.12	0.901
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	6.7835	6.8659	-2.9	80	-0.22	0.829
Num_of_Cr~09	Unmatched	5.4545	4.8867	20.3		2.78	0.006
	Matched	4.701	4.662	1.4	93.1	0.14	0.887
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.4845	7.3171	4.7	-44.2	0.31	0.757
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.68041	.65027	6.1	82	0.44	0.659
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.40206	.40117	0.2	85.8	0.01	0.990
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	3.0309	3	4.2	19.1	0.32	0.753
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.19724	.18962	3.9	-286.7	0.29	0.771
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.62887	.64371	-3.3	77.4	-0.21	0.831
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1228.5	1303.7	-4.1	83.4	-0.46	0.644

Figure G-11: Kafue Propensity Score Distribution, by T_0 and C_0

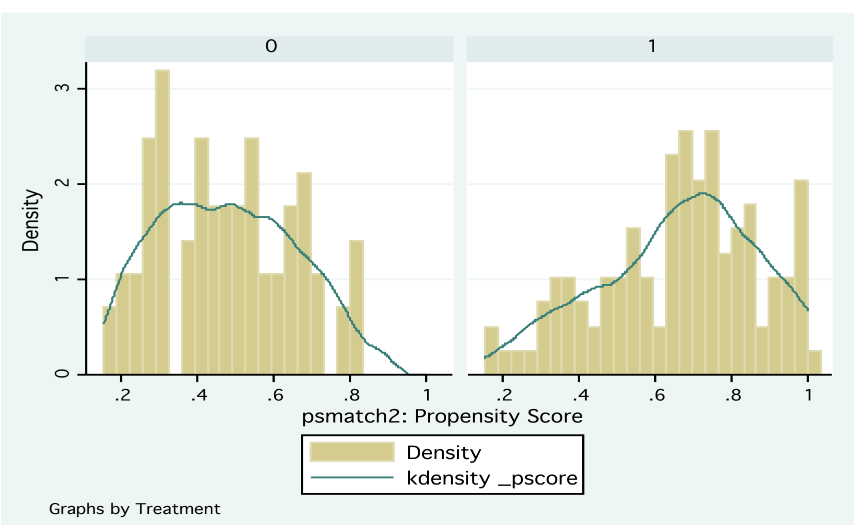

Table G-16: Choma/Livingstone Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
gndrhhhid	Unmatched	.6533	.76486	-24.7		-3.46	0.001
	Matched	.75862	.75693	0.4	98.5	0.03	0.979
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	41.08	41.407	-2.4	75.7	-0.17	0.867
distmrkt	Unmatched	23.39	27.003	-7.3		-1.02	0.308
	Matched	19.776	28.266	-17.1	-135	-2.40	0.017
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	7.4598	7.155	9.6	-791.6	0.66	0.509
Num_of_Cr~09	Unmatched	5.4545	4.8867	20.3		2.78	0.006
	Matched	6.8333	6.7126	4.3	78.7	0.23	0.816
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	6.1034	5.998	3.8	74.4	0.21	0.831
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.1724	7.455	-7.9	-143.5	-0.50	0.617
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.62069	.68306	-12.7	62.7	-0.86	0.391
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.58621	.64695	-12.2	-866.4	-0.82	0.413
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	2.9885	2.972	2.2	56.9	0.17	0.866
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.13614	.11724	9.7	-859.2	0.82	0.414
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.70115	.64095	13.2	8.3	0.84	0.401
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1480.7	1279.9	11	55.7	0.63	0.529

Figure G-12: Choma/Livingstone Propensity Score Distribution, by T_0 and C_0

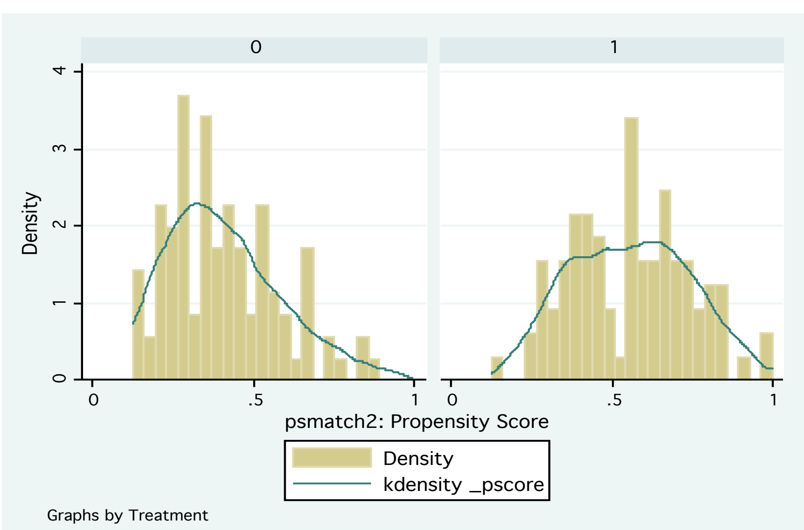

Table G-17: Male Sample Selection Model Balancing Test Results, by T_2 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
agehhh	Unmatched	43.669	41.333	16.6		1.62	0.106
	Matched	41.448	41.448	0	100	0.00	1.000
distmrkt	Unmatched	29.853	27.42	4.6		0.45	0.651
	Matched	35.333	34.349	1.9	59.6	0.09	0.926
eduhhhyr	Unmatched	7.5635	7.1754	11.6		1.13	0.259
	Matched	7.9885	7.7588	6.9	40.8	0.47	0.638
Num_of_As~09	Unmatched	7.8889	6.2143	59.5		5.70	0.000
	Matched	8.0345	7.9417	3.3	94.5	0.21	0.834
totnohhm	Unmatched	7.4762	7.3012	5.3		0.49	0.626
	Matched	7.2989	7.1689	3.9	25.8	0.28	0.777
VegetableP~9	Unmatched	.71654	.41813	63		5.94	0.000
	Matched	.72414	.73471	-2.2	96.5	-0.16	0.876
Livesto~2009	Unmatched	.51181	.54094	-5.8		-0.56	0.575
	Matched	.45977	.46727	-1.5	74.2	-0.10	0.922
VCR04	Unmatched	2.9683	3.0323	-9.6		-0.91	0.364
	Matched	3	3.001	-0.1	98.5	-0.01	0.991
Perc_IrrC~09	Unmatched	.15446	.14967	2.6		0.23	0.814
	Matched	.17861	.17056	4.4	-68	0.29	0.772
RegionalS~09	Unmatched	.64567	.73684	-19.8		-1.94	0.053
	Matched	.67816	.67441	0.8	95.9	0.05	0.958
P09_HHNCF	Unmatched	2008.7	1076.6	51.5		5.35	0.000
	Matched	2018.4	1934.8	4.6	91	0.26	0.793

Figure G-13: Male Propensity Score Distribution, by T_2 and C_1

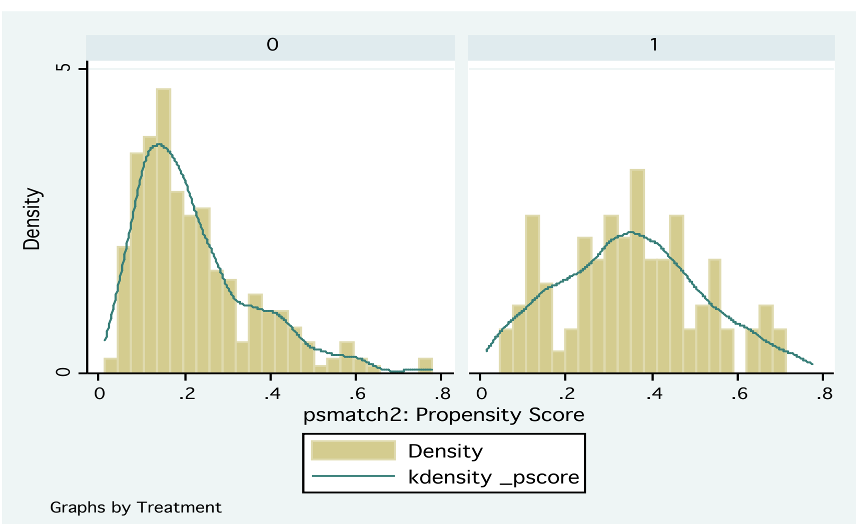

Table G-18: Female Sample Selection Model Balancing Test Results, by T_2 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
agehhh	Unmatched	43.669	41.333	16.6		1.62	0.106
	Matched	47.484	48.618	-8	51.4	-0.37	0.710
distmrkt	Unmatched	29.853	27.42	4.6		0.45	0.651
	Matched	17.21	16.96	0.5	89.8	0.06	0.956
eduhhhyr	Unmatched	7.5635	7.1754	11.6		1.13	0.259
	Matched	6.2581	5.4707	23.5	-102.9	0.88	0.381
Num_of_As~09	Unmatched	7.8889	6.2143	59.5		5.70	0.000
	Matched	7.2903	7.086	7.3	87.8	0.34	0.738
totnohhm	Unmatched	7.4762	7.3012	5.3		0.49	0.626
	Matched	6.9677	6.6478	9.6	-82.8	0.42	0.680
VegetableP~9	Unmatched	.71654	.41813	63		5.94	0.000
	Matched	.64516	.66624	-4.5	92.9	-0.17	0.865
Livesto~2009	Unmatched	.51181	.54094	-5.8		-0.56	0.575
	Matched	.58065	.54325	7.5	-28.4	0.29	0.773
VCR04	Unmatched	2.9683	3.0323	-9.6		-0.91	0.364
	Matched	2.871	2.9367	-9.8	-2.8	-0.62	0.541
Perc_IrrC~09	Unmatched	.15446	.14967	2.6		0.23	0.814
	Matched	.11741	.11463	1.5	41.8	0.08	0.934
RegionalS~09	Unmatched	.64567	.73684	-19.8		-1.94	0.053
	Matched	.6129	.67631	-13.8	30.5	-0.51	0.612
P09_HHNCF	Unmatched	2008.7	1076.6	51.5		5.35	0.000
	Matched	1850.1	1389.4	25.4	50.6	0.90	0.371

Figure G-14: Female Propensity Score Distribution, by T_2 and C_1

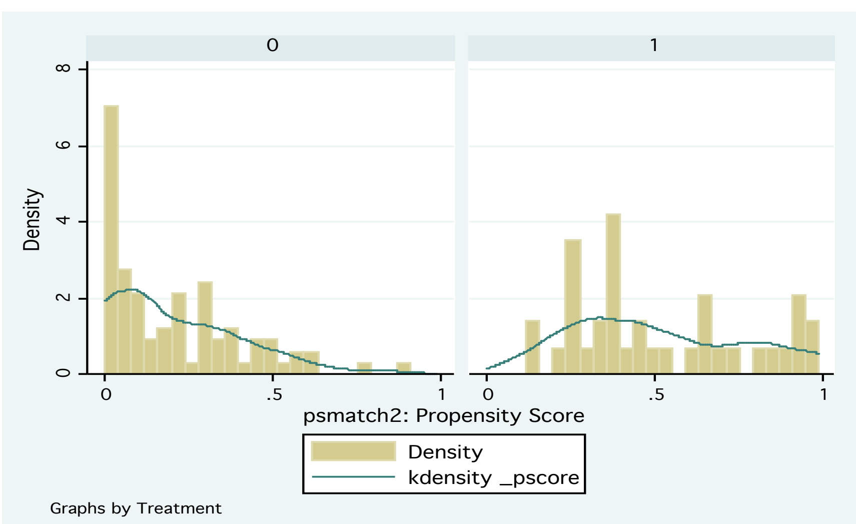

Table G-19: Male Sample Selection Model Balancing Test Results, by T_4 and C_1

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	42.364	42.213	1.1	90.2	0.10	0.919
distmrkt	Unmatched	20.86	27.42	-13.3		-1.66	0.098
	Matched	18.884	19.896	-2	84.6	-0.50	0.618
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	7.125	7.198	-2.4	69.7	-0.22	0.826
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	6.3977	6.4527	-2.1	33.7	-0.18	0.854
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	7.25	7.1826	1.8	63.2	0.19	0.846
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.60795	.59832	1.9	93.2	0.18	0.854
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.57955	.59288	-2.7	63.9	-0.25	0.800
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	3.0511	3.0378	1.9	62.9	0.17	0.863
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.13768	.14387	-3.2	-343.7	-0.32	0.751
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.72159	.74363	-4.9	46.7	-0.47	0.642
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1398.9	1491.2	-5.4	69.5	-0.45	0.656

Figure G-15: Male Propensity Score Distribution, by T_4 and C_1

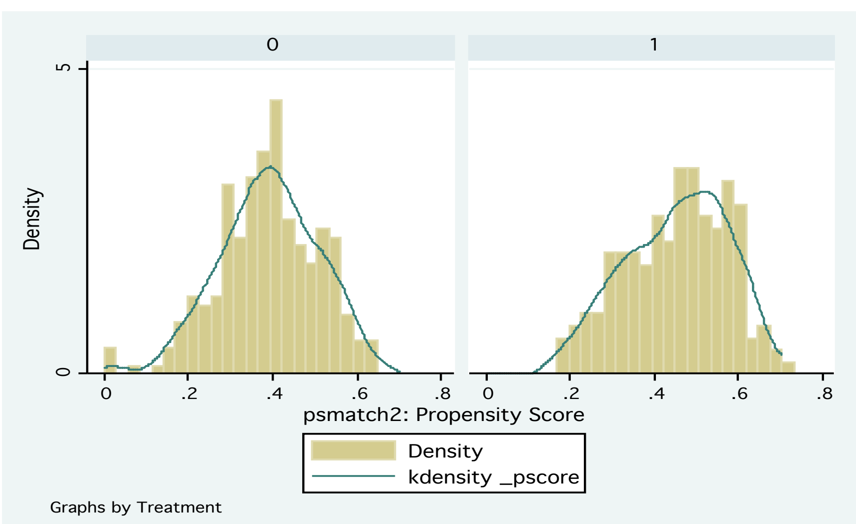

Table G-20: Female Sample Selection Model Balancing Test Results, by T_4 and C_1

Variable	Sample	Mean Treated	Mean Control	%bias	%reduction bias	t-test t	t-test p>t
agehhh	Unmatched	42.872	41.333	11.4		1.43	0.153
	Matched	43.516	43.856	-2.5	77.9	-0.19	0.849
distmrkt	Unmatched	20.86	27.42	-13.3		-1.66	0.098
	Matched	25.305	21.46	7.8	41.4	0.44	0.658
eduhhhyr	Unmatched	6.9343	7.1754	-7.8		-0.97	0.332
	Matched	6.5789	6.5876	-0.3	96.4	-0.02	0.983
Num_of_As~09	Unmatched	6.2972	6.2143	3.1		0.39	0.699
	Matched	6.0421	5.9144	4.8	-54	0.37	0.712
totnohhm	Unmatched	7.4844	7.3012	4.9		0.62	0.536
	Matched	7.1895	7.3796	-5.1	-3.7	-0.39	0.699
VegetableP~9	Unmatched	.56055	.41813	28.7		3.60	0.000
	Matched	.46316	.43744	5.2	81.9	0.35	0.723
Livesto~2009	Unmatched	.57785	.54094	7.4		0.93	0.353
	Matched	.57895	.60219	-4.7	37	-0.32	0.746
VCR04	Unmatched	2.9965	3.0323	-5.2		-0.64	0.519
	Matched	2.9263	2.9256	0.1	97.9	0.02	0.987
Perc_IrrC~09	Unmatched	.14827	.14967	-0.7		-0.09	0.929
	Matched	.17316	.1652	4.1	-470.4	0.28	0.779
RegionalS~09	Unmatched	.6955	.73684	-9.2		-1.15	0.251
	Matched	.66316	.68434	-4.7	48.8	-0.31	0.757
P09_HHNCF	Unmatched	1379.7	1076.6	17.6		2.22	0.027
	Matched	1171.6	1141	1.8	89.9	0.14	0.886

Figure G-16: Female Propensity Score Distribution, by T_4 and C_1

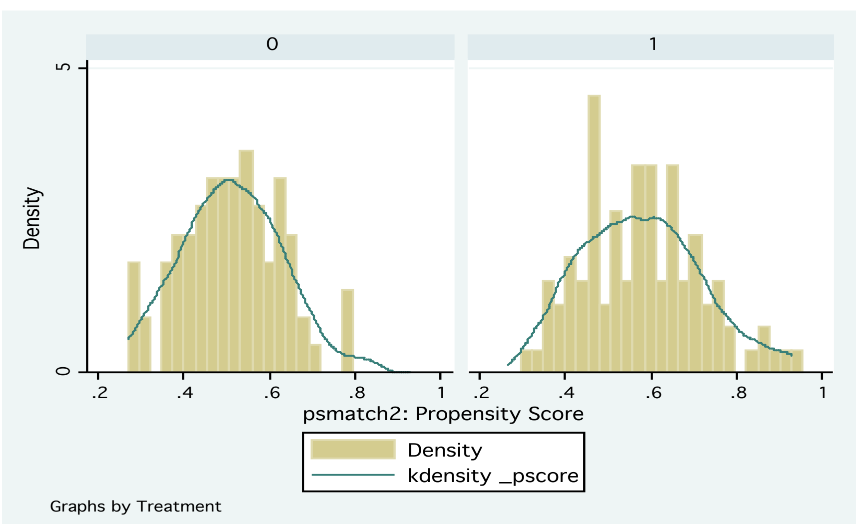

Table G-21: Male Sample Selection Model Balancing Test Results, by T_0 and C_0

Variable	Sample	Mean Treated	Mean Control	%bias	%reduction bias	t-test t	t-test p>t
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	42.062	41.483	4.3	56.9	0.48	0.630
distmrkt	Unmatched	23.39	27.003	-7.3		-1.02	0.308
	Matched	24.465	23.25	2.4	66.4	0.41	0.681
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	7.4186	7.4171	0	95.5	0.01	0.996
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	7.0155	7.0367	-0.8	94.8	-0.08	0.935
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.3101	7.1476	4.5	-40	0.61	0.544
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.66667	.65395	2.6	92.4	0.30	0.761
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.52713	.52445	0.5	57.3	0.06	0.951
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	3.0659	3.0671	-0.2	96.8	-0.02	0.987
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.15615	.15388	1.2	-15	0.14	0.886
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.69767	.68922	1.9	87.1	0.21	0.835
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1715.1	1677.5	2.1	91.7	0.21	0.834

Figure G-17: Male Propensity Score Distribution, by T_0 and C_0

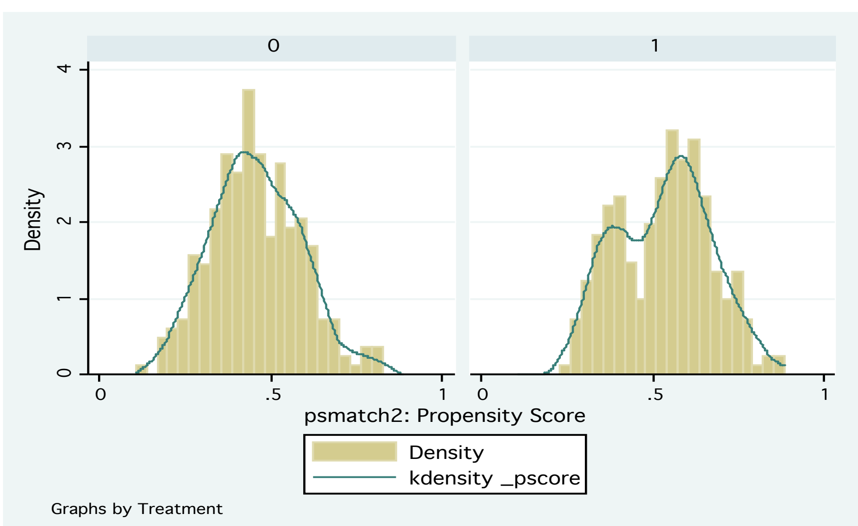

Table G-22: Female Sample Selection Model Balancing Test Results, by T_0 and C_0

		Mean			%reduction	t-test	
Variable	**Sample**	**Treated**	**Control**	**%bias**	**bias**	**t**	**p>t**
agehhh	Unmatched	43.132	41.789	9.9		1.39	0.166
	Matched	44.722	44.613	0.8	91.9	0.08	0.939
distmrkt	Unmatched	23.39	27.003	-7.3		-1.02	0.308
	Matched	17.323	19.704	-4.8	34.1	-1.08	0.281
eduhhhyr	Unmatched	7.1631	7.1973	-1.1		-0.15	0.880
	Matched	6.4812	6.2979	5.7	-436.2	0.51	0.613
Num_of_As~09	Unmatched	6.8186	6.4066	14.7		2.05	0.041
	Matched	6.5865	6.4853	3.6	75.5	0.32	0.747
totnohhm	Unmatched	7.4728	7.3568	3.2		0.45	0.649
	Matched	7.8195	7.4037	11.6	-258.3	0.86	0.391
VegetableP~9	Unmatched	.61321	.44595	33.9		4.78	0.000
	Matched	.55639	.54278	2.8	91.9	0.22	0.824
Livesto~2009	Unmatched	.54953	.54324	1.3		0.18	0.859
	Matched	.57143	.55893	2.5	-98.9	0.20	0.838
VCR04	Unmatched	3.0024	3.0407	-5.2		-0.73	0.467
	Matched	2.9173	2.9409	-3.2	38.3	-0.58	0.560
Perc_IrrC~09	Unmatched	.15148	.15345	-1		-0.14	0.887
	Matched	.16008	.16308	-1.5	-52.2	-0.14	0.889
RegionalS~09	Unmatched	.67217	.73784	-14.4		-2.02	0.043
	Matched	.64662	.67852	-7	51.4	-0.55	0.584
P09_HHNCF	Unmatched	1588.7	1135.2	24.8		3.46	0.001
	Matched	1509.9	1434.6	4.1	83.4	0.33	0.741

Figure G-18: Female Propensity Score Distribution, by T_0 and C_0