Three Essays on Evaluating the Impact of Natural Resource Management Programs

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To my family and Sarah

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Summary

This dissertation is composed of three papers describing the nexus between natural resource management programs, farmer well-being, and productivity. Our study sheds light on the effectiveness of actions that have been or could be implemented to address the “triangle of poverty.” This triangle connects low farm productivity to high poverty, which forces farmers to increase the pressure on natural resources thus further degrading the environment and resulting in even lower productivity and more poverty.

Natural resource management (NRM) imbeds key agricultural policies, which aim at handling resource degradation while enhancing productivity particularly among smallholder farmers. Technologies promoted through the use of NRM programs encompass conservation agriculture, water and integrated pest management, agroforestry, and silvopastoral activities. Although most of these technologies have been promoted since the early 1960s, it was not until 1989 when the CGIAR emphasized the value of NRM technologies as tools to ensure the sustainability of agricultural systems. Since then, the implementation of NRM programs have evolved around the following definition: “Sustainable agriculture should involve the successful management of resources for agriculture to satisfy changing human needs while maintaining or enhancing the quality of the environment and conserving natural resources (Consultative Group on International Agricultural Research [CGIAR] 2006, p.4).” In general, these programs aim at developing and disseminating technologies, which improve the quality of soil and water, diversify the agro-ecosystem and build farm capacity to mitigate the effects of climate change.

To examine to what extent NRM programs have achieved their aim, in the first essay, meta-regression analysis is used to explore the effect that natural resource management (NRM) programs have on monetary outcomes and on productivity. In doing so, we use a comprehensive

dataset of 75 impact evaluation studies and 215 observations from all over the world (equivalent to a sample of 31,991 treated and 42,936 control farmers) to explain why impact varies among studies and across different interventions, regions, and methods. Econometric results from ordered probit, probit, OLS regression, and Bayesian regression models consistently show that NRM programs have a significant positive effect on the monetary outcomes and productivity of beneficiaries relative to control farmers. Overall, NRM technologies increase monetary outcomes on average by 8%, and yields by 13%. Furthermore, the impacts of NRM programs could be larger if: i) participatory methods to transfer the technology to the final user are incorporated in the design; ii) appropriate training to boost the adoption of the technology is provided; iii) NRM technologies are tailored to the rainfall patterns of the intervention area; iv) government units are more efficient in the delivery of technologies; and v) the evaluation of NRM programs account for the time necessary for these programs to produce results.

The first essay compiles evidence from a large number of published analyses. We complement this evidence in the following two essays with original empirical analyses of a specific NRM intervention, the Socio-Environmental and Forestry Development Program-II (POSAF-II), which was implemented by the Nicaraguan Ministry of the Environment and Natural Resources (MARENA). The goal was to promote economic development and environmental sustainability. POSAF-II financed a total of 13,477 farmers occupying 69,767 hectares in several major river basins that were severely damaged by Hurricane Mitch in 1998. Therefore, this program represents a unique opportunity to evaluate the economic impact of NRM programs in an area affected by a massive weather event, characterized by high soil degradation and poverty.

The second essay is an analysis of the economic impact of natural resource technologies delivered by POSAF-II. We use cross-sectional data for 1,483 households, from 212 treated and control communities. Results obtained through propensity score matching (PSM), ordinary least squares (OLS), weighted least squares regression (WLS) based on PSM, and instrumental variables (IV) regression indicate that POSAF-II has had a positive impact on the total value of agricultural production of beneficiary farmers relative to appropriate control groups. The estimated internal rate of return supports the hypothesis that increasing household income while encouraging the sustainable use of natural resources through the implementation of suitable management programs can be complementary development objectives.

The third essay examines the impact of POSAF-II on two critical components of productivity: technological change (TC) and technical efficiency (TE). We use propensity score matching (PSM) to mitigate potential biases from observable variables along with a recently introduced stochastic production frontier (SPF) model that addresses sample selection bias arising from unobservable variables. Our results show that POSAF-II has had a positive impact on both TC and TE. This essay contributes to the literature on impact evaluation by showing how an intervention designed to improve natural resource management can also enhance the income of poor farm households through increases in productivity.

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Chapter 1 General introduction

In recent years, worldwide agricultural production has managed to more than keep pace with the growing global demand for food (World Bank, 2008). However, while the prevalence of hunger has been reduced, roughly 800 million individuals worldwide suffer from under-nutrition. Furthermore, the prospects for further growth in food demand and the increasing burden to channel agricultural resources for energy generation is expected to impose rising pressure on agricultural systems around the globe. Consequently, there is a growing need to increase agricultural productivity, not only to improve farmers' incomes but also to ensure the availability of affordable food for the growing urban population while protecting the natural resource base.

Achieving faster agricultural productivity growth is becoming more and more difficult in many areas where land and water resources are under pressure and rising climatic fluctuations, pests, and diseases threaten farm output (IFPRI, 2009). Furthermore, there is growing evidence that climate change has affected agricultural production and will cause increasing damage to the agricultural sector in the coming decades (Gornall et al., 2010). These challenges pose a significant threat to approximately 1.2 billion people who are currently living below the poverty line, 70% of whom live in rural areas. A significant number of these poor people earn their income directly from agricultural activities or rely to some degree on the agricultural sector for their livelihoods (Cleaver, 2012).

Agricultural productivity growth increases farmer incomes, which in turn augments the demand for goods and services in rural areas (Thirtle et al., 2003). De Janvry (2010) claims that during the Green Revolution in Asia, the agricultural sector demanded more labor due to a considerable increase in land productivity and that this change brought more income to rural families and led to a reduction in poverty.

Despite the evidence regarding the positive impact of agricultural growth on poverty reduction, since the 1980s both national governments and donors have reduced investments in the agricultural sector. Specifically, the share of investments in agriculture in total bilateral and multilateral aid fell from a peak of 22.5% in 1979–1981 to a low of 5.4% in 2003–2005 (Cleaver, 2012). This resulted in 20 years of gradually decreasing agricultural growth rates, a situation that started to turn around in 1995 (Fuglie and Nin-Pratt, 2012). Inadequate funding has had deleterious effects on world production. For example, from 2001 to 2010 world agricultural production grew only at a rate of roughly 2.4%. More recently, there has been a shift in agricultural research and development (R&D). From 2000 to 2008, world agricultural spending increased from US $26.1 to US $37.1 billion (PPP 2005), a change largely driven by China and India. In contrast, many low-income countries have experienced a negative trend on agricultural investments and a lack of research capacity is common in such countries (Beintema et al., 2012). Nigeria and Uganda are exceptions among low-income countries, where the 2008 food price crisis was followed by significant increases in funding for agricultural R&D. However, in many low-income countries funding remains bellow the level necessary to strengthen agricultural R&D capabilities (Stads and Beintema 2015).

The use of economic resources in an efficiencient manner is crucial, even more so when funding is inadequate. Thus, it is critical to allocate the limited resources available to programs and policies that can have real impact on reducing poverty while promoting the sustainable use of natural resources. In this context, generating compelling evidence on the effects that agricultural practices have on farmer income has become an important issue for policymakers and donors

(Khandker, Koolwal, and Samad, 2010; Kelley, Ryan, and Gregersen, 2008). Consequently, assessing the impact of policies and programs has also become an important area of research. The key rational for assessing this impact is to ensure accountability in public administration and to guide policy decisions. In addition, determining how impacts are—or are not—achieved and which interventions lead to which specific impacts is essential for producing the “proof” that validates public actions (Gertler, Martinez, Premand, Rawlings, and Vermeersch, 2011).

A number of natural resource management (NRM) programs designed to reduce poverty by increasing productivity and protecting natural resources have been implemented in Latin America and elsewhere (Barrett, Moser, and Mchugh, 2004; Dalton, Lilja, Johnson, and Howeler, 2005; District and Kingdom, 2011; Dutilly-diane, Sadoulet, and de Janvry, 2003). However, the available evidence concerning the impact and economic value of these programs is limited. First, rigorous documentation of the impact of these programs is scarce (Renkow and Byerlee, 2010; Kelley et al., 2008). Second, evaluations of NRM technologies have seldom applied state-of-the-art methodologies. Finally, in many cases, NRM technologies have been evaluated in controlled experimental environments which do not provide the evidence needed to determine the expected performance under actual farming conditions where many variables are beyond the control of the producer (Del Carpio and Maredia, 2011; Consultative Group on International Agricultural Research [CGIAR], 2006; Kelley et al., 2008; Pal 2011; Renkow and Byerlee, 2010). As a result, measured productivity gains under controlled conditions are likely to overestimate the real impact of NRM technologies. In other words, the expected performance of alternative technologies in various agro-ecological and socio-economic conditions needs to be better understood in order to generate useful data to guide resource allocation decisions (Renkow and Byerlee, 2010;Harwood, Kassam, Gregersen, and Fereres, 2005).

The general objective of this study is to address gaps in the literature concerning the impact of NRM interventions on low-income farmers through a comprehensive analysis of the nexus between natural resource management, farmer well-being and productivity. State-of-the-art techniques are used to generate new evidence concerning the impact of NRM programs. A distinguishing characteristic of this thesis is the combination of complementary impact evaluation and stochastic frontier techniques, which have only recently been used together. To accomplish the general objective set forth, we have developed the following specific goals:

1. Conduct a meta-analysis to examine the evidence available in the resource economics literature concerning the impact of natural resource management programs on agricultural production and poverty alleviation in developing countries.
2. Contribute to the literature on natural resource management programs and the link between these programs and farmer well-being by evaluating the effects of the Socio-Environmental and Forestry Development Program II (POSAF-II).
3. Examine the influence of POSAF-II on two critical components of productivity, that is, technological change and technical efficiency, using production frontier methods correcting for selectivity bias.

The rest of the dissertation is organized into four chapters. Chapter two addresses the first goal listed above by presenting a meta-analysis of NRM programs and examines the factors that influence positive or negative outcomes. A review of 75 studies generated 215 observations that are used to construct a database that we use in a meta-regression analysis. Several econometric methods are applied to estimate the effect of NRM on yields, income and techichal efficiency. The second goal is addressed in chapter three, which uses data from treated and control farmers to evaluate the impact of POSAF-II, to estimate the spillover effects of the program, and to calculate the rate of return on investment. In chapter four we address the third goal by evaluating the impact of natural resource management programs on technological change and technical efficiency for treated and control farmers. We first estimate separate stochastic frontier models for the treated and control groups, and then estimate a meta-frontier to compare the differences in technical efficiency scores within and between the two groups. The fifth chapter presents a summary and draws conclusions from the three preceding chapters.

Chapter 2 Do Natural Resource Management Programs Have an Impact? A Meta Regression Analysis

Abstract

A growing population imposes significant challenges on agricultural systems. It entails increased agricultural production to satisfy the world's demand for food and fiber, and thus puts more pressure on the available natural resources, especially soil and water. In addition, challenges derived from changes in rainfall and temperature patterns make agricultural systems more vulnerable to extreme conditions, such as extended droughts, flooding, and extreme heat. To face these challenges, natural resource management (NRM) technologies have been promoted by the Food and Agriculture Organization of the United Nations (FAO), Development Banks, CGIAR centers across the globe, and other international cooperation agencies. Although a significant body of evidence has been produced, the debate concerning the potential of NRM programs to increase productivity and incomes while decreasing environmental degradation is not over. Therefore, this paper uses meta-regression analysis to explore the effect NRM technologies have on monetary outcomes and productivity. To this end, we developed a comprehensive dataset of 75 studies and 215 observations from all over the world, equivalent to a sample of 31,991 treatment and 42,936 control farmers. Ordered probit, OLS regression, and Bayesian regression models are employed to examine the variability of various impact indicators across different interventions, countries, and methods. The results reveal that NRM increases both monetary outcomes and productivity. The specific impacts vary depending on factors such as training and whether government agencies oversaw the implementation of the program.

Key words - natural resource management, meta-regression analysis, impact evaluation

2.1 Introduction

The promotion of conservation agriculture (CA) and the sustainable intensification of agricultural production represent cornerstone strategies for policies that endeavor to tackle natural resource degradation while enhancing productivity and reducing poverty among smallholder farmers. Recent examples include the Sustainable Land Management (SLM) Program implemented by the Ethiopian government, the Africa Research in Sustainable Intensification (SI) for the Next Generation (Africa RISING) funded by the United States Agency for International Development and implemented in southern Saharan regions including Mali, Ghana, Malawi, Tanzania, Zambia and Ethiopia, and the Sustainable Livestock Management program in Nicaragua, funded by the Inter-American Development Bank (Haile, Azzarri, Roberts, & Spielman, 2017). Similar interventions are also promoted by international agencies such as ICARDA, CIMMYT, CIAT, ICRISAT, and others (Giller et al. 2011). The implementation of these programs are a response to the increasing need for more sustainable agricultural production, which addresses environmental degradation through technologies that improve soil and water quality, and promotes diversified agro-ecosystems while building farm capacity to mitigate the effects of climate change (Arslan et al. 2015; FAO 2008).

Conservation agriculture is based on the following three key management principles: 1) continuous minimum mechanical soil disturbance; 2) permanent organic soil cover; and 3) the diversification of crop species grown in rotations/or association (Kassam et al. 2012). Moreover, the latter are complemented by other natural-based activities, such as water and integrated pest management, as well as the implementation of agroforestry and silvopastoral practices (Food and Agriculture Organization of the United Nations [FAO], 2017). Overall, the implementation of these natural resource management (NRM) practices have the potential to make agriculture more sustainable, making it possible to feed a growing population while reducing environmental stress particularly as we contemplate the vagaries of climatic change (Giller et al., 2011; Jat, Sahrawat, & Kassam, 2014; Pretty, Toulmin, & Williams, 2011; Vanlauwe et al., 2011). Choosing inferior management strategies could result in soil or water losses, which are critical assets, thereby bringing instability to established production systems (Jat et al. 2014).

Although there is much evidence of the impact that NRM technologies can have on productivity and efficiency (e.g., Barrett, Moser, Mchugh, & Barison, 2004; Bravo-Ureta, Almeida, Solís, & Inestroza, 2011; De los Santos-Montero & Bravo-Ureta, 2017; District & Kingdom, 2011; Dutilly-diane, Sadoulet, & de Janvry, 2003), the debate surrounding the potential of these technologies for increasing productivity and reducing environmental degradation remains controversial. Giller et al. (2009) have questioned the performance of NRM in Sub-Saharan Africa (SSA) arguing that the evidence is not sufficiently robust to point toward a positive impact of these technologies. They claim that research reveals adverse effects such as drops in productivity and higher labor costs. They also point out the need for a more critical assessment of the ecological and socio-economic conditions that preclude or enhance the adoption of NRM technologies. Alongside the previous critics, Govaerts et al. (2009) also question the contribution of conservation agriculture to carbon sequestration. After reviewing 78 cases, they found that 31 of them showed no significant advantages of conservation agriculture relative to conventional tillage and in seven cases soil carbon concentration was even lower under the latter.

To shed light on the NRM debate , various scholars have attempted to organize different findings through the use of meta-analyses. Pretty et al. (2006) conducted a meta-analysis of 286 interventions that tackle poverty and environmental degradation by disseminating resource-conserving technology packages in 57 developing countries. According to those authors, NRM interventions increased productivity on 12.6 million farms with smallholder farmers experiencing a gain in excess of 100%, while improving the supply of critical environmental services regarding water infiltration and carbon sequestration. However, Phalan, Rodrigues, and Balmford (2007) argue that much of the evidence presented by Pretty and colleagues is weak because many of the studies examined lacked control groups, and thus the results are subject to selection bias from both observable and unobservable variables (Khandker et al. 2010). In similar work, Branca et al. (2011) examined 160 publications from Asia, Latin America, and Sub-Saharan Africa that reported on the effects that agronomy, integrated nutrient management, tillage and residue management, water management, and agroforestry had on yields. However, as noted in relation to the work of Pretty et al. (2006), this work uses data from projects that did not consider a counterfactual situation. Authors conclude that, in general, the use of NRM technologies increased agricultural productivity. However, they point out that the reported effects vary across different practices and climatic conditions.

The most recent meta-evidence is presented by Pittelkow et al. (2015) who analyzed 610 studies with 5,463 observations that focus on the effect of no-till practices on productivity, using data for 48 crops. They show that under rainfed conditions, no-till reduces yields; however, when no-tillage is combined with crop rotation and cover crops, yields can be equal or larger than conventional tillage systems. A shortcoming of this study is the use of data from field experiments, which more than likely do not reflect conditions on operating farms.

In light of the previously mentioned results, we review 215 observations from 75 econometric studies on the impact of natural resource management technologies. Unlike the preceding literature, we focus on those studies that clearly incorporate a counterfactual situation or that use econometric methods to address selection biases (Khandker et al. 2010). Moreover, we exclusively examine scenarios under farmer conditions; therefore, we exclude studies that report results from controlled experiments. Similar to Pretty et al. (2006), we focus on impact evaluation studies that reflect all kinds of conservation agriculture technologies as well as practices that are considered complementary such as integrated pest management, agroforestry, aquaculture, silvopastoral technologies, and water management. Our database allows us to exploit the heterogeneity of NRM programs to examine the impact evaluation results. Furthermore, this data enables us to estimate the impact that NRM programs have on yields and monetary outcomes.

The remainder of the paper is structured as follows. Section 2 describes the salient features of meta-analyses followed by a discussion of the data and analytical framework in section 3. Then, section 4 discusses the main results and section 5 contains a summary and key conclusions.

2.2 Meta-analysis

Meta-analysis is a method for aggregating the results from a number of studies through the use of statistical procedures (Glass 1976). Meta studies are frequently designed in connection with previous research focusing on a similar issue or may also aim to answer new questions as findings appear through the advance of scientific enquiry. Results from newer studies may contradict or may appear to support previous findings; in either case, narrative or descriptive reviews are not enough to analyze the emerging findings (Stanley 2001). Meta-analysis is an appropriate method for drawing conclusions from myriad reported results (Glass, 1976; Nelson and Kennedy, 2008). A key contribution is to bring objectivity to literature reviews because instead of using casual judgment, meta-analysis relies on statistical procedures that facilitate the formulation of more consistent inferences (Glass 1976; Stanley and Doucouliagos 2012).

Nelson and Kennedy (2008) argue that in economics the use of meta-regression is the most common type of meta-analysis. It varies in design from the meta-analysis used in natural science experiments because in economics different designs, model specifications, and econometric techniques are employed. Similarly, the Bayesian method has been applied in economics to systematize the results from different studies and different outcome indicators (Eddy, Hasselblad, and Shachter, 1990). Moeltner et al. (2007) contend that the Bayesian method is appropriate when estimating a large set of parameters or when the number of studies in the meta-analysis is considered to be small.

Given the value of meta-analysis in synthesizing research findings the approach has been used by economists to examine a number of topics including: to explain the variability of technical efficiency in agriculture (Bravo-Ureta et al. 2007); to explore how geographical distance and separation via an international border affects the strength and speed of price transmission in the cereal market (Kouyat and von Cramon-Taubadel 2016); to examine the impact of genetically modified crops (Klümper and Qaim 2014); to estimate consumers' marginal willingness to pay (MWTP) for health benefits in food products (Dolgopolova and Teuber 2017); to gauge the impact of public investment in economic recovery and growth (Núñez-Serrano and Velázquez 2017); and to understand the hedonic relationship between the price of wine and its quality (Oczkowski and Doucouliagos 2017).

Meta-analyses of impact evaluation studies have been conducted in education and natural resource conservation. Evans, Cherrett, and Pemsl (2011) examined 29 impact assessment cases of small-scale fisheries (SSF). The authors set a selection criteria based on country, topic, method, data quality and variability, and indicators of impact. In a similar study, Oltmer et al. (2000) applied an ANOVA-type meta-analysis to evaluate the impact of agri-environmental policies in the European Union. Other meta-analyses have evaluated the environmental impact of organic farming (Tuomisto, Hodge, Riordan, and Macdonald, 2012), agribusiness-related finance and farmer/business training (Nankhuni and Paniagua, 2013), and labor market policies (Card, Kluve, and Weber, 2010).

The only meta-analysis of impact evaluations that looks at several dimensions of NRM programs can be found in the study carried out by Del Carpio (2011). However, the study did not apply statistical methods because the heterogeneity of the studies considered did not make it possible to find enough comparable outcome variables. The CGIAR (2006) carried out a similar assessment of NRM programs but the focus was on the internal rates of return rather than on evaluating the impact of the technologies. In sum, as far as we can determine by closely examining the literature, no study has conducted a systematic review of the impact of NRM programs using a meta-analysis. Therefore, the contribution of this paper is to narrow an existing gap in the literature by being the first to offer a meta-regression analysis which synthesizes the available empirical studies on impact evaluations of NRM programs. To do so, we develop a new and comprehensive dataset including 75 studies and 215 observations, encompassing information from 31,991 treated and 42,936 control farmers. We specifically seek to explain why impact varies among studies and across different interventions, countries, and methods. Our estimation strategy uses different econometric procedures, starting with an ordered probit model, and then, based on a subsample of the data, we estimate OLS and Bayesian regression models.

2.3 Data and Analytical Framework

2.3.1 Data

We develop a data set for this study based on a comprehensive search of both published and gray literature papers that have undertaken rigorous impact evaluations of NRM studies written in

English between 2000 and 2017. The range of words used to characterize NRM technologies varies significantly, so our search was based on a variety of terms as follows: agroforestry; natural resource management technologies; water management; rice intensification; conservation technologies; climate smart technologies; sustainable agriculture; and no-tillage.

A multi-step procedure was used to identify the relevant papers before constructing the data set. First, the following databases were used in the search: Google Scholar, ECOLIT, JSTOR, AgEcon search, Smart Economist, and Ideas. Second, searches were conducted in the databases of the following institutions: The Inter-American Development Bank (IDB); the World Bank (WB); the African Development Bank; the International Fund for Agricultural Development (IFAD); the International Food Policy Research Institute (IFPRI); FAO; and the Asian Development Bank. In addition, a complementary search was performed in the 3ie's Impact Evaluations Database and on the website of the Abdul Latif Jameel Poverty Action Lab (J-PAL), and Innovations for Poverty Action (IPA). In the selection process, the reference list in some key articles was used as a source to identify other potential studies, a process known as snowballing (Waddington et al. 2012). Thus, we considered peer reviewed articles and gray literature including working papers, book chapters, dissertations, policy documents, impact evaluation reports, and conference papers.

Our search yielded a total of 125 studies. However, to be included in the meta-analysis, studies had to fulfill the following criteria: be an impact evaluation using a counterfactual situation derived from experimental or quasi-experimental methods; contain clear impact indicators reported as a statistic; clearly report the sign of the treatment effect (i.e., positive or negative, and statistical significance); and focus on farm performance. From the initial 125, the meta-sample was reduced to 75 because 50 studies did not meet the inclusion criteria. Of the 75, five authors were contacted by email to obtain information not reported in their studies but needed for our analysis (e.g., sample size, number of technologies evaluated). Since most of the papers reported more than one estimate of impact, the database has a total of 215 observations or an average of 2.9 data points from each of the 75 studies.

2.3.2 *Descriptive analysis*

Table 2.1 presents a set of variables and their corresponding descriptive statistics included in the meta dataset used to analyze the impact of NRM programs. As indicated earlier, the data include impact evaluation studies published between 2000 and 2017, and report on data collected between 1997 and 2015. Of the 75 studies included 50 correspond to journal articles (67%) and 25 to working papers, impact evaluation reports, or Ph.D. theses (33%).

The largest group of observations is from Africa (52%) followed by Asia (30%), and 18% from North America, Europe, and Latin American and Caribbean countries, grouped as RESTWORLD. The countries in this is group share a similarity in that they have a long history of using conservation agriculture practices (Knowler and Bradshaw 2007). Observations included in our sample evaluate the impact of one to 16 technologies, with an average of three technologies. De los Santos-Montero and Bravo-Ureta (2017), and Branca et al. (2011) find that technology packages are more likely to be successful than single technologies.

As previously mentioned, one of the inclusion criteria is that the studies use experimental or quasi-experimental methods to construct a counterfactual situation. Only one study was found that applied experimental methods, although in the J-PAL website seven were in progress by the time that we concluded the data collection. For quasi-experimental methods, multiple econometric techniques are often applied, which yields significant heterogeneity. As can be seen in Table 2.1, the estimation of the impact of NRM is dominated by regression methods (58%) followed by a combination of PSM with regression models (28%) and PSM alone (14%). The dominance of the regression methods could explain why most of the observations use a larger treatment group which leads to a TSRATIO of 1.20. The size of this ratio is standard in regression-based methods. However, in matching methods, a larger control group is typically used to facilitate matches that satisfy the common support assumption without losing treated observations (Khandker et al. 2010). A surprising finding is that only 64 (30%) observations use panel data and this clearly suggest that a number of impact evaluation studies do not have baseline data (Del Carpio and Maredia 2011). However, since 2010 the drive to promote the implementation of effective development aid has become the norm, with more policymakers and international aid offices monitoring, generating and maintaining better data sets in order to generate more robust impact evaluation measures (Khandker et al. 2010).

An important feature that can be expected to play and important role on the effectiveness of an NRM program is the presence or absence of training. In our data, 189 (88%) observations report that training was a component in the project while the remaining 12% did not incorporate training to accompany the delivery of the NRM technologies. Participatory methods such as Farmer Field Schools are often used as a means to transfer technologies to farmers. This method was used in 95 observations (44%) in our sample and the data indicate that the use of Farmer Field Schools has increased over time. Another variable used to account for the heterogeneity among the NRM studies is IMPLEBY which refers to whether or not the government is responsible for the implementation of the program, and this is the case for 82 of the observations in our database.

A significant component of the meta-analysis is the selection of the outcome variables that measure the size of the effect produced by a development program. Like other features in impact evaluation design, outcome variables vary significantly within and across studies; therefore, building a standardized measure is no easy endeavor. Hence, we follow two coding strategies.

First, we coded the sign of every outcome variable reported in the paper according to its significance level into “negative and significant,” “not significant,” or “positive and significant” and these signs were then correspondingly converted to -1, 0, and 1. In the case of integrated pest management, whose outcome variable is cost reduction, the sign was inverted. Second, we grouped the outcome variables into three categories (some indicators did not fit into these categories, but they were captured in the first step whenever possible): monetary outcomes expressed in US Dollars; Yields; and TE. The monetary outcomes, such as the total value of agricultural production, profit, revenues, and cost reductions, account for 81 observations (41% of the total of our sample) while Yields and TE represent 48 (23%) and 15 (7%) data points, respectively. Table 2.2 shows an overview of the sign of the impact evaluation studies. As is shown, 122 (57%) observations report positive impacts vs. 84 (39%) and 9 (4%) that show non significant and negative impacts, respectively.

Technology packages delivered through NRM programs could simply include soil or water conservation technologies, and in our meta-analysis these represent 58 (27%) and 24 (11%) observations, respectively. These packages could also be composed of other complementary technologies and this case accounts for 62% of the NRM observations. Another important feature of the impact evaluation design is the length of time between the end of the intervention (i.e., and the evaluation. This variable displays significant heterogeneity across studies, going from zero years (i.e., that NRM technologies are evaluated before the program is closed) to 21 years, which is a considerable amount of time to accrue the benefits of the technologies.

Variable	No. of obs.	Definition	Mean	SD
PUBLICATION	145	1 if the evaluation has been published in a peer review journal (compared to: Working paper, conference papers, book chapter, etc.)	0.67	0.46
PYEAR	-	Years of publication.	2012	4
DYEAR	-	Year when the data of collected, the last year in panel data case	2007	4.5
AFRICA	112	1 if the evaluation has been done in Africa, (base comparison RESTWORLD)	0.52	0.50
ASIA	65	1 if the evaluation has been done in ASIA, (base comparison RESTWORLD)	0.30	0.46
RESTWORLD	38	Include North and Latin America and Caribbean, EUROPE, (This is the omitted category)	0.18	0.38
NTECHN	-	Number of technology under evaluation	3.34	3.32
METHOD1	30	1 if a matching method is used	0.14	0.34
METHOD2	60	1 if PSM is used in combination with other regression methods	0.28	.45
METHOD3	125	1 if regression methods are used alone	0.58	0.49
PARTICIP	95	If a participatory approach was used to deliver the technology	0.44	0.49
TRAINING	189	If was written in the project that training was offered to participants	0.88	0.32
COVPRE		coefficient of variation of the monthly rain during the year of the data collection	0.93	0.47
IMPLEBY	82	1 if the project was implemented for the government alone, 0 otherwise	0.38	0.48
PANEL	64	1 if the Panel data was used	0.30	0.45
TCRATIO		Treatment sample size/control sample size	1.20	0.87
SAMPLES		Number of observations	819.82	1997.4
MONVAL	81	1 if the effect has been measured in monetary terms expressed in US$ per hectare (e.g., total value of agricultural production, profits, revenues, cost reduction, income)	0.61	0.49
TEFF	15	if the effect is measured as a technical efficiency score	0.07	0.26
YIELD	48	if the effect has been measured as Yield (Kg/ hectare)	0.23	0.42
CONPRA1	24	1 if Soil conservation practices are used alone	0.27	0.44
CONPRA2	58	1 if Water conservation practices are used alone, the base comparison are technologies such as, rice conservation, IPM, and SWC+ agroforestry	0.11	0.31
CONPRA3	133	1 If both water and soil conservation are used together	0.62	0.48
TIME		Number years between the implementation and the evaluation	4.07	3.60

Table 2.1. Definition of variables and descriptive statistics

One additional virtue of a meta-analysis is the possibility of adding relevant information beyond what is provided originally in the study that can help to explain the variability of the different effects (Stanley and Doucouliagos 2012). In so doing, we added annual rainfall variability that corresponds to the production season when the last round of data is collected. This variability is expressed as a coefficient of variation over the 12 months registered until harvest. A similar approach has been used by Arslan et al. (2015). We paired each observation in our dataset with the annual rainfall information from the climate change knowledge portal of the Work Bank (World Bank 2017a). For cases where primary studies reported the use of panel data, the rainfall corresponds to the last year of the data collection of the study.

2.3.3 Analytical Framework

The first step in this meta-analysis entails the analysis of publication bias in the reported estimates. Publication bias arises when journals publish articles that fulfill a pre-conceived expectation of the results and in our context this would mean restricting publications to articles that show impact (Osborne 2008; Stanley and Doucouliagos 2012). Econometric methods are used to assess the presence (or absence) of publication bias. A positive correlation between the reported treatment effect and its standard error serves as a test to reveal the presence of publication bias, thus in its absence, both are independent (Stanley 2008).

The presence can be estimated by the following equation:

$$t_i = \beta_1 SE_i + \beta_2 (1/SE_i) + v_i \qquad (1)$$

where t_i is the *t*-static of each treatment effect reported, $1/SE_i$ is the precision estimate given by the inverse of the standard error of the treatment effect, and $v_i = \varepsilon_i/SE_i$. In equation 1, we identify publication bias by testing $H_0: \beta_1 = 0$, and $H_0: \beta_2 = 0$ is a test of the existence of any empirical effect beyond the presence of publication bias. Therefore, failing to reject these null hypotheses would indicate the presence of publication bias and the lack of effect of NRM (Stanley 2008).

Beyond the presence (or absence) of publication bias, the impact of NRM projects can be explained by factors related to the nature of the technology, the context where the technology is implemented or the evaluation design used to measure the effect. As previously mentioned, our main objective is to explain the effect of the latter two factors on a qualitative impact measure (i.e., positive or negative) and the size of the impact. In doing so, we first estimate an ordered probit model, where the dependent variable is the ordered response which, as defined above, is equal to -1, 0, or 1. A similar specification in the context of meta-analysis has been used by Busch and Ferretti-Gallon (2017) and Card et al. (2010).

The theoretical specification of the ordered probit model can be expressed as:

$$E_i^* = \beta x_i + e_i, \qquad e|x \sim Normal(0,1) \tag{2}$$

where E_i^* represents the latent measurement of the pertinent impact indicator reported in study i, x_i represents a set of explanatory variables shown in Table 2.1, β is a vector of parameters to be estimated and e_i is an error term (Wooldridge 2002). The following thresholds define the parameters of the discrete latent variables when the parameter values go over the threshold:

$$\begin{aligned} E_i &= -1 \;\; if\; E_i^* < \alpha_1 \;\; (negative\ and\ significant), \\ E_i &= \;\;\; 0 \;\; if\; \alpha_1 < E_i^* < \alpha_2 \; (\,insignificant), \\ E_i &= \;\;\; 1 \;\; if\;\; E_i^* > \alpha_2 \; (positive\ and\ significant), \end{aligned} \tag{3}$$

where α_1 and α_2 present the cut-off points or thresholds to be estimated.

Since the number of observations reporting significantly negative effects is low, as shown in Table 2.2, and to check the robustness or the ordered probit estimate, we fit a probit model excluding the significantly negative observations and recoding the insignificant as 0 and the significantly positive as 1 and compare the estimated coefficients with those obtained from the ordered probit model.

In addition, we use two subsamples of our dataset to estimate a linear regression model of the effect of NRM on monetary values (i.e., any type of possible monetary variable used as an outcome variable) and Yields, both expressed in logs. This kind of aggregation of the monetary values has been used in the literature including Saginor, Simons, and Throupe (2011) and Simons and Saginor (2006). For this purpose, we estimate the following two models:

Model 1:

Log(MONVAL) = *f*(ASIA, AFRICA, NTECHN, METHOD1, METHOD2, PARTICIP, TRAINING, COEVPRE, IMPLEBY, PANEL, TIME, TIME2)

Model 2:

Log(Yield) = *f*(PUBLICATION, PYEAR, ASIA, AFRICA, NTECHN, METHOD1, METHOD2, PARTICIP, TRAINING, COEVPRE, IMPLEBY, PANEL, TSRATIO, COMPRA2, COMPRA3, TIME,TIME2, SAMPLE)

These explanatory variables are introduced in order to explain the variability in the two indicators of impact presented on the left hand side of models (1) and (2). It has been argued that peer review publications could be biased toward reporting significant effects, which would influence researchers to scrutinize the work they prepare for journal submission (Borenstein, Hedges, and Rothstein 2007; Stanley 2001). A useful starting point to infer the presence of publication bias is the level of significance of the variable “PUBLICATION”. Likewise, publication year is intended to capture any trend on the impact of NRM over the years. If this effect is significant it would suggest changes to more robust |methods or better ways to implement NRM programs (Maredia 2009). Another variable worth examining is NTECHN, which represents the number of technologies analyzed by each observation, and it is intended to capture the effect of using technology packages instead of one technology at a time. METHOD 1, 2, 3 serves as a reference to capture the high level of methodological heterogeneity of these types of studies. Meanwhile, PARTICIP and TRAINING represent programs features associated with the technology transfer process (Knowler and Bradshaw 2007). Since NRM programs are implemented by different organizations, is informative to ascertain if the type of implementer makes a difference; thus, we introduce the dummy IMPLEBY, to compare governments vs. other organizations such as NGO's and development banks. Further, CONPRA1, 2 represent groups of the different NRM technologies, and if the associated parameters are significant then this would suggest that technologies may have a different level of success. Another important issue in the evaluation of NRM technologies is the time elapsed between the delivery of the technology and the time that it takes for the effect of these technologies to be observed (Branca et al. 2011); thus, TIME captures the effect of years on the impact of NRM technologies, and TIME2 is used to estimate whether or not this effect decreases over time.

To estimate Model 1, the database has 81 observations and this could be sufficient to estimate the different parameters of the model (Stanley and Doucouliagos 2012). However, only 48 observations are available to estimate Model 2, which might not be enough to proceed with the estimation using standard regression methods. The loss in degrees of freedom and the noise introduced by the estimation of a large number of parameters reduces the efficiency of the model (Moeltner et al. 2007). Moreover, since some observations are coming from the same study, cluster standard errors at the study level are needed which further reduces the degrees of freedom and these factors lead to imprecise parameter estimates (Wooldridge 2002). Moeltner et al. (2007) argue that given data limitations Bayesian methods should be used. Eddy et al. (1990) come to a similar conclusion, and also argue that Bayesian analysis is more appropriate when data from different settings is combined.

Bayesian methods make it possible to introduce previous information about the parameters and their variance. which allows for parameter estimation based on a posterior probability distribution

(Koop 2003). In this case, the incorporation of prior information can mitigate the effect of a small sample size. Therefore, we estimate Model 2 using a Bayesian approach relying on sampling from a posterior distribution using the Metropolis–Hastings (MH) algorithm. Unlike classical econometrics, in Bayesian analysis the precision of the estimates is not limited by sample size (Rossi, Allenby & Mcculloch, 2005). In order to produce an efficient sampling from the posterior distribution and to improve the efficiency of the model parameter, we blocked[1] each of the parameters and used Gibbs sampling (i.e., a hybrid MH sampling with Gibbs updates). These strategies allow us to improve the overall sampling efficiency of the posterior distribution (Greenberg 2008).

In Bayesian estimation, the prior information can rely on non-informative priors, an approach that is often questioned (Greenberg 2008). Hence, we use informative priors from the probit estimation, although priors from other meta-analyses could have been used. However, as mentioned above, the estimates of the meta-analysis studies are not estimated based on impact evaluation analysis and are likely to introduce biases in the model.

A general specification of the Bayesian model is as follows:

$$f(\beta,\sigma^2|y,X) \propto \prod_i \big(f(y_i \big| \mu_{i,}\sigma^2\big) \times f(\beta,\sigma^2) \qquad (4)$$

where β represents the set of coefficients of the posterior distribution to be estimated, and X is the matrix whose i*th* row is x_i. $\prod_i$ is a prior independent of (β,σ^2) and, in this case, it is obtained from the probit model. $f(\beta,\sigma^2)$ the rightmost term represents the posterior for the regression parameters. Equation (4) is fundamental in Bayesian analysis and states that the posterior

[1] Blocking means that model parameters are separated into different subsets or blocks and the Markov chain is obtained by sampling within each separate block.

distribution (rightmost term) of model parameters is proportional to their likelihood (second term) and prior probability distributions (first term).

Table 2.2. Distribution of the program's estimates by significance of effect

Effects sign	No. Observations	%
Significantly positive (1)	122	57
Insignificant (0)	84	39
Significantly negative (-1)	9	4
	215	100%

For Model 1, as a check of robustness, we estimate two additional models, the first is based on the partial correlation between the t value of the estimated coefficient for the treatment effect and the corresponding degrees of freedom. This represents a measure of the association between the significance of the reported outcomes while controlling for the number of explanatory variables. It also allows us to compare different outcomes from different studies (Stanley and Doucouliagos 2012). The calculation of the partial correlation is as follows:

$$r = \frac{t}{\sqrt{t^2 + df}} \tag{5}$$

where t denotes the t-statistic of the treatment effect, and df reports the degrees of freedom of the t-statistic. The second check of robustness is based on the use of the t-statistic as a dependent variable in the following model:

The null hypothesis is that the effect of NRM programs is equal to zero, which is rejected or accepted depending on the mean value of the t-statistic and its level of significance (Corć and Pugh 2010).

2.4 Results and Discussion

Before conducting a meta-analysis of the results we first test for publication bias. To this end, we apply both graphical and econometric methods. The first method implies the use of a funnel plot that shows a graphical display between the partial correlation (horizontal axis) from equation (5) and the inverse of the standard errors (vertical axis) of the parameters of the treatment effect (Stanley and Doucouliagos 2012; Sterne and Harbord 2004). If studies with small sample display larger effects then there is evidence of publication bias. Thus, in the absence of bias, results from small studies will be spread at the bottom of the graph (Sterne and Harbord 2004). As shown in Figure 2.1, the relation between the empirical treatment effect and the inverse standard errors suggest that there is no bias, i.e., the bulk of the studies cover zero and are displayed at the bottom of the graph. This is confirmed by the results in Table 2.3, where the hypothesis of $\beta_1 = 0$ is rejected, i.e., 1/SE is significant (p<0.001). In addition, β_2 is significant which means that there is a positive significant effect of NRM technologies on the different outcome variables. (Stanley and Doucouliagos 2012).

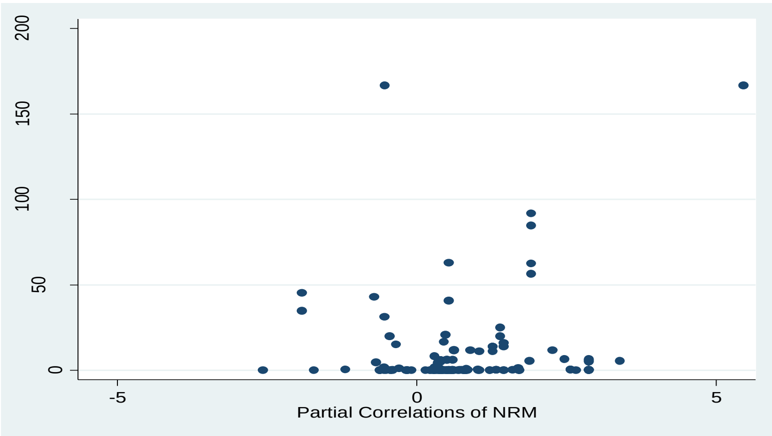

Figure 2.1Funnel plot of NRM partial correlations and precisions

Table 2.3. Meta-regression analysis of publication selection

Variables	Coefficient
Intercept: $\hat{\beta}_1$	0.919***(0.74)
1/SE: $\hat{\beta}_2$	0.012***(0.003)
N	213

Standard errors (SE) are clustered by study id and reported in parenthesis.

As specified earlier, one of our estimation strategies was based on using the significance level (significantly positive, statistically insignificant or significantly negative) of the estimated impact to identify the characteristics of the studies that play a role on the effect of the NRM technologies. Table 2.4 contains the main findings of the meta-ordered probit model alongside the estimation of the marginal effects used in this analysis. In general, in both the ordered probit and probit models, the null hypothesis that all coefficients are simultaneously zero is rejected. Furthermore, a pseudo-R^2 of 0.17 and 0.20 indicates that the variation of the impact indicator of NRM technologies is well explained by the variables included in our model.[2] On the whole, both models display very similar parameter estimates. Since the number of negative significant observations is very low, we focus on the marginal effect of the probit model estimates in column 4 of Table 2.4. However, we do point out cases where major discrepancies arise between the ordered probit and probit models.

The models include characteristics of the intervention as well as covariates related to the evaluation design. As shown in Table 2.4, positive significant results are not correlated with publication in peer review journals or in other type of outlet. Likewise, the year of publication is not correlated with the probability of finding a positive impact. Although our expectation was that the increase in impact evaluations coupled with the availability of more evaluation techniques

[2] Further details about the use of pseudo-R^2 in ordered probit models can be found in O'Donnell and Connor (1996).

would have led toward more positive impacts, this is not the case. Moving to the dummies for the country groups, we find that impact evaluation studies implemented in Asia and Africa are 36% and 30%, respectively, more likely to be associated with positive significant impacts than evidence from the rest of the world. The rest of the world includes North America and Latin America and the Caribbean, where NRM technologies have already been largely adopted (Knowler and Bradshaw 2007), and therefore makes it less likely that a positive impact will be found in the region. However, it is more likely that a positive and significant impact will be found in Africa and Asia where there is not yet a high adoption rate.

Training is a very important factor for boosting the effectiveness of NRM technologies; its absence or presence is considered to be a key factor for the successful adoption of these technologies (Knowler and Bradshaw 2007). Our results in Table 2.4 suggest that the use of participatory approaches while implementating NRM programs increases the likelood of finding a positive impact by 15.5%. Likewise, programs that implement training activities are 25.6% more likely to have a positive impact than programs implemented without training. Although for many program the need to deliver appropriate technical packages and training is clear, some NRM programs failed to incorporate them to a sufficient extent. Our results are consistent with previous evidence which found that training increases overall knowledge and productivity (Godtland et al. 2004; Lahmar 2010).

In order to account for the potential role that weather plays on the effects of NRM technologies, we introduce the coefficient of variation for the annual rainfall during the year that the impact evaluation was carried out in each study. The econometric results (Table 2.4) suggest that a better distribution of annual rainfall increases the probability of finding a positive outcome by 24.2%. This suggests that the success of NRM technologies may be tied to rainfall distribution. For instance, Arslan et al. (2015) found that high rainfall variability during the growing season is associated with positive effects of NRM on productivity. Similar results are reported by Khan et al. (2016), who found that zero tillage users in India experienced between a 24%-28% lower yield losses than non-users after an unseasonal rainfall event. However, Kassie et al. (2011) argued that in areas with high rainfall, the use of terraces has adverse effects on productivity. In this context, our results allow us to draw a conclusion based on the sign of the expected impact, but not about the possible magnitude. Furthermore, NRM technology involves a very large set of practices, an issue that is cannot be disentangled in our meta-analysis. Moreover, the effects of NRM may also vary depending on the crop under analysis. Needless to say, the literature is still mixed regarding where NRM interventions perform better.

Confirming previous evidence regarding the effectiveness of governmental agencies in program implementation (Cho and Honorati 2013), we find that the likelihood of observing a positive effect decreases by 40% if the NRM program is implemented by a government agency compared to NGOs, development banks or other international institutions. The greater effectiveness of NGOs and other institutions in program implementation indicates that government agencies need to enhance their project managerial skills in order to accomplish better results. Furthermore, in the short run, governments should work closely with NGOs and international agencies on the delivery and implementation of NRM technologies.

The econometric results presented in Table 2.4 indicate that the type of outcome variables matter when evaluating the impact of NRM programs. Yields and Monetary Outcomes tend to exhibit a negative probability of reporting positive effects compared to the use of technical efficiency (TE). Knowler & Bradshaw (2007) claim that NRM leads to a more efficient use of natural resources and better utilization of fertilizer, however this does not necessarily imply an increase in productivity. Moreover, Bravo-Ureta, Greene, and Solís (2012) and Solís, Bravo-Ureta, and Quiroga (2007) argue that development programs might create both technology and managerial gaps (i.e., TE) in favor of program beneficiaries and thus it is important to measure both effects. They also argue that the estimation of TE in the context of impact evaluation analysis has been neglected. Reasons behind the low use of the TE on the evaluation of NRM effectiveness may lie behind the lack of understanding by policymakers about the conceptualization of TE, i.e., it is easier to communicate an increase in yield than a higher TE score. The lack of straightforward econometric methods that allow for causal conclusions could be another reason for disregarding TE in impact evaluation work.

Other characteristics, such as econometric methods, the type of data, sample size, or technology grouping are not statistically significant; thus, these covariates do not play a role on the effectiveness of the program. However, one evaluation characteristic that does play a part in the effectiveness of the program is the number of years that have elapsed between the program implementation and the evaluation. The econometric results in Table 2.4 indicate a positive association between years and the likelihood of finding a positive impact. It has been argued that NRM technologies need an appropriate amount of time to generate significant effects. Our econometric estimation (Table 2.4) points toward the confirmation of the previous evidence (Jat et al. 2014; Kassam et al. 2012). For each additional year between the end of the project and the impact evaluation, NRM programs are 10 % more likely to report positive effects. Furthermore, our results indicate that time displays a quadratic effect; hence, after a certain period the effect diminishes. Two possible explanations come to mind: diminishing returns; or abandonment of the technology by beneficiaries.

Table 2.4. Ordered probit models for sign⁄significance of estimated of NRM technologies

Variable	OProbit Coef.	OProbit(ME) Coef.	Probit SD	Probit(ME)
PUBLICATION	-0.210	-0.079	-0.197	-0.059
	(0.311)	*(0.117)*	*(0.378)*	*(0.113)*
PYEAR	-0.023	-0.009	-0.055	-0.016
	(0.039)	*(0.014)*	*(0.042)*	*(0.013)*
ASIA	0.716	0.272	1.193**	0.362**
	(0.573)	*(0.216)*	*(0.554)*	*(0.159)*
AFRICA	0.617	0.234	0.998**	0.303*
	(0.454)	*(0.170)*	*(0.437)*	*(0.122)*
NTECHN	0.064	0.024	0.072	0.022
	(0.041)	*(0.155)*	*(0.047)*	*(0.014)*
METHOD 1	-0.369	-0.139	-0.173	-0.052
	(0.348)	*(0.132)*	*(0.302)*	*(0.092)*
METHOD 2	0.131	0.049	0.247	0.075
	(0.278)	*(0.106)*	*(0.290)*	*(0.088)*
PARTICIP	0.488**	0.185**	0.511**	0.155**
	(0.245)	*(0.092)*	*(0.249)*	*(0.074)*
TRAINING	0.701*	0.266*	0.845*	0.256*
	(0.419)	*(0.159)*	*(0.464)*	*(0.138)*
COEVPRE	0.758***	0.287***	0.798***	0.242***
	(0.262)	*(0.1000)*	*(0.304)*	*(0.086)*
IMPLEBY	-0.020***	-0.387***	-1.346***	-0.408***
	(0.373)	*(0.139)*	*(0.339)*	*(0.094)*
PANEL	-0.088	-0.033	-0.114	-0.035
	(0.338)	*(0.128)*	*(0.336)*	*(0.111)*
TSRATIO	-0.020	-0.008	-0.091	-0.028
	(0.142)	*(0.054)*	*(0.127)*	*(0.037)*
SAMPLE-S	0.000	0.000	0.000	0.000
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
MOVAL	-0.789*	-0.299*	-0.928**	-0.282**
	(0.444)	*(0.166)*	*(0.480)*	*(0.136)*
YIELD	-1.423***	-0.539***	-1.573***	-0.477***
	(0.542)	*(0.200)*	*(0.578)*	*(0.154)*
CONPRA2	0.097	0.037	-0.029	-0.009
	(0.488)	*(0.185)*	*(0.496)*	*(0.150)*
CONPRA3	-0.195	-0.074	-0.117	-0.036
	(0.295)	*(0.112)*	*(0.307)*	*(0.093)*
TIME	0.219	0.083	0.331**	0.100**
	(0.169)	*(0.064)*	*(0.157)*	*(0.045)*
TIME2	-0.023*	-0.008*	-0.032***	-0.009***
	(0.013)	*(0.005)*	*(0.012)*	*(0.003)*
Observations	215		215	
Pseudo R^2	0.171		0.203	

note: *** p<0.01, ** p<0.05, * p<0.

Standard errors (SE) are clustered by study id and reported in parenthesis.

Marginal effects (ME) calculated at the sample mean, using the delta method

Now we move to the effect size analysis of estimates from observations that use monetary outcomes as a dependent variable. Econometric results using 81 observations are presented in Table 2.5 along with the estimation of two more OLS regressions in columns 2 and 3. We use *t*-statistic values reported by each study and the partial correlation coefficients as dependent variables. Both methods are commonly used in the meta-analysis literature to summarize empirical evidence, especially when different outcomes are reported. These statistics allow for the comparison of different estimates and studies (Stanley 2001; Stanley and Doucouliagos 2012). We use these two estimations to check for the robustness of the model presented in column 1 of Table 2.5. The R^2 of the three models are high, which indicates that a significant part of variability of NRM measured on monetary values is explained by the covariates included in the models.

Table 2.5 shows that ASIA displays negative coefficients contrary to what is observed in the probit estimation. Thus, the meta-regression results (Table 2.5) indicate that countries in ASIA exhibit a lower impact than the rest of the world. For Africa, this parameter also has a negative sign, although it is not statistically significant. These results indicate that both regions need to establish additional policies to increase the size of the effect of NRM. This could be achieved by increasing the productivity per hectare or by increasing the value of the crop, or by a combination of both.

The results for rainfall form the meta-regression differ from those obtained from the probit model. In areas with poor rainfall distribution, the size of the effect is 42% compared with areas that have better rainfall patterns. These results are relevant since NRM technologies are considered to be a technological option to address adverse effects of climatic change such as drought and periods with heavy rains (Arslan et al. 2015; Khan et al. 2016). Furthermore, areas such as Sub-Saharan Africa and South Asia, where a significant part of agricultural production come from rainfed areas, could benefit from the adoption of NRM technologies. Since our data is very heterogeneous in terms of NRM technologies, it is not possible to disentangle the particular contribution that each technology makes on the aggregate impact. For instance, NRMs that favor water infiltration may not be appropriate for rice production where farmers need to retain water. Thus, the relation between NRM technology and crops is a matter of careful consideration. It is possible that different technologies have different effects on productivity. Moreover, the effects of NRM technologies may also vary depending on the crop under analysis.

The constant parameter (Table 2.5), which indicates whether or not there is any significant effect of NRMs on the outcome variable, is positive and significant among the different model specifications. The intercept coefficient in column 1 shows that after controlling for programs and evaluation characteristics, NRM technologies increase monetary outcomes on average by 8%. The models in columns 2 and 3 display similar results; however, their interpretations are more statistical than economical (Stanley and Doucouliagos 2012). For instance, the average *t*-statistic of 2.7 in column 2 indicates that, on average, the reported effect is statistically significant, i.e., the reported *p*-values are larger than 0.05, yet this is not economically meaningful. Nonetheless, they show a strong indication of the positive impact of NRM.

Table 2.5. Meta-regression of the effect of NRM technologies on Monetary Values

Variable	MONVAL (1)	*t*- statistic (2)	Partial correlations (3)
	Coef.	Coef.	Coef.
CONSTANT	8.127***	2.70407***	10.361***
	(1.22)	*(0.642)*	*(1.803)*
ASIA	-6.29***	-1.804**	-0.995
	(0.794)	*(0.799)*	*(1.802)*
AFRICA	-0.015	-0.193	0.163
	(0.437)	*(0.272)*	*(0.693)*
NTECHN	0.049	-0.026	-0.066
	(0.107)	*(0.045)*	*(0.158)*
METHOD 1	0.573**	-0.069	0.091
	(0.246)	*(0.114)*	*(0.311)*
METHOD 2	-0.728	0.152	-0.887
	(0.465)	*(0.272)*	*(0.833)*
PARTICIP	1.698**	0.957***	1.749*
	(0.782)	*(0.274)*	*(0.999)*
TRAINING	0.357	0.825	2.376
	(1.057)	*(0.759)*	*(2.001)*
COEVPRE	-1.223***	-0.866**	-3.231***
	(0.421)	*(0.413)*	*(1.028)*
IMPLEBY	-1.919*	-1.242***	-1.258
	(1.216)	*(0.386)*	*(1.231)*
PANEL	1.501***	-0.646***	-1.033
	(0.312)	*(0.296)*	*(0.684)*
TIME	0.068	-0.721***	2.523***
	(0.162)	*(0.210)*	*(0.545)*
TIME2	-0.004	0.040*	-0.172*
	(0.004)	*(0.024)*	*(0.062)*
Observations	81	81	81
R^2	0.94	0.91	0.88

note: *** p<0.01, ** p<0.05, * p<0.
Standard errors (SE) are clustered by study id and reported in parenthesis.
Regressions 1–3 are weighted by the inverse of the standard deviation of the primary studies.

The final econometric model is based on a Bayesian approach and estimates the impact of NRM technologies on yield and the credible intervals using a subsample of 48 observations. Column 1 in Table 2.6 reports the mean and the standard deviations of the posterior distribution of model parameters, which in turn are means and standard deviations of the marginal posterior distributions of the parameters (Koop 2003). At a quick glance, the estimated model parameters display similar signs compared to those obtained in both the probit and OLS models (Table 2.4), which support previous estimations. The coefficient of the constant also shows that the average effect of NRM on Yields is equal to 13%. Furthermore, the probability that the coefficient for the constant is between 9.15 and 16.5 is about 95%. Since the lower interval is larger than zero, we can conclude that NRM technologies have a positive effect on yield. Overall, these findings strongly support the conclusions derived from the different estimations in this paper. Furthermore, both the acceptance rate and efficiency criteria[3] indicate that the model quality is above the threshold of 10% and 1%, respectively (Greenberg 2008).

Table 2.6. Meta-Bayesian regressions of the effect of NRM technologies on Yields

Variable	Mean (SD)	[95% Cred. Interval]	
CONSTANT	13.034(1.878)	9.156	16.543
PUBLICATION	-0.146(0.782)	-1.657	1.394
PYEAR	0.049(0.011)	0.028	0.071
ASIA	0.705(0.672)	-0.591	2.024
AFRICA	-0.269(0.567)	-1.369	0.852
NTECHN	0.555(0.218)	0.136	0.984
METHOD 1	-3.165(0.606)	-4.346	-1.965
METHOD 2	-2.258(0.818)	-3.886	-0.674
PARTICIP	1.158(0.756)	-0.3006	2.640
TRAINING	1.261(1.121)	-0.8866	3.471
COEVPRE	0.877(0.504)	-0.0616	1.921
IMPLEBY	-1.979(0.34)	-2.674	-1.3021
PANEL	1.564(0.632)	0.346	2.826
TSRATIO	0.385(0.285)	-0.179	0.941
CONPRA2	-0.272(0.545)	-1.3409	0.802
CONPRA3	-1.009(0.766)	-2.559	0.465
TIME	13.769(1.040)	11.748	15.851
TIME2	-6.798(0.038)	-6.8708	-6.723
SAMPLES	-0.045(0.024)	-0.094	0.003
Observations	48		
Acceptance rate	.630		
Efficiency	0.03		
Log marginal likelihood =	-418.01753		

Bayesian normal regression Metropolis-Hastings and Gibbs sampling and MCMC with125,000 iterations.

[3] These two criteria define the overall efficiency of the Bayesian model, the first measures the degree of autocorrelation of sample from the posterior probability, while the acceptance measures how many of proposed sampling through the Monte Carlo Markov chain are accepted (Rossi et al. 2005).

2.5 Summary and conclusions

The available experimental and econometric evidence shows ambiguous results on the effect that natural resource management (NRM) technologies have on productivity and other outcomes. In order to analyze these contradictory research findings and estimate the "macro effect" of NRMs, we employ meta-regression analysis techniques. In so doing, we develop a unique data set of impact evaluation studies of NRM programs. These data comprise 75 studies with a total of 215 observations. The meta-dataset that we developed is the basis for our econometric work which relies on fitting ordered probit, probit, ordinary least squares, and a Bayesian regression models. These different approaches allow us to explain why impact varies among studies and across different interventions, countries, and econometric methods.

The econometric results reveal that study and program characteristics can play a significant positive effect on the impact of NRM technologies. Among these features, studies implemented in Asia and Africa are more likely to report more significant estimates. However, the average impact is lower than the estimated impact reported in North American, Latin American and Caribbean countries and also in Europe. Likewise, the inclusion of training and participatory extension methods appears to increase the likelihood of finding a positive impact. Both characteristics also matter when it comes to finding a larger average impact. Although with our data it is not possible to decide how long training periods should be, we believe the design of appropriate training activities is an essential program component. With respect to which organization is responsible for the implementation of the program, it seems that NRM programs implemented solely by government agencies yield lower effects than those implemented by a financial institution, NGO, or international cooperation agencies.

Although there is no clear indication that the econometric methods used to measure the impact of the program matter, the outcome variables used to determine the impact do matter. The estimation of technical efficiency produces more favorable impacts than the use of yield or monetary outcomes. The time that passes between the end of the program and its evaluation can also be a major determinant of impact. In terms of policy implication, this opens the door to a possible revision of those impact evaluations where insignificant or negative impacts were found in the short term. In addition, this is also an important point to consider for development agencies that often include impact evaluation analysis only at the end of their projects.

In conclusion, the promotion of NRM programs to tackle natural resource degradation and to increase productivity is a win-win public policy. Overall, NRM programs increase monetary outcomes on average by 8%, and the effect on productivity ranges between 9.15% and 16.5%, which leads to a substantial welfare gain for farmers. In a context where natural resources constitute the most valuable assets for smallholder farmers, these results are particularly relevant for policymakers searching for appropriate interventions. Furthermore, it is noteworthy to mention that this meta-analysis is based on the benefit that is accrued by farmers. Therefore, benefits that accrue to the society need to be added to estimate the total effect that NRM programs have. We also point out that future impact evaluation studies should clearly report detailed information concerning sample size, standard deviation, and the mean of the estimated effect. This will help to increase the size of the available evidence to support or reject NRM technologies.

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Table. 2.A.1. Apendix : List of references used in the meta-analysis

Code	Autor(s)	Title	Country	obs.
1	Kassie, M.; Pender, J; Yesuf, M.; Kohlin, G.; . ; Mulugeta, E.	Estimating returns to soil conservation adoption in the northern Ethiopian highlands	Ethiopia	4
2	Todo, Y.; Takahashi, R.	Impact of Farmer Field Schools on Agricultural Income and Skills: Evidence from an Aid-Funded Project in Rural Ethiopia	Ethiopia	3

3	Dutilly-Diane, C.; Sadoulet, E.; Janvry, A. de	Household Behaviour under Market failures: How Resource Management in Agriculture Promotes Livestock Production in the Sahel	Burkina Faso	3
4	Dalton, T. J.; Lilja, N. K.; Johnson, N.; Howeler, R.	Impact of Participatory Natural Resource Management Research in Cassava-Based Cropping Systems in Vietnam and Thailand	Vietnam, Thailand	2
5	Dey, M. M.; Paraguasb, F. J.; Kambewac, P.; Pemsld, D. E.	The impact of integrated aquaculture–agriculture on small-scale farms in Southern Malawi	Malawi	3
6	Place, F.; Adato, M.; Hebinck, P.; Omosa, M.	The Impact of Agroforestry-Based Soil Fertility Replenishment Practices on the Poor in Western Kenya	Kenya	2
7	Barrett, C. B.; Moser, C. M.; McHugh, O. V.; Joeli Barison, J.	Better Technology, Better Plots or Better Farmers? Identifying Changes in Productivity and Risk Among Malagasy Rice Farmers	Malagasy	3
8	Bravo-Ureta, B. E.; Nunes-Almeida, A.; Solı´s, D.; Aarón Inestroza	The Economic Impact of Marena's Investments on Sustainable Agricultural Systems in Honduras	Honduras	2
9	Cocchi, H; Bravo-Ureta, B. E.	On-Site Costs and Benefits of Soil Conservation among Hillside Farmers in El Salvador	El Salvador	1
10	International Bank for Reconstruction and Development ; The World Bank (SRSP - Sriramasager Project)	An Impact Evaluation of India's Second and Third Andhra Pradesh Irrigation Projects	India	2
11	Jaleta, M.; Kassie, M.; Tesfaye, K.; Teklewold, T.; .. ; Erensteinf, O.	Resource saving and productivity enhancing impacts of crop management innovation packages in Ethiopia	Ethiopia	2
12	Kassie, M; Zikhali, P.; Pender, J.; Köhlin, G.	The Economics of Sustainable Land Management Practices in the Ethiopian Highlands	Ethiopia	3

13	Kassie, M.; Köhlin, G; Bluffstone, R.; Holden, S.	Are soil conservation technologies “win-win?” A case study of Anjeni in the north-western Ethiopian highlands	Ethiopia	2
14	Huang, Q.; Wang, J.; Rozelle, S.; Polasky, S.; Liu, Y.	The Effects of Well Management and the Nature of the Aquifer on Groundwater Resources	China	1
15	Takahashi, K.; Barrett, C. B.	The System of Rice Intensification and its Impacts on Household Income and Child Schooling: Evidence from Rural Indonesia	Indonesia	2
16	Pender, J.; Gebremedhin, B.	Land Management, Crop Production, and Household Income in the Highlands of Tigray, Northern Ethiopia: An Econometric Analysis	Ethiopia	5
17	Mekonnen, D. K.; Channa, H.; Ringler, C.	The impact of water users’ associations on the productivity of irrigated agriculture in Pakistani Punjab	Pakistan	2
18	Schmidt, E.; Tadesse, F.	Ensuring Agricultural Productivity over Time: Impact of Sustainable Land Management Program on Rural Farmers in Ethiopia	Ethiopia	2
19	Tajuddin Khan, Md.; Kishore, A.; Pandey, D.; Joshi, P. K.	Using Zero Tillage to Ameliorate Yield Losses from Weather Shocks	India	1
20	Judith Beatrice Auma Oduol, Joachim Nyemeck Binam, Luke Olarinde, Aliou Diagne and Adewale Adekunle	Impact of adoption of soil and water conservation technologies on technical efficiency: Insight from smallholder farmers in Sub-Saharan Africa	Uganda	3
21	Noltze, M.; Schwarze, S.; Qaim, M.	Impacts of NRM technologies on agricultural yield and household income The system of rice intensification in Timor Leste	Timor Leste	2
22	Haile, B.; Azzarri, C.; Roberts, C.; Spielman, D. J.	Targeting, bias, and expected impact of complex innovations on developing-country agriculture: evidence from Malawi	Malawi	4

23	Hope, R. A.	Evaluating Social Impacts of Watershed Development in India	India	2
24	Rodriguez, D. G. P.; Rejesus, R. M.; Aragon, C. T.	Impacts of an Agricultural Development Program for Poor Coconut Producers in the Philippines: An Approach Using Panel Data and Propensity Score Matching Techniques	Philippine	2
25	Jumbe, C. B. L.; Angelsen, A.	Has forest co-management in Malawi benefited the poor	Malawi	3
26	Saleth, R. M.; Inocencio, A.; Noble, A.; Ruaysoongnern, S.	Economic gains of improving soil fertility and water holding capacity with clay application: the impact of soil remediation research in Northeast Thailand	Thailand	3
27	Bandyopadhyay, S.; Shyamsundar, P.; Xie, M.	Yield Impact of Irrigation Management Transfer: Story from the Philippines	Philippine	1
28	Faltermeier, L.; Abdulai, A.	The impact of water conservation and intensification technologies empirical evidence for rice farmers in Ghana	Ghana	2
29	Wanyama, J. M.; Nyambati, E. M.; Mose, L. O.; Mutoko, C. M.; .. ; Rono, S. C.	Assessing impact of soil management technologies on smallholder farmers' livelihoods in North Western Kenya	Kenya	7
30	Weber, J. G.; Sills, E. O.; Bauch, S.; Pattanayak, S. K.	Do ICDPs Work? An Empirical Evaluation of Forest-Based Microenterprises in the Brazilian Amazon	Brazil	4
31	Rejesus, R. M.; Palisb, F. G.; Rodriguezc, D. G. P.; Lampayand, R. M.; Boumand, B. A.M.	Impact of the alternate wetting and drying (AWD) water-saving irrigation technique Evidence from rice producers in the Philippines.	Philippines	4
32	Kato, E.; Nkonya, E.; Place , F. M.	Heterogeneous Treatment Effects of Integrated Soil Fertility Management on Crop Productivity	Nigeria	2
33	Dalton, T. J.; Lilja, N. K.; Johnson, N.	Farmer Participatory Research and Soil Conservation in	Vietam	2

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34	Schmidt, E.; Tadesse, F.	Household and Plot Level Impact of Sustainable Land and Watershed Management (SLWM) Practices in the Blue Nile	Ethiopia	6
35	Palmer-Jones, R.; Dilokkunanant, N.; Phonyiam, B.; Punyaratabandhu, S.; Sutthiwongse, T.; Hanpongpandh, S.	Impact Evaluation of Mae Lao Irrigation Improvement Project, Thailand	Thailand	1
36	Asfaw, S.; McCarty, N.; Lipper, L.; Arslan, A.; Cattaneo, A.	Climate variability, adaptation strategies and food security in Malawi	Malawi	3
37	Zhunusova, E.; Willy, D. K.; Holm-Müller, K.	Estimating the joint effect of multiple soil conservation practices: A case study of smallholder farmers in the Lake Naivasha basin, Kenya	Kenia	2
38	Admasu, B.; Jema, H.; Chisholm, N.; Enright, P.	Impact of protected forests on rural households' fuel tree planting in Chiro district, eastern Ethiopia	Ethiopia	1
39	Zingiro, A.; Okello, J. J.; Guthiga, P. M.	Assessment of adoption and impact of rainwater harvesting technologies on rural farm household income: the case of rainwater harvesting ponds in Rwanda	Rwanda	4
40	Datta, N.	Evaluating Impacts of Watershed Development Program on Agricultural Productivity, Income, and Livelihood in Bhalki Watershed of Bardhaman District, West Bengal	India	6
41	Bauch, S. C.; Sills, E. O.	Have We Managed to Integrate Conservation and Development? ICDP Impacts in the Brazilian Amazon	Brazil	6

42	Kankwamba, H.; Mangisoni, J. H.	Are sustainable agricultural practices improving output and incomes of smallholder farmers in Malawi?	Malawi	4
43	Arslan, A.; McCarthy, N.; Lipper, L.; Asfaw, S.; . ; Kokwe, M.	Climate Smart Agriculture? Assessing the Adaptation Implications in Zambia	Zambia	3
44	Kokoye, S.; Jolly, C. M.; Molnar, J.; Shannon, D.; Bayard, B.	Adoption and Impact of Soil Conservation Practices on Farm Income: Evidence from Northern Haiti	Haiti	1
45	Persha, L.; Meshack, C.	A triple win? The impact of Tanzania's Joint Forest Management programme on livelihoods, governance and forests	Tazania	6
46	Abdul-Nafeo Abdulai; Abdulai, A.	Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia	Zambia	1
47	Gebremariam, G.; Wünscher, T.	Combining sustainable agricultural practices pays off: evidence on welfare effects from Northern Ghana	Ghana	10
48	Kinuthia, E. K.	The Effects of the International Smallgroup and Tree Planting Program on Household Income in Nyeri District, Kenya	Kenya	1
49	Haile, B.; Azzarri, C.; Roberts, C.; Spielman, D. J.	Targeting, bias, and expected impact of complex innovations on developing-country agriculture: evidence from Malawi	Malawi	6
50	Forstson, K.; Rangarajan, A.; Blair, R.; Lee, J.; Gilbert, V.	Evaluation of water-to-Market Training in Armenia	Armenia	3
51	Peralta, A.; Swinton, S. M.	Neighbor effects on Adoption of Conservation Agriculture in Nicaragua	Nicaragua	4
52	Hope, R. A.	Evaluating Social Impacts of Watershed Development in India	India	2

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60	Sanglestsawai, S.; Rejesusb, R. M.; Yorobe Jr.c, J.M.	Economic impacts of integrated pest management (IPM) farmer field schools (FFS): evidence from onion farmers in the Philippines	Philippines	12
61	Yamazaki, S.; Resosudarmo, B. P.	Does Sending Farmers Back to School Have an Impact? Revisiting the Issue	Indonesia	6
62	Rejesus, R. M.; Mutuc, M. E. M.; Yasar, M.; Lapitan, A. V.; . ; Truong Thi Ngoc Chi	Sending Vietnamese Rice Farmers Back to School: Further Evidence on the Impacts of Farmer Field Schools	Vietnam	2

63	Godtland, E. M.; Sadoulet, E.; Janvry, A. de; Murgai, R.; Ortiz, O.	The Impact of Farmer Field Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes	Peru	1
64	Rejesus, R. M.; Palis, F. G.; Lapitan, A. V.; Truong Thi Ngoc Chi; Hossain, M.	The Impact of Integrated Pest Management Information Dissemination Methods on Insecticide Use and Efficiency: Evidence from Rice Producers in South Vietnam	Vietnam	2
65	J.M. Yorobe Jr.R.M. Rejesus; Hammig, M. D.	Insecticide use impacts of Integrated Pest Management (IPM) Farmer Field Schools: Evidence from onion farmers in the Philippines	Philippines	2
66	Praneetvatakul, S.; Waibel, H.	Impact Assessment of Farmer Field Schools using A Multi-Period Panel Data Model	Thailand	3
67	Solís, D.; Bravo-Ureta, B. E.; Quiroga, R. E.	Soil conservation and technical efficiency among hillside farmers in Central America: a switching regression model	Honduras, El Salvador	1
68	Mugonola, B.; × Vranken, L.; Maertens, M.; Deckers, S.; .. ; Mathijs, E.	Soil and water conservation technologies and technical efficiency in banana production in upper Rwizi micro-catchment, Uganda	Uganda	1
69	El-Shater, T.; Yigezu, Y. A.; Mugera, A.; Piggin, C.; … ; Aw-Hassan, A.	Does Zero Tillage Improve the Livelihoods of Smallholder Cropping Farmers?	Syria	4
70	Yang Z.; Mugera, A. W.; Yin, N.; Wang, Y.	Soil conservation practices and production efficiency of smallholder farms in Central China	China	1
71	Abdulai, A.; Huffman, W.	The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application	Ghana	2
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75	De los Santos Montero, L. A.; Bravo-Ureta, B.	Productivity Effects and Natural Resource Management: The Case of POSAF-II in Nicaragua	Nicaragua	6

Chapter 3 Natural Resource Management and Household Well-being:The Case of POSAF-II in Nicaragua

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Abstract: Measuring the impact of natural resource programs is a key element in the formulation and implementation of policies designed to promote farm income while enhancing the quality of the surrounding environment. In this paper, we analyze the economic impact of natural resource technologies delivered by the Socio-environmental and Forestry Development Program-II (POSAF-II) in Nicaragua. We use cross-sectional data for 1,483 households, from 212 treated and control communities. Results obtained from propensity score matching (PSM), ordinary least squares (OLS), weighted least squares regression (WLS) based on PSM, and instrumental variables (IV) regression indicate that POSAF-II has had a positive impact on the total value of agricultural production of beneficiary farmers. An internal rate of return analysis supports the hypothesis that increasing household income while encouraging the sustainable use of natural resources through the implementation of suitable management programs can be complementary development objectives.

Keywords: natural resource management, impact evaluation, intention-to-treat, spillover, internal rate of return, Nicaragua

3.1 Introduction

Over the past several years, agricultural production worldwide has managed to effectively meet global demand for food and fiber (World Bank, 2008). However, the ongoing rise in food demand stemming from population and income growth along with the uncertainty from climate change is expected to increase pressure on the agricultural system around the globe (Schmidhuber and Tubiello 2007; Wheeler and VonBraun 2013). Consequently, promoting agricultural productivity while ensuring farming resilience and sustainability is a priority. Achieving these goals is becoming more and more difficult in many areas where land and water resources are under pressure, and production is threatened by rising climatic variability, pests, and diseases (Cleaver 2012; FAO and ITPS 2015). Furthermore, there is growing evidence that climate change has affected agricultural production and will inflict increasing damage to farming in the coming decades (Gornall et al., 2010; World Bank., 2016). These challenges pose a significant threat to about 1.2 billion people worldwide that are living below the poverty line, and 70% of them live in rural areas. A significant number of these people earn their income directly from agricultural activities or have some reliance on farming for their livelihoods (Cleaver, 2012).

The challenges facing agriculture make it imperative to harmonize the need to promote the sustainable use of natural resources with the choice of policies that can be effective in reducing poverty (Barrett, Travis, and Dasgupta 2011). In this context, generating compelling evidence regarding the effects of changes in agricultural practices on farm income has become an important issue for policy makers and donors (Khandker, Koolwal, & Samad, 2010; Kelley, Ryan, & Gregersen, 2008). Assessing the impact of policies on people’s lives has also become an important area of scholarly work. One of the reasons for assessing this impact is to build accountability in public administration and to guide policy decisions. Along with these reasons, determining what works and why impacts are reached or not reached are additional justifications for producing the "proof" that validates public actions (Gertler, Martinez, Premand, Rawlings, & Vermeersch, 2011).

A number of natural resource management (NRM) programs, designed to simultaneously reduce poverty, increase productivity and protect natural resources, have been implemented in Latin America and elsewhere (e.g., Barrett, Moser, Mchugh & Barison, 2004; Bravo-Ureta, Almeida, Solís, & Inestroza, 2011; Dalton, Lilja, & Johnson, 2011; Dutilly-diane, Sadoulet, & de Janvry, 2003; Kassie, Shiferaw, & Muricho, 2011; Tsiboe, Dixon, Nalley, Popp, & Luckstead, 2016). Moreover, in many cases, NRM technologies have been evaluated in controlled experimental or on-farm technology trials, but these types of data are not useful to evaluate actual farming conditions where many variables are beyond the control of the producer (Del Carpio and Maredia 2011; Kelley et al. 2008; Pal 2011; Renkow and Byerlee 2010). As a result, productivity gains measured under controlled conditions are likely to overestimate the real impact of NRM technologies. Furthermore, the results of impact evaluations using a counterfactual group vary from highly positive to very negative (Del Carpio and Maredia 2011). Therefore, the performance of specific technologies under real farming conditions needs to be better understood so that robust interventions can be formulated and implemented (Renkow & Byerlee, 2010; Harwood, Kassam, Gregersen, & Fereres, 2005).

Latin American countries, like others in different parts of the developing world, have implemented NRM programs delivering technologies with the intention of reducing rural poverty while improving productivity and protecting natural resources (Bravo-Ureta et al. 2011; Cavatassi, Salazar, et al. 2011; Solís et al. 2007). However, the literature contains limited reliable evidence concerning the effects of these interventions on farmers' incomes. Likewise, most of these programs focus only on the benefits generated while ignoring more comprehensive measures of performance, such as the internal rate of return (IRR) on the investment, which is critical information for policymakers (Del Carpio and Maredia 2011). A few exceptions include the Environmental Program of El Salvador or PAES (Cocchi and Bravo-Ureta 2007) and the Natural Resource Management in Priority Watersheds Project (MARENA) in Honduras (Bravo-Ureta et al., 2011).

The general objective of this study is to contribute to the literature on impact evaluation of natural resource management programs and the link between these programs and farmer well-being through the evaluation of the Socio-environmental and Forestry Development Program II (POSAF-II). This evaluation focuses on Component I of the Program, which promoted the sustainable management of natural resources at the farm level. Our study sheds light on the effect of actions that can address the “triangle of poverty”, which ties low farm productivity to increased poverty, forcing farmers to place pressure on the environment leading to increasing degradation and in turn to even lower productivity and more poverty. This is a cycle that without intervention continues overtime with dire consequences to both people and the environment. Vosti and Reardon (1997) argue that the reversal of this downward spiral requires suitable policies, institutions, programs, and technologies. Duraiappah (1998) adds that market failures preclude the adoption and diffusion of sustainable practices by failing to impose a price for environmental degradation and/or the deforestation of tropical forests. Moreover, the author contends that there is a feedback loop between environmental degradation and poverty, i.e., environmental degradation causes poverty and poverty causes environmental degradation. Along similar lines, Scherr (2000) reinforces the role of institutions and calls for the need to promote the adoption of technologies that jointly address poverty and environmental degradation, while pointing out that more research is required to explore interactions between poverty, agriculture and the environment.

Swinton, Escobar, and Reardon (2003) take a close view of the situation in Latin America and conclude that policies are needed to implement sustainable agricultural practices. They also argue that these policies need to be tailored to address specific environmental problems. Pretty et al. (2006) undertake a meta-analysis including 286 interventions that tackle poverty and environmental degradation in 57 poor countries from throughout the globe. The authors claim that NRM interventions have increased productivity on 12.6 million farms while improving the supply of critical environmental services. However, Phalan, Rodrigues, and Balmford (2007) argue that much of the evidence presented by Pretty and colleagues is weak because many studies lack control groups and thus results are likely to be biased. In 2015, the United Nations' "International Year of Soil" declaration highlights the importance of more sustainable soil use and the crucial nature of this resource (FAO and ITPS 2015). In addition, the Sustainable Development Goals express the need for the promotion of sustainable farming while, increasing investments in agriculture as a path to reduce poverty and doubling agricultural productivity (UN 2016).

A central challenge in evaluating the impact of development programs is the construction of a suitable counterfactual to mitigate biases from observable and unobservable variables (Khandker et al. 2010). To address this challenge, in this article we use PSM or propensity score matching[4] (Rosenbaum and Rubin 1983) along with instrumental variables and weighted least squares regression (Angrist and Pischke 2015; Hirano and Imbens 2001). These econometric techniques

[4] PSM allows for the construction of comparable groups of beneficiaries and non-beneficiaries, based on the conditional probability of being treated, which is estimated using a set of observable characteristics (Khandker et al. 2010). Further details are presented in Section 4.

allow us to estimate unbiased benefits, which we then use along with administrative data to generate expected cash inflows and outflows and to calculate the expected IRR of the Program under various scenarios. The analysis shows that the estimated impact of POSAF-II is positive and statistically significant while the calculated IRR ranges from 35% to 75%, depending on the scenarios examined.

3.1.1 Description of POSAF-II

The Nicaraguan Ministry of the Environment and Natural Resources (MARENA) implemented POSAF-II between 2002 and 2008. The IDB (2001) stated that the Program sought to improve socioeconomic conditions and living standards of beneficiaries and to lessen the impact of natural disasters in priority watersheds, through the sustainable development and use of renewable natural resources. The goal was to promote economic development and environmental sustainability. POSAF-II financed a total of 13,477 farmers occupying 69,767 hectares in several major river basins that were severely damaged by Hurricane Mitch in 1998 (Figure 3.1). POSAF-II was organized into the following three components: Component I - sustainable management of natural resources at the farm level; Component II - infrastructure and training to prevent and mitigate natural disasters; and Component III - institutional strengthening and training in natural resource management. The total funding of POSAF-II amounted to US$38 million[5].

[5] Further information about the design of the POSAF-II can be found in IDB (2001).

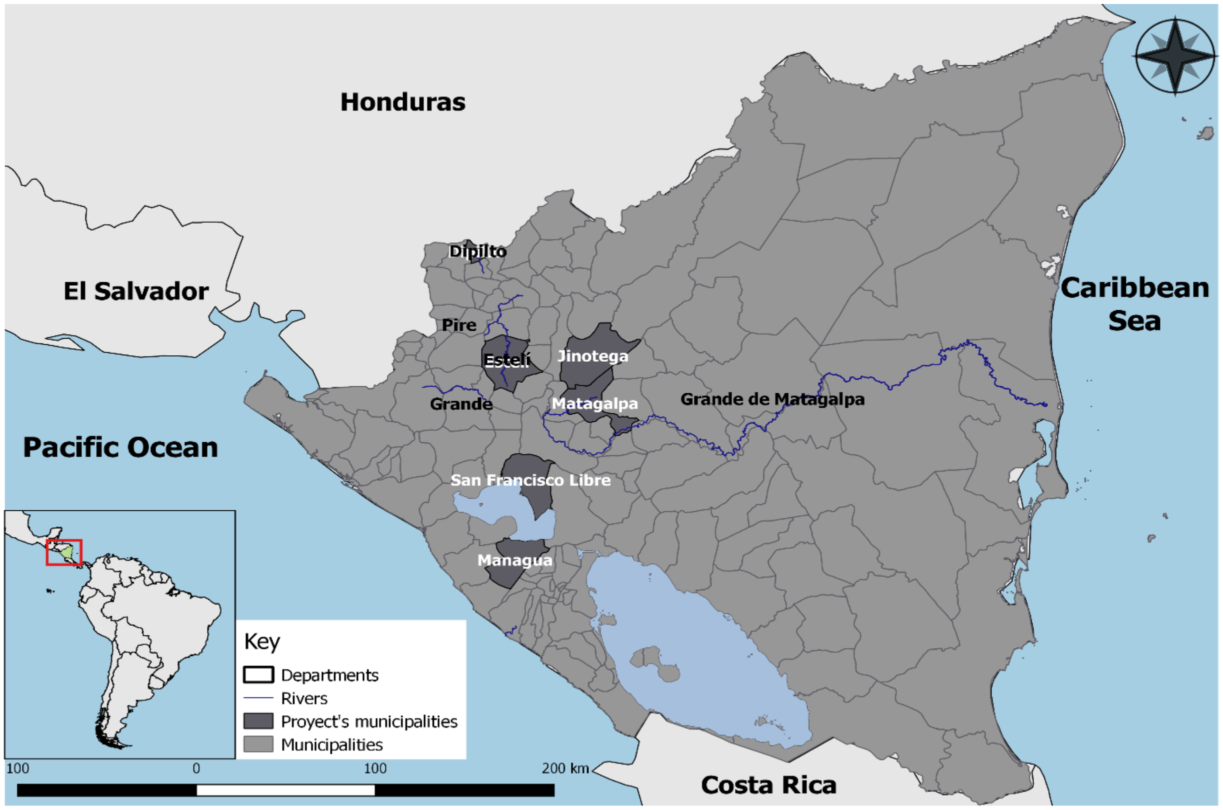

Figure 3.1 Area of influence of POSAF-II.

Component 1 of POSAF-II, the central part of the Program, had a budget of US$20.2 million and was designed to introduce and encourage the adoption of agroforestry, silvopastoral, reforestation, and woodlot management systems. Producers, with technical advice from extension agents, prepared farm management plans that took into account the overall management strategy for their respective sub-basin. Technical assistance consisted of a two level-strategy. The first level was based on a monthly farm visit that allowed beneficiaries to receive individual technical advice. The second level involved an advisory group service where farmers interacted with each other and also received information from an extension agent who served as the meeting coordinator. This approach allowed each farmer to be in contact with an extension agent twice a month. Each extension agent was responsible for a group of between 50-70 farmers, with a total of 227 extension agents dispersed throughout the POSAF-II area of influence.

The farm management plans incorporated a combination of practices drawn from the following pre-established options: soil conservation, integrated pest management, live barriers, stone walls, contour plowing, infiltration ditches, terracing, pruning, green manure production, composting, wood-saving stoves, and slope correction. The maximum incentive provided to a farmer to implement a management plan was US$1,300, and POSAF-II covered the costs for technical assistance from another line of the overall budget. To promote the sustainable adoption of these practices, extension agents provided continuing support to Program beneficiaries over a period of three years (IDB, 2001).

The following three production systems were defined: i) Agroforestry (SAGF), including the planting of fruit trees, introduction of soil conservation practices (stone barriers, terraces, live barriers, among others); ii) Forestry (SFOR) including forest plantation and regeneration, and management of natural resources; and iii) Mixed (SMIX) incorporating elements of both SAGF and SFOR in the context of silvopastoral production systems. To induce adoption of these systems the Program provided technical assistance for three years and materials to participating farmers. Component 1 served two types of farmers: i) poor small-scale subsistence farmers; and ii) middle-sized market-oriented farmers with limited ability to adopt new technologies and that required substantial technological innovations in order to alleviate environmental problems. To be eligible, farmers had to demonstrate: land ownership or any clear documentation of possession of a farm larger than 1.06 hectares (1.5 Manzanas) located in one of the selected river basins; no previous participation in similar programs; and be committed to participate in all POSAF-II activities. Based on these criteria, POSAF-II was implemented in three different rounds with a total of 6,049 farms in the first round, 4,549 in the second and 2,879 in the third.

3.1.2 Impact Evaluation Studies and Natural Resource Management

This section presents a review of impact evaluation analyses that have relied on "good practices", i.e., where impact has been estimated by comparing beneficiaries with a proper control group. Although there is a sizable amount of research illustrating the impact of agricultural growth on poverty reduction, the literature on the impact of different interventions, including technology transfer, is rather limited. Recently, more impact evaluations have been completed, although only a few can be considered as rigorous. A meta-analysis by Del Carpio and Maredia (2011) examined 286 evaluation projects. Only 86 of these projects use a counterfactual group to measure the effects of the interventions, which was a requirement for inclusion in the meta-analysis. However, a shortcoming of the subgroup of 86 studies is that only two of them examined the internal rate of return (IRR) or net present value (NPV) of the program. Moreover, of the 86 only 12 focused on NRM.

Among the few available impact evaluations of NRM initiatives, Dalton et al. (2011) assessed the project "Improving the Sustainability of Cassava-based Cropping Systems in Asia" between 1994 and 2003. The project activities had a significant impact on the adoption of soil management technologies. The IRR reported is 41.2% for the implementation period and 49.2% for the following five years. A similar IRR is reported by Cocchi and Bravo-Ureta (2007), who evaluated the Environmental Program of El Salvador (PAES). The authors examined the effects of the adoption of conservation technologies and output diversification on farm income. The estimated NPV was $13,674,100 with a discount rate of 12%, while the IRR was 48.5%. These results suggest that the soil conservation practices and crop diversification implemented had a high payoff at both the farm and program levels.

Dey, Paraguas, Kambewa, and Pemsl (2010) carried out an impact evaluation of a 15-year program run by The WorldFish Center and its national and international partners in Malawi. The study assessed the effects of a technology transfer model based on the integration of aquaculture and agriculture (IAA), and the welfare effects on farm households. These authors collected survey data in 2004 for both adopting and non-adopting (counterfactual) farmers. Several methods were used to estimate the different effects of the program, and the main effects were: i) Total factor productivity of IAA adopters exceeded those of non-adopters by 11%; and ii) Net farm income of IAA adopters exceeded those of non-adopters by 62%.

More recently, Bravo-Ureta et al. (2011) evaluated the impact of Module 3 in Component II of the MARENA Program in Honduras. The aim was to determine the impact of the program on farm income as well as the IRR. This study used panel data for 109 participants and 262 non-participants (control group). The researchers used propensity score matching techniques and difference-in-difference methods to deal with possible biases. The increases in incomes attributable to MARENA ranged from US$263 to US$331 per beneficiary household, which generated an IRR of 49%.

Cavatassi et al. (2011) examined the impact of linking smallholder potato farmers to high-value markets while working with Plataformas de Concertación in Ecuador. The authors found positive effects on household welfare and these results were achieved without a significant increase in the use of agrochemicals. Bravo-Ureta, Greene, and Solís, (2012) reexamined the MARENA Program in Honduras by combining propensity score matching with stochastic frontier models.

These authors found that the technical efficiency level in the treatment group was higher than in the control group and that selectivity bias was an issue.

A key contribution of our study is to provide a detailed impact evaluation using different methodologies of a sizeable NRM program while also accounting for spillover effects and examining the internal rate of return under various alternative situations. The IRR is often neglected in impact evaluations (Del Carpio and Maredia 2011) even though policy makers require such analysis when assessing the contributions of development projects. Therefore, this study adds to the limited literature on impact evaluation of natural resource management programs and the link to farmers' well-being in Central America.

3.2 Analytical Framework and Data

3.2.1 Analytical Framework

Impact evaluations can be conducted through a randomized design where the treated and control groups are assigned before the intervention to ensure that, on average, both groups have the same characteristics in terms of observable and non-observable variables (Angrist and Pischke 2009; Duflo, Glennerster, and Kremer 2007; Gertler et al. 2011; Khandker et al. 2010; Ravallion 2005, 2008). In cases where there is neither an experimental design nor a baseline, as is the case with *POSAF-II*, an alternative is to use quasi-experimental methods (Hirano and Imbens 2001; Khandker et al. 2010; Mendola 2007). In studies that rely on quasi-experimental methods, careful attention is needed to deal with possible biases stemming from observable and non-observable variables. If one can assume that the source of bias comes only from observable variables, then PSM provides a relatively simple way to mitigate such biases (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002). To implement this approach, it is necessary to have a set of covariates associated with the eligibility requirements and other time invariant variables that are not affected by the intervention. In addition, endline data for a suitable sample of beneficiaries and non-beneficiaries is also required (Khandker et al. 2010). PSM makes it possible to construct statistically a group of non-treated or control units, which is very similar to a group of treated or participating units. This is typically accomplished using a Logit or Probit model to estimate the probability of participating in the program (B = 1) conditioned on a set of observable variables (X) and this can be expressed as (Khandker et al. 2010):

$$P(X) = \Pr(B = 1|X) \tag{1}$$

The model makes it possible to calculate propensity scores and then match beneficiaries and control groups based on these scores or probabilities. There is a fairly extensive menu of matching criteria, and in this paper we use 1-to-1 nearest neighbor (NN) without replacement. This matching method has a straightforward interpretation and applies the matching based on the common support assumption (Caliendo & Kopeinig, 2008). In addition, it is good practice to apply alternative matching criteria to examine the robustness of the results (Cavatassi et al., 2011; Khandker et al., 2010) and to this end we use the Genetic Matching method. This method is a generalization of the Mahalanobis metric that includes an additional weight matrix to find the particular measure that optimizes post-matching covariate balance (Diamond and Sekhon 2013).

After matching, the effect of the program is equal to the average difference of the outcome indicator(s) between the beneficiary and the control group. This difference, known as the Average Treatment Effect (ATE), can be expressed as:

$$\alpha = E(Y_{Bi} - Y_{Ci} \,|\, \Pr(X), B = 1) \tag{2}$$

where Y_{Bi} and Y_{Ci} represent the value of the pertinent indicator, total value of agricultural production (TVAP) in this study, for beneficiaries (*B*) and the control group (*C*), respectively.

A second approach to evaluate the impact is a standard OLS regression, where the program's impact on the outcome variable Yi is determined by the following equation:

$$Y_1 = \alpha_0 + \alpha_1 B_i + \sum \gamma_i X_{ij} + \varepsilon_i \tag{3}$$

where α_1 measures the average treatment effect of the Program, Bi = 1 if households participate and 0 otherwise, γ_i are the parameters to be estimated associated with covariates Xij, and εi is the typical error term. A problem with this simple approach is that the Bi indicator of participation is likely to be correlated with the error term, which would yield biased estimates (Angrist and Pischke 2009).

Thus, in addition to OLS, equation (3) can be estimated using weighted least squares (WLS) where the weights are based on the propensity scores obtained from the PSM. This approach was introduced by Hirano and Imbens (2001) and has been used by Todd, Winters, and Hertz (2010) and Cavatassi et al. (2011), among others. An advantage of WLS is that it mitigates biases from observables while making use of all the observations available including those that fall outside the area of common support. This method is implemented as follows: a) Propensity scores (PS) are estimated using a Logit or a Probit model; b) Yi and Xij are weighted by 1/PS(X) for beneficiaries and 1/(1-PS(X)) for controls; and c) Equation (3) is estimated using OLS and the weighted data (Khandker et al. 2010).

Again the estimates from equation (3), although superior to those obtained from the conventional OLS model, would be biased if program participation is correlated with unobservables captured in the error term. To address this endogeneity problem and thus ensure that the estimated impact of POSAF-II is not biased due to unobservables, an instrumental variable (IV) approach is implemented. This method requires finding an instrument Z, which is related to participation in POSAF-II but not correlated with the error term, i.e., cov (Z, ε) = 0. Following Cavatassi et al. (2011) and Khandker et al. (2010), we use 'Intention to Treat' (ITT) as an instrument. This method is appropriate given that "ITT analysis captures the causal effect of being assigned to the treatment" (Angrist & Pischke, 2015, p.119). ITT relies on the fact that some of those assigned to be treated chose not to receive the treatment. Before using ITT as an instrument, we conduct a Hausman and a Durbin-Wu-Hausman tests for exogenous regressors (Khandker et al. 2010).

The IV approach entails a two stage procedure as follows:

$$Stage\ 1\colon B_i = \rho Z_i + \sum \phi_j X_{ij} + \nu_i \tag{4}$$

$$Stage\ 2\colon Y_i = \lambda_0 + \lambda_1 \hat{B}_i + \sum \delta_j X_{ij} + \mu_i \tag{5}$$

In the first stage (equation 4), the instrument Zi is introduced in an equation that explains the participation in POSAF-II (Bi). In the second stage, the Bi variable is replaced by the predicted participation in POSAF-II ($\hat{B}_i$) obtained in the first stage. This model is then estimated to obtain the measure of impact given by λ_1 in equation (5). All Greek characters (i.e., ρ, ϕ, λ and δ) are the parameters to be estimated.

Once the impact of POSAF-II has been estimated, these results are used to calculate the Program's IRR. The IRR is equal to the interest rate that yields a net present value (NPV) equal to zero or:

$$NPV = \sum_{n=0}^{N} \frac{C_n}{(1+r)^n} = 0 \tag{6}$$

where r is the IRR to be calculated; Cn is the incremental net cash flow of the program in period n; and N represents the total number of periods (years). The IRR for POSAF-II is calculated assuming a 15 year time horizon, spanning from 2003 to 2018, and 2003 is considered as year zero.

3.2.2 Data

POSAF-II started at the end of 2003 and ended at the end of 2007 resulting in a 4-year implementation period. The data for the impact evaluation was collected in 2012 reflecting information for the 2011 agricultural year. The data use in this evaluation was collected four years after the implementation ended which made it possible for beneficiaries to derive benefits attributable to *POSAF-II*.

The data collection procedure followed two-stages similar to the approach used by Cavatassi et al. (2011). In the first stage, PSM was used to match treatment and control communities. Information regarding treated communities was obtained from the monitoring and evaluation system implemented by POSAF-II, known as SIMOSE (Sistema de Monitoreo y Seguimiento). The list of control communities was based on the National Water Resources Plan for Basins, Sub-basins, and Micro-basins, obtained from the Ministry of the Environment and Natural Resources. The matching at the community level was conditional on agro-ecological characteristics including: altitude (ALT); temperature (TEMP); precipitation (PRECI); and short-term-drought or canículas (STD). These variables, defined in Table 3.1, were selected based on data availability as well as on information obtained from local experts and POSAF-II personnel who considered such variables as critical in matching communities consistent with the technologies offered.

Table 3.1. Definition of variables

Variable	Unit	Definition
TVAP	US$/hectare	Total value of agricultural production
BENE	Dummy	1 if the household is a beneficiary of *POSAF-II*
CONI	Dummy	1 if the household is a non-beneficiary of *POSAF-II* and lives in a treatment community
CONO	Dummy	1 if the household is a non-beneficiary of *POSAF-II* and lives in a non-treated community
AGE	Years	Age of the household head
EDUC	Years	Years of schooling of the household head
NET	Dummy	1 if the farmer is a member of an organization focused on social activities or agricultural production
LAND	Hectares	Total land devoted to agricultural production
DIST	Kilometers	Plot distance to main town
ALT	Meters	Meters above sea level
PAVE	Dummy	1 if the farm is located next to a paved road
ACCE	Dummy	1 if the farm is accessible all year
TEMP	Celsius	Average temperature in the region
PRECI	Millimeters	Annual precipitation
STD	Days	Number of drought days during a raining season
COST	US$	Variable production costs, excluding labor
FLABOR	US$	Total value of family labor
LABOR	US$	Total value of hired labor expense

The Logit model used to match communities can be written as:

$$\text{COMU} = f\,(\text{ALT, TEMP, PRECI, STD}) + \text{error term} \tag{7}$$

where COMU is equal to 1 for POSAF-II communities and 0 for control communities. The results of the Logit model were used to match the communities based on the 1-to-1 nearest-neighbor (NN) criterion. The range of propensity scores for the beneficiary communities goes from 0.11 to 0.99 and for the control group from 0.05 to 0.93. Therefore, the area of common support ranges from 0.11 to 0.93 and, after matching, 618 communities (309 treated and 309 control communities) were selected. From this total of 309 pairs, 106 pairs were randomly chosen using the RAND procedure of SQL. The quality of this final selection was evaluated and deemed appropriate by a local panel of experts.

Table 3.2 shows the mean and standard deviation of the pre-treatment variables included in the community level Logit model. The predicted probabilities show that communities located at higher altitudes, with higher temperatures, and lingering short-term-drought periods were less likely to be selected for program implementation. In addition, those communities with higher precipitation were more likely to receive the program. Among those characteristics, the parameters for ALT and PRECI are statistically significant, which is consistent with the program implementation criteria (IDB 2001). Furthermore, at the 1% level of significance, the null hypothesis that all parameters are jointly equal to zero is rejected.

Table 3.2. Logit model of *POSAF-II* participation

Variable	Mean	Std.	Coefficient	S.E.
ALT	721.9	302.2	-0.003 [a]	0.001
TEMP	22.7	2.8	-0.017	0.054
PRECI	1251.1	250.1	0.002 [a]	0.000
STD	23.8	21.8	-0.008	0.006
Constant			0.796	1.438
Log likelihood				*-471.7*
LR $chi^2(4)$				*125.5* [a]
N				*797*

a = significant at the 1%

In the second stage of the data collection process, SIMOSE was used to create a list including all beneficiaries of POSAF-II and a group of eligible non-beneficiaries located in the 106 treated communities selected in the first stage. Hereafter, the beneficiaries6 are referred to as BENE, and

[6] We only have data for 2011, four years after the program ended, and adoption rates at that time were 91%, 90% and 85% for SAGF, SFOR, and SMIX, respectively. In addition, 36% of the beneficiaries remained fully engaged with the technologies adopted with support from the Program and 63% were using some of the technologies prescribed or had made some modifications. In the

the non-treated in beneficiary communities as CONI for control in. An additional control group was generated from the 106 matched non-treated communities, hereafter referred to as CONO for control out. As will be discussed in more detailed below, having controls outside the program allows for the examination of spillover effects, i.e. whether untreated farmers located in treated communities received indirect benefits by interacting with neighboring beneficiaries (Angelucci & De Giorgi, 2009). These potential spillover effects can be a significant benefit derived from a project and are thus important to quantify. Moreover, this type of design, as alluded to earlier, makes it possible to define the ITT instrument.

Once the sampling frame was defined, households from each group were randomly selected. Following the procedures in Wassenich (2007), the final sample size for beneficiaries was 257, 327 and 288 for SAGF, SFOR and SMIX, respectively. The same sample size was defined for the control group for SAGF and SFOR. Since SMIX is a combination of SAGF and SFOR, no additional data was collected and the matching is done using all SAGF and SFOR observations. Given that some observations are lost because of the lack of common support, it is good practice to increase the sample size ahead of time in order to avoid the need to find replacements while in the field, which can be a difficult task. Thus, the final sample contains a total of 1,483 farmers (842 BENE, 318 CONI, and 323 CONO), which represents 98.7% of the sample size calculated originally. The subgroups under each grouping are as follows: BENE (239 SAGF, 309 SFOR, and 294 SMIX), CONI (318), CONO (216 Agroforestry and 107 Forestry). In Section 5 below, we describe the matching undertaken at the farmer level.

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case of CONI, a farmer was considered to be an adopter if he/she was using at least one of the POSAF-II practices implemented by neighboring beneficiaries.

3.2.3 Descriptive analysis

As aforementioned, the impact of POSAF-II is analyzed separately for the three production systems SAGF, SFOR, and SMIX. Table 3.3 presents descriptive statistics for all variables for each system. The BENE group for each system is compared with the corresponding control group to determine whether the means under analysis are the same. The comparisons reveal no difference in means indicating that the counterfactual groups are appropriate. On average, the TVAP of BENE is higher for the three systems (SAGF $1,045, SFOR $1,041, SMIX $1,754) compared to the respective controls; however, the difference is not statistically significant for SMIX. Another variable to note is *LAND*, which refers to the area used for agricultural production. For the SAGF group, BENE and CONO have similar farm sizes, with 15.8 and 14.9 hectares, respectively. Similarly, average farm size is equal for BENE and CONO in SFOR; hence, these groups are comparable.

POSAF-II beneficiaries share most of the characteristics of the control farmers. As would be expected, the t-tests show statistically significant differences among variables affected by the program's implementation, such as TVAP. An exception is COST, which does not exhibit any statistical difference between treated and controls for SAGF (BENE $520, CONI $825, CONO $754) and for SMIX (BENE $1176, CONI $865, CONO $800). In SFOR, BENE is statistically different from the control groups (CONI $799, and CONO $580); however, the mean value ($489) is lower than those in the comparison groups. Even though the program required that beneficiaries worked in the implementation of the various technologies, the cost variable does not display higher means for any of the systems. In addition, EDUC, and NET in the treatment group are not statistically different from CONI and CONO; hence, as already indicated, this analysis shows that we have been able to define a suitable counterfactual situation based on observables. The variable

EDUC ranges from 4.2 to 4.9 years of schooling for SAGF, 4.3 to 5.2 years for SFOR, and 4.6 to 5.9 years for SMIX.

Annual precipitation is between 1,285 to 1,314 millimeters for SAGF, and between 1,281 to 1,304 millimeters for SFOR, indicating that both treatment and control received nearly the same amount of rain. For SMIX, TEMP is slightly higher for BENE than for CONI, but is equal to CONO, which is the main comparison group. The mean values for STD across treatment and control groups are very similar among systems. Again, comparisons based on these variables indicate that we have a reasonable counterfactual.

Table 3.3. Descriptive statistics for variables included in the analysis by system before matching

	Agroforestry (SAGF)				Forestry (SFOR)				Mixed (SMIX)			
Variable	BENE	CONI	CONO	CON	BENE	CONI	CONO	CON	BENE	CONI	CONO	CON
TVAP	1044.7 [a,b,c]	878.5 [c]	792.2	838.9	1040.8 [a,b,d]	613.0 [c]	503.4	580.8	1753.8	1202.8	1365.6	1268.6
AGE	53.5 [a,b,c]	42.3[c]	49.9	45.8	54.7 [a,b,d]	42.6 [c]	50.4	54.7	51.9 [a,c]	42.6 [c]	51.0	46.0
EDUC	4.2	4.3	4.9	4.6	4.8	4.3	5.2	4.5	4.6 [b]	4.8 [c]	5.9	5.0
NET	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
LAND	15.8 [a,c]	6.4 [c]	14.9	10.3	24.4 [a,d]	6.9 [c]	26.5	12.7	10.3 [d,b]	6.6 [c]	29	15.7
DIST	44.1[a,b,c]	37.5 [c]	27.4	32.9	42.8 [b,d]	42.3 [c]	24.4	37.2	30.7 [b]	36.1[c]	24.1	31.3
ALT	492.9 [b,d]	557.0 [c]	752.9	492.9	524.7 [b,c]	563.2 [c]	696.2	602.3	642.3 [a,b]	564.3 [c]	731.1	631.9
PAVE	0.3 [b,d]	0.3 [c]	0.5	0.4	0.3	0.3	0.3	0.3	0.1 [a,b,d]	0.3	0.3	0.3
ACCE	0.6 [b,c]	0.6 [c]	0.7	0.7	0.6	0.6	0.6	0.6	0.7	0.6	0.7	0.7
TEMP	24.0 [b,c]	23.6 [c]	22.5	23.0	23.7 [b,d]	23.6 [c]	22.4	23.2	23.0 [b]	23.6 [c]	22.3	23.1
PRECI	1284.5	1314.1	1286.3	1284.5	1280.5	1289.6	1303.9	1293.8	1349.5	1330.4	1300.1	1318.1
STD	23.6	20.3	23.4	23.6	21.7	18.6	27.7 [c]	21.3	19.9 [b]	19.8 [c]	26.8	22.6
COST	520.0	825.2	753.8	792.5	488.6 [a,b,d]	799.4	580.3	735.0	1176.0	865.2	799.7	833.4
FLABOR	127.9 [a,b]	171.0 [c]	82.4	127.9	82.7 [a,c]	161.9 [c]	84.8	139.2	155.4 [b]	175.0 [c]	71.1	133.0
LABOR	368.3 [a,b]	688.2 [c]	458.9	438.8 [a,b]	664.1 [c]	573.2	877.8 [a,b]	766.9 [c]	599.9	368.3 [a,b]	688.2 [c]	458.9

"a" the difference between the mean of BENE and CONI is statistically significant at least at the 10% level
"b" the difference between the mean of BENE and CONO is statistically significant at least at the 10% level
"c" the difference between the mean of CONO and CONI is statistically significant at least at the 10% level
“d” the difference between the mean of BENE and CON is statistically significant at least at the 10% level

3.3 Results and Discussion

3.3.1 Matching beneficiaries with control farmers

As discussed earlier, the first stage in defining the samples was to match treatment and control communities. Now we proceed to match farmers for each of the three systems SAGF, SFOR, and SMIX. Three Logit models, one for each system, are estimated to determine the probability of being a POSAF-II beneficiary. In each Logit model, the dependent variable is equal to 1 for BENE, and zero for controls, CONI and CONO.

As depicted in Table 3.4, some of the parameters for the Logit model differ across systems; namely, the parameter for EDUC is positive and significant for SFOR which indicates that more educated farmers signed up for these technologies; however, this parameter is not statistically significant for SAGF and SMIX. Land has a positive and significant effect on the participation in SFOR and a negative and significant effect on SMIX, which indicates that farmers with larger farms were more likely to participate in forestry activities. This is consistent with the idea that forestry is more appealing to larger operators who are likely to have other sources of income and thus can withstand the years that are required to enjoy the income flows from the harvest of trees. In contrast, small farms are more income constrained and need to see returns in a shorter time period. Other covariates relate to agro-ecological conditions, such as PRECI, ALT, STD, and TEMP. Farmers located in areas with higher levels of precipitation are less likely to be SFOR beneficiaries. The parameter for PRECI has a negative effect on SMIX and SAGF but is not statistically significant. Farms located at higher elevations are less likely to participate in both SAGF and SFOR. These signs are as expected given that agricultural activities in these locations are less common due to lack of adequate infrastructure. The results for short-term-drought are similar, while the respective parameters for SMIX are not significant. The percentage of correct predictions for being a beneficiary of POSAF-II is 70.4%, 66.7%, and 66.4% for farmers in SAGF, SFOR and SMIX, respectively. Furthermore, chi-squares of 118.8, 118.9, and 84.0 with 11 degrees of freedom and p-values lower than 0.001 indicate that the parameters in all three models are jointly significantly different from zero. In sum, the statistical results shown in Table 3.4 suggest that the models are appropriate to explain the participation in the program.

In order to check the common support condition, we provide a graphical balance check with the kernel density estimates of the estimated propensity scores of treatment and control groups for each system (Figure 3.2). The results show that most of the propensity scores estimated for the BENE and both control groups fall within the common support area for the three systems. We then use the nearest neighbor 1-to-1 matching method and check the balancing property between the control and treatment groups using t-tests (Table 3.A.1 – 3.A.3) and some of the results are inconclusive (Caliendo and Kopeinig 2008). Consequently, as suggested by Sekhon (2011), we also ran a bootstrapped Kolmogorov-Smirnov test (KS) following Abadie (2002) and the analysis of differences in means shows that matching significantly improved the covariate balance for both SAGF and SFOR implying that beneficiaries and controls are not statistically different. Even though the matching process improves the covariate balance in all cases, the mean values for two variables for SMIX remain significantly different. Therefore, in addition to the nearest neighbor 1-to-1 matching method, we use genetic matching following Diamond and Sekhon (2013) to check the robustness of the matching process. The genetic matching does not improve the covariate balance since the nearest-neighbor 1-to-1 has a smaller KS test statistic with p-values lower than 0.01. However, both matching techniques produce similar p-values for the difference in means. In sum, the t-tests for the three systems show that based on observable characteristics the control groups represent a good counterfactual.

Table 3.4. Logit model of POSAF-II participation used to match farmers

Variables	SAGF		SFOR		SMIX	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
AGE	0.018 [a]	0.004	0.033 [a]	0.004	0.019 [a]	0.004
EDUC	-0.008	0.015	0.039 [b]	0.013	0.008	0.012
NET	0.198	0.157	0.005	0.136	0.181	0.129
LAND	0.003	0.002	0.003 [c]	0.001	-0.006 [c]	0.002
DIST	0.012 [a]	0.003	0.008 [a]	0.001	0.001	0.002
ALT	-0.012 [a]	0.003	-0.000 [c]	0.000	0.000	0.000
PAVE	-0.199	0.159	-0.175	0.126	-0.811 [a]	0.134
ACCE	-0.036	0.152	0.255 [c]	0.126	0.224 [c]	0.127
TEMP	-0.017	0.054	0.083	0.049	0.046	0.040
PRECI	-0.001	0.000	-0.001 [c]	0.000	-0.000	0.000
STD	-0.022 [a]	0.005	-0.014 [b]	0.004	-0.005	0.004
Constant	1.258	1.437	-2.849	1.374	-2.020 [c]	1.069
Total observations		680		643		669
BENE		239		289		293
CON		441		354		376
Log likelihood		-289.3		-397.8		-416.6
LR $chi^2(11)$		118.8 [a]		118.9 [a]		84.0 [a]
Pseudo R^2		0.17		0.13		0.09
Correctly classified		70.4%		66.7%		66.4%

a = significant at the 1%, b = significant at the 5% and c = significant at the 10%

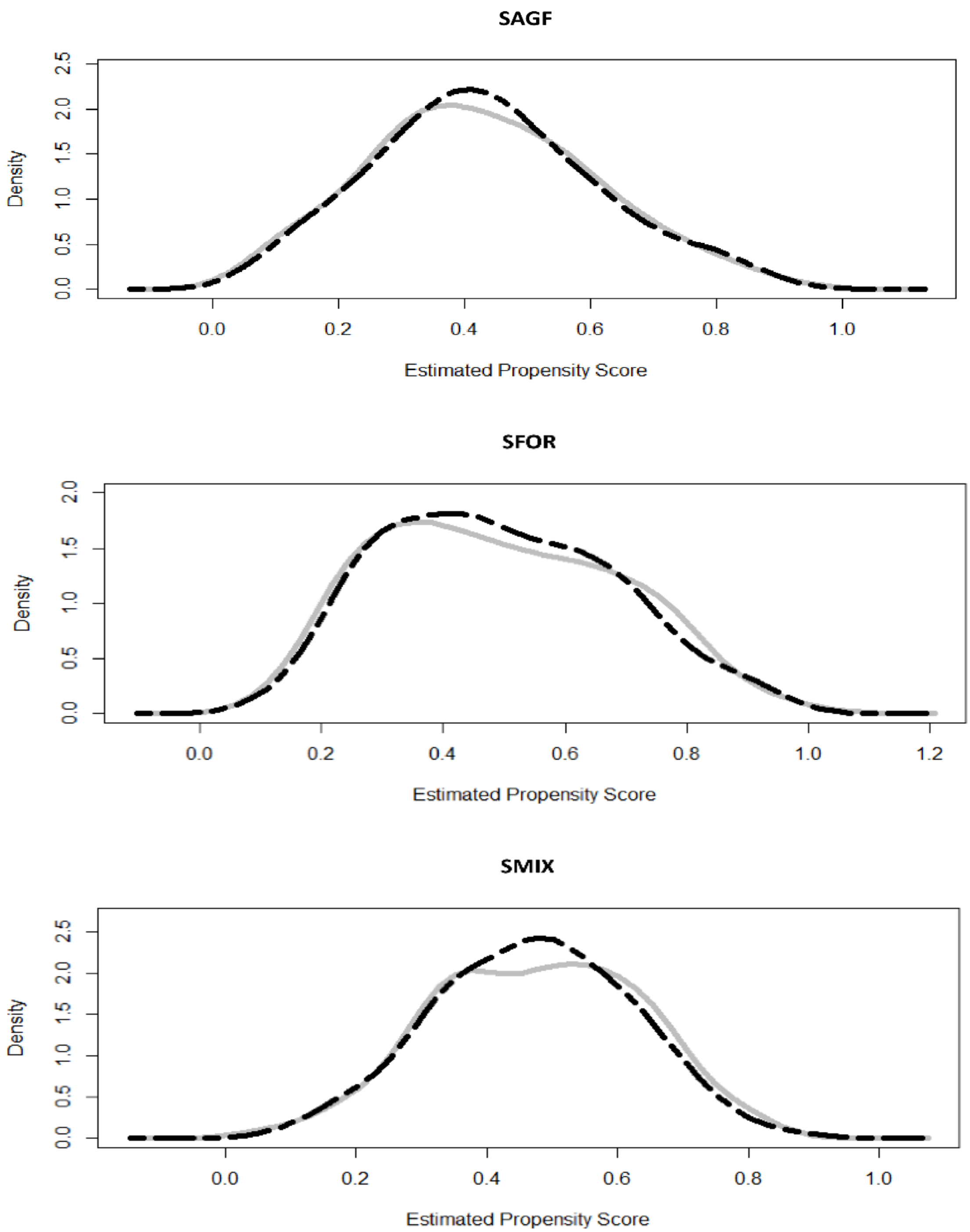

Figure 3.2 Kernel distribution of propensity scores for BENE (broken black line) and corresponding control groups (continuous gray line).

3.3.2 Impact on farmer incomes

The economic impact of POSAF-II is examined based on four alternative estimation techniques, PSM, OLS, WLS and IV. The indicator of impact is the TVAP for each of the three systems. All of the estimated models represent production functions where the dependent variable is expressed in monetary values. The total value of agricultural production (TVAP) is measured in US dollars, is equal to the sum of the value of the different outputs produced by each farm using average prices reported by the farmers surveyed to conduct the study. The key point is to value all production including what the household consumes and what is sold in the market. This kind of indicator is often used in impact evaluations in agriculture (e.g., Bravo-Ureta et al., 2011; Cavatassi et al., 2011; Kassie et al., 2008; Yorobe et al., 2016). To conserve space, Table 3.5 only presents the key parameters concerning the estimated impact of POSAF-II on the TVAP for SAGF, SFOR, and SMIX. The *F*-statistics for the three regression models for each system are significant at the 1% level; therefore, the joint hypothesis that all coefficients are equal to zero in each model is rejected.

Our estimates show consistently that POSAF-II has a positive and significant effect on the TVAP of beneficiaries relative to controls for SAGF and SFOR based on all four procedures used, i.e., PSM, OLS, WLS and IV. In contrast, the results for SMIX are positive but not significant for the PSM and OLS models, and negative but also not significant for the WLS and IV models. The average increase in TVAP attributable to POSAF-II for SAGF farmers is US$330 (PSM), US$343 (OLS), US$695 (WLS) and US$1058 (IV). For SFOR, the average impact of POSAF-II on TVAP is US$23, US$604, US$650 and US$913 for PSM, OLS, WLS, and IV models, respectively. As indicated earlier, SMIX farmers use some of the technologies included in SAGF and SFOR for silvopastoral production systems. Such systems are known for their high level of complexity, a relatively long time to recover the investment, and rather high farmer skills and technical assistance requirements (Calle, 2008; Calle, Montagnini, & Zuluaga, 2009). For these reasons, to perform well, silvopastoral systems need to be complemented by participatory research, training, payments for environmental services and policies to strengthen the livestock sector (Calle et al. 2013; Murgueitio et al. 2011; Pagiola et al. 2007). Another challenge of silvopastoral systems is the identification of the optimal time to measure outcomes as well as the quantification of associated benefits (Thornton and Herrero 2001). Moreover, Pagiola et al. (2007) find that the sustainable adoption of silvopastoral systems in Nicaragua is associated with long-term support payments to farmers. Hence, our findings for SMIX are consistent with the difficulties reported in the literature concerning the successful adoption of silvopastoral systems in Central and South America.

As mentioned previously, PSM deals with biases that stem from observable characteristics. However, it is possible that there are biases from unobservables and to deal with this we use the IV approach as an alternative estimation method. To check the validity of the intention to treat or ITT as an instrument, we use a weak instrument test (Angrist and Pischke 2009) and reject the null hypothesis of a weak instrument with an F-statistics larger than the rule of thumb of 10, which means that ITT is a valid instrument. Subsequently, we use a modification of the Hausman test (Khandker et al., 2010) to check whether participation in POSAF-II is exogenous and the results confirm exogeneity. Hence, there should be no difference between the OLS and IV coefficients, while OLS guarantees a higher efficiency in the estimates (Greene 2007). Moreover, Wooldridge (2002) argues that a correctly specified WLS leads to more efficient estimates than OLS and this makes the former the more desirable method of the four considered here. It is worth noting that Cavatassi et al. (2011) also concluded that the WLS approach was the best method in the impact evaluation of the *Plataformas* program in Ecuador.

Table 3.5. Impact of POSAF-II on SAGF, SFOR, and SMIX

Models	PSM[a]	OLS	WLS	IV
Agroforestry System (SAGF)				
POSAF-II	330.32** (130.1)	342.78*** (131.4)	695.03*** (233.8)	1057.96*** (331.5)
N	478	680	680	680
F(Chi^2)		2.75***	2.52***	4.02***
R^2		0.08	0.11	0.06
Forestry System (SFOR)				
POSAF-II	23.19* (15.3)	603.62*** (204.7)	650.36*** (162.4)	912.92*** (336.9)
N	578	643	643	643
F(Chi^2)		3.04***	2.82***	1.76***
R^2		0.05	0.07	0.05
Mix System (SMIX)				
POSAF-II	215.83 (279.8)	177.93 (247.6)	-61.50 (119.6)	-136.93 (478.7)
N	586	669	669	669
F(Chi^2)		17.90***	9.45***	41.97***
R^2		0.47	0.25	0.46

Robust standard errors for OLS and WLS, standard errors for IV in parenthesis.
[a] Values in parenthesis. Bootstrap with 1000 replications is used to estimate the standard errors. * p<0.10; ** p<0.05; *** p<0.01

In the previous estimations (Table 3.5), the counterfactual group includes all control farmers, i.e., both CONI and CONO. To examine the possible presence of spillover effects, we now compare the BENE with the CONO groups and the results, presented in Panel-A of Table3.6, show that the parameters are positive and statistically significant. These results reveal that the impact of

POSAF-II on TVAP is US$852 and US$938 for SGAF and SFOR, respectively, and both are higher than the estimates obtained when all controls (CONO) are used. The parameters for SMIX are again negative but not significant, and these results are in line with the previous findings. To further examine the effect of POSAF-II on the beneficiary communities, we re-estimate the models contrasting the CONO vs. the CONI groups. Panel-B of Table 3.6 shows that the average TVAP for control farmers in treated communities is US$425 (SAGF) and US$302 (SFOR) higher than their counterparts in the non-treated communities. These results are evidence of significantly positive spillover effects on farmers living in proximity to the treated groups.

According to Knowler and Bradshaw (2007), the adoption of NRM technologies in agriculture is correlated with individual motivation, household structure, and agro-ecological characteristics. Among the BENE and CONI groups, the latter characteristics are similar so knowledge diffusion is likely to occur. Another possible explanation behind these spillover effects is the level of complexity of the technology. Greiner and Gregg (2011) suggest that the adoption of conservation practices is motived by the technological characteristics of the practices. POSAF-II delivered some technologies with a relatively low level of complexity and considerable positive effects on production such as fencing, contour plowing, high-quality fruit trees, banana plants with sanitary treatment, and forest trees. Pannell et al. (2006) discuss additional characteristics that facilitate the adoption of new technologies including low short-term input and adjustment costs, significant impact on profits in the medium and long term, and a positive impact of the new technologies on other elements of the farming system. Some technologies offered by POSAF-II meet these characteristics, in particular, terracing, natural fertilizers, ditching, and slope correction.

Table 3.6. Spillover effect of POSAF-II on the three systems

	SAGF	SFOR	SMIX
	WLS	WLS	WLS
Panel A.			
BENE vs. CONO	852.5**	938.4***	-226.2
	(368.5)	(282.1)	(160.6)
N	364	354	420
R^2	0.09	0.10	0.32
Panel B.			
CONI vs. CONO	425.2*	301.6**	-25.0
	(285.9)	(133.8)	(199.9)
N	441	330	420
R^2	0.09	0.14	0.51

Robust standard errors in parenthesis * p<0.10; ** p<0.05; *** p<0.01

3.3.3 Is POSAF-II *a good investment?*

We start this section by explaining the calculation of the cash flows necessary for the analysis of the IRR of the Program, which is a commonly used economic indicator in project analysis (Blank and Tarquin 2005). These calculations require the projection of relevant inflows and outflows over the period of analysis, assumed to be 15 years. The annual inflows for SAGF and SFOR along with the inflows for the Program are obtained from the results of the WLS regressions shown in Table 3.5. These inflows are assumed to remain constant overtime. We do not calculate the IRR for SMIX separately given that TVAP gains for this system are not significant. However, all three systems are incorporated in the analysis at the Program level. The annual inflow is equal to the average farm size per system times the annual income gain times the number of beneficiaries, as presented in Tables 3.A.4-1 to 3.A.4-4. Thus, the incremental cash flows account for the incorporation of new beneficiaries in the earlier years of the analysis starting with 2004 (year 1 in the 15 year period of analysis) reaching a steady state of 13,477 members in 2007 (year 4 in the 15 year period).

The calculation of the outflows assumes that to maintain the annual benefits derived by beneficiaries from the POSAF-II technologies several expenses (outflows) are needed including:

maintenance cost; labor and material expenses associated with hoeing, fertilization, crop protection, tree pruning and replanting; and miscellaneous items. This type of data is usually not available which explains why IRR or NPV analyses are rarely included in impact evaluations (Del Carpio and Maredia 2011). Fortunately, the data needed to generate the outflows is available for POSAF-II primarily for two reasons. First, the data used to undertake the initial impact evaluation of the project was collected in 2012, four years after the implementation was completed, which gave farmers sufficient time to implement the various technologies adopted through POSAF-II and to get a good idea of the associated inflows and outflows (Bravo-Ureta 2012). Second, a consortium of consulting firms (F7-Consult, ENSOME, ViSKon Aps 2012) was hired by MARENA in 2012 to collect specific data on the productivity of various technologies along with the associated expenses listed above. The Consortium generated information based on both a workshop with farmers and a survey encompassing 92 producers from 27 communities and nine different municipalities. These communities are a sample of those used in the initial matching implemented to identify the farms to be interviewed, so the associated data is representative of POSAF-II beneficiaries constituting a good basis to generate the cash flows required to examine the IRR of the Program.

Based on the available information on inflows and outflows, we developed two baseline scenarios: 1) Baseline-1 (Tables 3.A.4-1 to 3.A.4-4) where we use the WLS results; and 2) Baseline-2 where we add spillover effects presented at the top of Table3.6 (i.e., the difference between BENE and CONI) assuming that one beneficiary affects one neighboring control. As we show in Table 3.7, the IRR for Baseline-1 is 62% for SAGF and 65% for SFOR, and 35% for the Program as a whole. This suggests that the impact of POSAF-II on SAGF and SFOR farmers is sufficiently high to compensate for the lack of impact of SMIX. The introduction of spillover effects in Baseline-2 yielded an IRR equal to 85%, 83% and 53% for SAGF, SFOR and POSAF-II, respectively. These results indicate that spillover effects can have a major impact, which confirm the importance of including such flows in the analysis of projects (Angelucci and De Giorgi 2009).

3.3.4 Sensitivity and risk analyses

In order to check the robustness of the IRR results, we undertake both sensitivity and risk analyses. The sensitivity analysis involves changes in individual model parameters to test the impact of such changes on the final results (Iman and Helton 1988). Here we examine four scenarios, the first three without spillover effects and the fourth with. Scenario-1 assumes a reduction of 20% in the number of beneficiaries and this yields an 18% expected IRR for the Program (Table 3.7). Scenario-2 introduces an increase of 20% in maintenance costs and in this case the expected IRR for the Program is 25%. Scenario-3 combines the assumptions of scenarios 1 and 2 and the IRR drops to 8% for the Program. These results show that POSAF-II is more sensitive to changes in the level of beneficiaries than changes in maintenance cost. It is clear that the lack of impact of SMIX imposes a significant burden on the overall economic results of POSAF-II. Scenario-4 introduces spillover effects (Table 3.6) to Scenario-3, and this yields a 30% expected IRR.

The risk analysis is performed by undertaking a micro-simulation exercise using the program @Risk (Palisade Corporation 2016). To conduct the simulations, we use the observed TVAP values for each farmer in a given system. These TVAP values are introduced in the @Risk program to generate alternative statistical distributions, and the program provides an assessment of the most desirable distribution for the data under consideration. We then take the average impact value from the WLS regressions and use the most suitable distribution obtained from @Risk, which is the log-normal, to generate an expected impact value for each farm based on Baseline-1. Once we have these expected values, @Risk is used to run Monte Carlo simulations with 10,000 replications. The results from these simulations are used to calculate the distribution of IRRs for the Program. Table 3.7 shows that, on average, the IRR is equal to 75%. Figures 3.3 and 3.4 show that with 94% confidence the IRR lies between 0% and 82.5%. Furthermore, the simulations results are consistent with those reported by Lutz, Pagiola, and Reiche (1994), and by Cocchi and Bravo-Ureta (2007). These authors evaluate similar NRM programs and obtained expected average IRRs of 40% and 84%, respectively.

Table 3.7. Expected internal rate of return (IRR) of POSAF-II over a 15 year horizon

		SAGF	SFOR	POSAF-II
Baseline-1		62%	65%	35%
Baseline-2		85%	83%	53%
Scenario	1	47%	56%	18%
	2	57%	59%	25%
	3	42%	51%	8%
	4	59%	70%	30%
Simulation	Mean	64%	75%	75%
	Minimum	-30%	-35%	-43%
	Maximum	194%	106%	154%
	IRR< 12%	4%	0.4%	3%

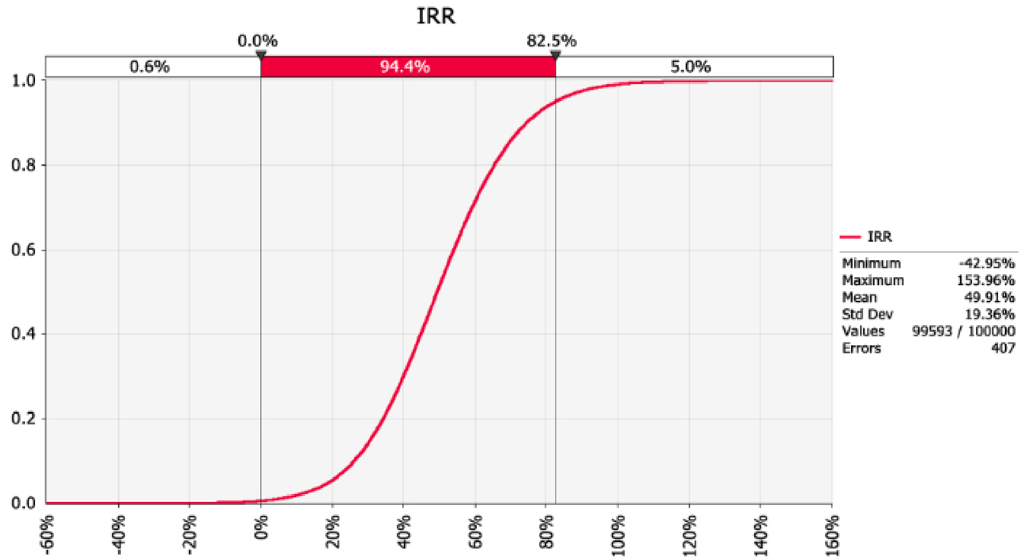

Figure 3.3 Cumulative probability density of the expected IRR for POSAF-II

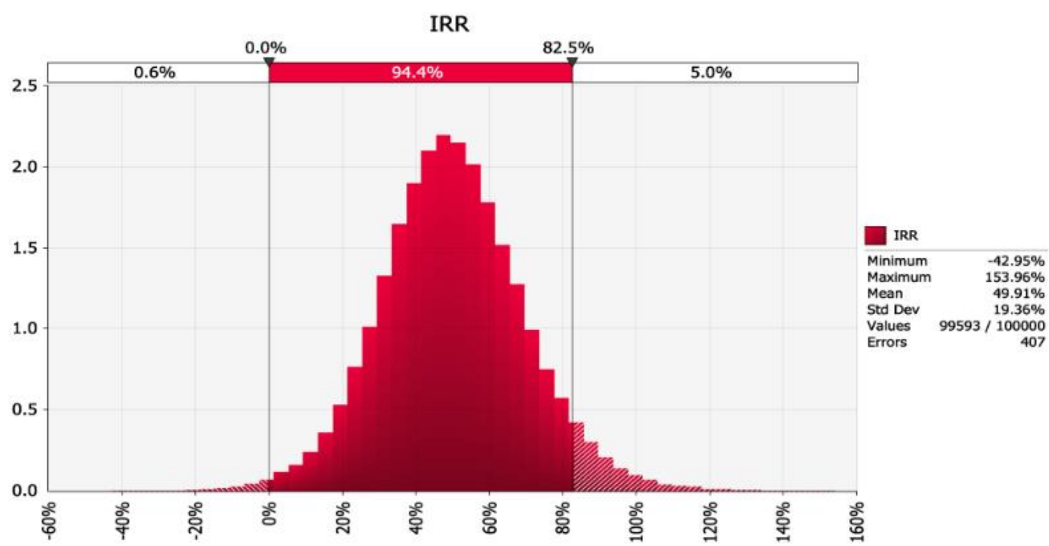

Figure 2.4 Probability density for the expected IRR of POSAF-II

3.4 Summary and conclusions

In this study, we examine the economic impact of POSAF-II, a natural resource management (NRM) program implemented in Nicaragua between 2002 and 2008, on the total value of agricultural production (TVAP) for beneficiaries relative to control farmers. The Program supported small and medium scale producers in improving the use of natural resources, increasing productivity and reducing environmental degradation. The farmers received technologies associated with agroforestry (SAGF), forestry (SFOR), or mixed (SMIX) systems where the latter combined technologies from the first two in the context of silvopastoral production systems. The econometric analysis relies on methodologies designed to reduce biases that stem from both observable and unobservable variables when only cross-sectional (endline) data is available. The methodologies implemented include propensity score matching (PSM), ordinary least squares (OLS), weighted least squares (WLS) and instrumental variables (IV). The motivation behind the use of different methods is to assess the robustness of the analysis. If different methodologies lead to similar outcomes, then the likelihood that results are reliable is high.

The results for SAGF and SFOR indicate that POSAF-II had a positive and significant impact on the beneficiaries attributable to the Program. While the outcomes are consistent across the four methodologies used, the results derived from WLS are the most robust. These results indicate that the impact of POSAF-II on the TVAP of beneficiaries with respect to controls is US$695 for SAGF, US$650 for SFOR, and non-significant for SMIX. Moreover, the analysis clearly suggests that POSAF-II generated an overall increase in the total value of agricultural production of beneficiaries. It is important to underscore that the analysis reported in this study was done from the point of view of the state of Nicaragua since the financial support provided to beneficiaries, the expenses incurred in the provision of the extension services and the opportunity costs of labor contributed by the beneficiaries, were all included as cash outflows.

In addition to the direct impact on beneficiaries, the analysis suggests that POSAF-II had positive spillover effects on non-treated farmers living inside treated communities. To calculate the spill over effect, we first compared beneficiaries vs. control farmers residing outside treated communities. In this case, the impact of POSAF-II on TVAP was US$852 for SGAF and US$938 for SFOR. These estimates are higher than those obtained when beneficiaries are compared with all control farmers. In addition, we compared control individuals inside treated communities with control individuals living outside treated communities and the results revealed average spillover effects per farm equal to US$425 and US$302 for SAGF and SFOR, respectively.

The 35% internal rate of return obtained from a baseline scenario illustrates that investments in NRM technologies like those delivered by POSAF-II for SAGF and SFOR have a positive economic return. It is useful to keep in mind that the analysis was done separately for each of the three NRM systems and not for specific technologies included within each system. Therefore, this analysis does not make it possible to understand the contribution of specific technologies to the economic results; however, it does appear that the combination of technologies for the SAGF and SFOR systems was appropriate. Nevertheless, in formulating similar projects, it would be informative to develop and examine alternative bundling of technologies to see if the performance of recommended systems could be improved. This is a matter that deserves further study.

A lesson derived from this study is the importance of identifying the most suitable time for carrying out an impact evaluation. The bulk of the data available for POSAF-II was collected four years after the program had closed and this is different from the typical case when endline data is collected just before the project is closed. The implication of this typical case is that farmers have very limited time to implement the technologies received so the measured benefits tend to be very low. In contrast, in this study the four years that had elapsed since completion of POSAF-II gave farmers sufficient time to fully adopt the technologies. Ideally, however, one would be able to revisit these farmers 10 or 15 years after closing to be able to fully gauge the accrued benefits and the long term sustainability of the intervention.

Regarding the design of future projects, our analysis suggests that an important feature is the strategy that should be used to deliver agricultural technologies including the length of time that technical assistance should be afforded to farmers to support adoption. POSAF-II provided an initial training phase that led farmers to choose the technologies that better fit their needs; thus, the demand for a specific package came from a knowledge based delivered to farmers as part of the intervention. In contrast, development projects often deliver technologies that extension agents or researchers deem suitable without much or any farmer input; this approach is likely to lead to a low level of empowerment and interest from beneficiaries in the technologies promoted. In addition, three years of extension support with an average contact of two visits per month seems to be appropriate to induce the adoption of the technologies offered by POSAF-II. These factors plus an implementation scheme compatible with the constraints faced by different types of beneficiaries can be considered crucial for the success of an NRM program like POSAF-II.

In sum, and very importantly, the results for POSAF-II suggest that it is possible to have interventions that increase farm income and preserve or enhance environmental conditions, and that this is achievable while obtaining relatively high rates of return for both society and farmers. Finally, we point out that the present study was conducted in the absence of baseline data.

Although the robustness of the impact estimates was gauged by applying various methodologies, the timely collection of baseline data should be undertaken in order to enrich studies of this type and thus generate even more reliable results.

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Appendix

Table 3.A.1. Balancing test of SAGF

	Unmatched samples				Genetic Matching				Nearest Neighbor			
Variables	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value
AGE	53.48	48.36	0.00	**0.01**	53.48	51.01	0.09	**0.05**	52.25	48.98	0.02	0.03
EDUC	4.20	4.84	0.10	0.28	4.20	4.93	0.06	**0.00**	4.18	4.87	0.08	0.35
NET	0.21	0.17	0.31	-	0.21	0.23	0.45	-	0.18	0.18	1	-
LAND	15.77	12.42	0.19	**0.06**	15.77	12.45	0.24	**0.00**	12.96	15.89	0.26	0.97
DIST	44.08	31.95	0.00	**0.00**	44.08	45.36	0.61	**0.01**	38.71	36.78	0.46	0.24
ALT	492.89	670.94	0.00	0.00	492.89	491.21	0.94	0.45	603.36	581.51	0.46	0.68
PAVE	0.28	0.41	0.00	-	0.27	0.23	0.32	-	0.35	0.32	0.46	-
ACCE	0.57	0.69	0.00	-	0.57	0.52	0.33	-	0.65	0.61	0.37	-
TEMP	24.01	22.91	0.00	**0.00**	24.01	24.03	0.90	0.14	23.24	23.48	0.33	0.41
RIAN	1284.50	1285.30	0.98	**0.03**	1284.50	1355.40	**0.01**	0.02	1289.10	1284	0.85	0.92
STD	23.62	25.03	0.47	0.05	23.62	20.84	0.12	0.01	22.93	24.66	0.37	0.39
									Before Matching Minimum p.value: < 2.22e-16		After Matching Minimum p.value: 0.1253	

Note: In bold: statistical differences higher than 10% level

Table 3.A.2. Balancing test of SFOR

	Unmatched samples				Genetic Matching				Nearest Neighbor			
Variables	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value
AGE	54.65	44.91	**0.00**	**0.00**	54.65	53.94	0.39	0.11	49.79	48.83	0.45	0.82
EDUC	4.75	4.53	0.53	0.73	4.75	4.39	0.32	0.94	4.58	4.42	0.66	0.85
NET	0.18	0.18	0.86	-	0.18	0.15	0.30		0.17	0.18	0.73	-
LAND	24.42	12.72	**0.00**	**0.00**	24.42	20.81	0.23	**0.00**	16.48	18.21	0.62	0.11
DIST	42.65	37.35	**0.03**	**0.07**	42.65	47.44	0.06	**0.00**	40.57	38.23	0.32	0.49
ALT	524.68	602.26	**0.00**	**0.00**	524.68	525.76	0.96	0.24	559.74	551.95	0.76	0.79
PAVE	0.32	0.29	0.36	-	0.32	0.30	0.53		0.32	0.31	0.79	-
ACCE	0.62	0.63	0.79	-	0.62	0.66	0.29	-	0.62	0.62	0.93	-
TEMP	23.86	23.22	**0.00**	**0.00**	23.86	23.87	0.98	0.96	23.63	23.56	0.73	0.88
PRECI	1280.50	1293.80	0.47	**0.04**	1280.50	1283.20	0.89	0.10	1279.20	1283.10	0.84	0.90
STD	21.66	21.26	0.79	**0.03**	21.66	21.67	0.99	**0.05**	22.03	21.66	0.83	0.93
									Before Matching Minimum p.value: < 2.22e-16		After Matching Minimum p.value: 0.109	

Note: In bold: statistical differences higher than 10% level

Table 3.A.3. Balancing test of SMIX

	Unmatched samples				Genetic Matching				Nearest Neighbor			
Variables	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value	BENE	Control	Diff: p-value	KS p-value
AGE	51.88	46.02	**0.00**	**0.00**	51.88	52.52	0.47	0.26	50.90	47.55	**0.00**	0.00
EDUC	4.66	5.024	0.32	0.10	4.66	4.26	0.28	0.06	4.83	4.87	0.92	0.84
NET	0.22	0.16	**0.05**		0.22	0.16	0.07	-	0.22	0.17	0.10	
LAND	10.27	15.74	**0.02**	0.42	10.27	10.59	0.81	0.50	13.42	11.60	0.02	0.08
DIST	30.69	31.46	0.70	0.00	30.69	31.82	0.58	**0.00**	31.57	30.80	0.72	0.34
ALT	642.32	631.91	0.72	0.00	642.32	682.37	0.17	0.00	642.61	634.36	0.78	0.23
PAVE	0.12	0.30	**0.00**		0.12	0.12	0.88	-	0.13	0.21	**0.01**	
ACCE	0.71	0.65	0.09		0.71	0.69	0.52	-	0.66	0.68	0.72	
TEMP	23.17	23.05	0.54	0.27	23.17	22.97	0.37	0.49	23.18	23.08	0.66	0.41
PRECI	1349.5	1318.10	0.14	0.00	1349.5	1380.2	0.17	0.12	1338.10	1332.60	0.81	0.60
DDAYS	19.91	22.62	0.07	**0.00**	19.91	16.13	0.01	**0.00**	20.59	21.28	0.66	0.00
									Before Matching Minimum p.value: < 2.22e-16		After Matching Minimum p.value: 0.001	

Note: In bold: statistical differences higher than 10% level

Table 3.A.4-1. Cash flow and expected internal rate of return (IRR) of SAGF

Beneficiaries	7,051
Hectares	14,864.71
Average farm (ha)	2.11
*Interest rate (15 years)	1%
Income gains per year (Inc.)	695.03

Year	Investment cost (1a)	Cost (2a)	Interest (3a)	Total outflows (4a) (1a + 2a + 3a)	Beneficiaries per year (5a)	ATE (6a) (5a*Inc.*ha)	Net flow (7a) (6a-4a)
00/2003	2,112,085			2,112,086	-	-	**-2,112,086**
01/2004	3,104,995	943,150	21,121	4,069,266	1,313	1,923,862	**-2,145,404**
02/2005	2,053,901	1,146,679	52,171	3,252,752	3,244	4,753,244	**1,500,492**
03/2006	2,104,182	1,647,154	72,710	3,824,047	4,521	6,624,358	**2,800,311**
04/2007	1,964,812	1,974,151	93,7512	4,032,715	5,829	8,540,894	**4,508,179**
05/2008		4,722,221	113,400	4,835,621	7,051	10,331,419	**5,495,798**
06/2009		2,496,231	93,752	2,589,982	7,051	10,331,419	**7,741,437**
07/2010		2,388,164	93,752	2,481,916	7,051	10,331,419	**7,849,503**
08/2011		2,499,352	93,752	2,593,104	7,051	10,331,419	**7,738,315**
09/2012		2,388,164	93,752	2,481,916	7,051	10,331,419	**7,849,503**
10/2013		4,722,221	93,752	4,815,973	7,051	10,331,419	**5,515,447**
11/2014		4,722,221	187,503	4,909,725	7,051	10,331,419	**5,421,695**
12/2015		4,722,221	187,503	4,909,725	7,051	10,331,419	**5,421,695**
13/2016		4,722,221	187,503	4,909,725	7,051	10,331,419	**5,421,695**
14/2017		4,722,221	187,503	4,909,725	7,051	10,331,419	**5,421,695**
15/2018		4,722,221	187,503	4,909,725	7,051	10,331,419	**5,421,695**
IRR							62%

*Interest rate increases from 1% to 2% after the tenth year

Table 3.A.4-2. Cash flow and expected internal rate of return (IRR) of SFOR

Beneficiaries	3,461
Hectares	26,927.00
Average farm (ha)	7.78
*Interest rate (15 years)	1%
Income gains per year (Inc.)	650.36

Year	Investment cost (1b)	Cost (2b)	Interest (3b)	Total outflows (4b) = (1b + 2b + 3b)	Beneficiaries per year (5b)	ATE (6b) (5b*Inc.*ha)	Net flow (7b) (6b-4b)
00/2003	825,400	-	-	825,400			**- 825,400**
01/2004	1,361,200	1,455,091	8,254	2,824,545		-	**- 2,824,545**
02/2005	901,400	1,067,089	21,866	1,990,355		-	**- 1,990,355**
03/2006	2,008,700	1,274,704	30,880	3,314,284		-	**- 3,314,284**
04/2007	1,620,600	1,816,119	50,967	3,487,686	2,626	13,287,244	**9,799,558**
05/2008		8,220,062	67,173	8,287,235	3,461	17,512,244	**9,225,009**
06/2009		1,826,246	67,173	1,893,419	3,461	17,512,244	**15,618,825**
07/2010		1,826,246	67,173	1,893,419	3,461	17,512,244	**15,618,825**
08/2011		1,889,255	67,173	1,956,428	3,461	17,512,244	**15,555,816**
09/2012		1,826,246	67,173	1,893,419	3,461	17,512,244	**15,618,825**
10/2013		7,246,113	67,173	7,313,286	3,461	17,512,244	**10,198,958**
11/2014		460,509	101,934	562,443	3,461	17,512,244	**16,949,801**
12/2015		460,509	101,934	562,444	3,461	17,512,244	**16,949,800**
13/2016		460,509	101,934	562,444	3,461	17,512,244	**16,949,799**
14/2017		7,246,113	101,934	7,348,047	3,461	17,512,244	**10,164,197**
15/2018		7,246,113	101,934	7,348,047	3,461	17,512,244	**10,164,197**
IRR	65%						

*Interest rate increases from 1% to 2% after the tenth year

Table 3.A.4-3. Cash flow and expected internal rate of return (IRR) of SMIX

Beneficiaries	7,051
Hectares	14,864.71
Average farm (ha)	2.11
*Interest rate (15 years)	1%
Income gains per year (Inc.)	695.03

Year	Investment cost (1c)	Cost (2c)	Interest (3c)	Total outflows (4c) = (1c + 2c + 3c)	Beneficiaries per year (5c)	ATE (6c) (5c*Inc.*ha)	Net flow (7c) (6c-4c)
00/2003	887,362			887,362	541		**-887,362**
01/2004	1,416,198.	1,245,190	8,873	2,670,262	1,405	-	**-2,670,262**
02/2005	919,045	1,905,374	23,035	2,847,456	1,966	-	**-2,847,456**
03/2006	843,207	2,636,062	32,226	3,511,495	2,480	-	**-3,511,495**
04/2007	792,935	9,843,616	40,658	10,677,210	2,964	-	**-10,677,210**
05/2008		7,006,685	48,587	7,055,272	2,964	-	**-7,055,272**
06/2009		4,549,196	40,658	4,589,854	2,964	-	**- 4,589,854**
07/2010		3,849,290	40,658	3,889,948	2,964	-	**- 3,889,948**
08/2011		11,800,562	40,658	11,841,220	2,964	-	**-11,841,220**
09/2012		3,985,076	40,658	4,025,734	2,964	-	**- 4,025,734**
10/2013		6,263,297	40,658	6,303,955	2,964	-	**- 6,303,955**
11/2014		6,263,297	81,316	6,344,614	2,964	-	**- 6,344,614**
12/2015		6,263,297	81,316	6,344,614	2,964	-	**- 6,344,614**
13/2016		6,263,297	81,316	6,344,614	2,964	-	**- 6,344,614**
14/2017		6,263,297	81,316	6,344,614	2,964	-	**- 6,344,614**
15/2018		6,263,297	81,316	6,344,614	2,964	-	**- 6,344,614**
IRR	-						

*Interest rate increases from 1% to 2% after the tenth year

Table 3 A.4-4. Cash flow and expected internal rate of return (IRR) of *POSAF-II*

Year	Investment cost (1d) = (1a+1b+1c)	Cost (2d) = (2a+2b+2c)	Interest (6d) = (3a+3b+3c)	Total outflows (4d) = (1d + 2d + 3d)	Beneficiaries per year (5) = (5a+5b)	ATE (6) = (6a +6b + 6c)	Net flow (7d)
00/2003	3,824,849			3,824,849	0	-	**-3,824,849**
01/2004	5,882,394	3,643,431	38,248	9,564,074	1,313	1,923,862	**-7,640,211**
02/2005	3,874,348	4,119,143	97,072	8,090,563	3,244	4,753,244	**-3,337,319**
03/2006	4,956,090	5,557,920	135,816	10,649,827	4,521	6,624,358	**-4,025,469**
04/2007	4,378,348	13,633,887	185,377	18,437,628	8,455	21,828,138	**3,630,526**
05/2008		19,948,969	229,160	20,494,464	10,512	27,843,663	**7,665,534**
06/2009		8,871,673	185,377	9,373,385	10,512	27,843,663	**18,786,613**
07/2010		8,063,701	185,377	8,565,413	10,512	27,843,663	**19,594,585**
08/2011		16,189,170	185,377	16,690,882	10,512	27,843,663	**11,469,116**
09/2012		8,199,486	185,377	8,701,199	10,512	27,843,663	**19,458,799**
10/2013		18,231,631	185,377	18,733,344	10,512	27,843,663	**9,426,655**
11/2014		11,446,027	370,754	12,133,116	10,512	27,843,663	**16,026,882**
12/2015		11,446,027	370,754	18,918,720	10,512	27,843,663	**16,028,347**
13/2016		11,446,027	370,754	12,133,116	10,512	27,843,663	**16,029,813**
14/2017		11,446,027	370,754	18,918,720	10,512	27,843,663	**16,026,882**
15/2018		18,231,631	370,754	18,918,720	10,512	27,843,663	**9,241,278**
IRR	35%						

Chapter 4 Productivity effects and natural resource management: econometric evidence from POSAF-II in Nicaragua

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Abstract

Understanding how natural resource management (NRM) technologies impact agricultural productivity is essential in order to ensure that policies designed to reduce environmental degradation and alleviate poverty are successful. In this paper, we analyze the impact of natural resource technologies delivered by the Socio-environmental and Forestry Development Program-II (*POSAF-II*) in Nicaragua. Using cross-sectional data for 1,201 farmers (475 beneficiaries, 726 control farmers), we provide empirical evidence concerning the effects of an NRM program on two critical components of productivity: technological change (TC) and technical efficiency (TE). We use propensity score matching (PSM) to mitigate potential biases from observable variables and a recent stochastic production frontier (SPF) model that addresses sample selection bias arising from unobservable variables. Our results show that *POSAF-II* has had a positive impact on the two dimensions of productivity analyzed, i.e., TC and TE. This study contributes to the literature on impact evaluation by showing how an intervention designed to improve natural resource management can also enhance the income of poor farm households through increases in productivity.

Keywords: Natural resource management; technological change; technical efficiency; propensity score matching; stochastic production frontier; sample selection bias; meta-frontier.

3.2 Introduction

Unsustainable agricultural practices, such as monoculture cropping, the overuse of chemical inputs, slash and burn, and tillage on steeply sloping land, present a threat to the stability of production systems in Central American countries (FAO & ITPS, 2015; Gardi et al., 2015). Along with factors like extreme climatic events, unsustainable agricultural practices are a major cause of soil degradation, particularly in areas where cultivation occurs on hillsides or land with steep slopes (FAO, 2011). The World Resources Institute reported that by 1990, 26% of Central America's territory had been exposed to soil degradation, representing the highest share worldwide (Gardi et al., 2015). Soil degradation and natural resource depletion have had particularly detrimental effects in rural areas where many of the most impoverished people reside. For example, between 1982 and 2003, Central America suffered degradation rates of nearly 60%, as well as associated reductions in agricultural gross value product of up to 13% (Gardi et al., 2015). Hence, the sustainable management of natural resources is an important issue for farmers and policy makers (EC, 2013; FAO & ITPS, 2015).

In the search for ways to address the fragile nature of natural resources and in order to increase crop and livestock productivity, as well as to reduce poverty among hillside households, Central American governments and development institutions, funded by international donors, have implemented a number of natural resource management (NRM) programs. A prime example of the latter is Nicaragua's Socio-environmental and Forestry Development Program (POSAF-II). This program was designed to improve socioeconomic conditions and living standards for residents in key watersheds while decreasing the impact of natural disasters through the development and sustainable use of renewable natural resources. POSAF-II financed a total of 13,477 farmers occupying 69,767 hectares in several major river basins (Figure 4.1). POSAF-II was funded jointly by the Inter-American Development Bank and the Nordic Development Fund, and was executed by the Nicaraguan Ministry of Environment and Natural Resources (MARENA). We focus on Component I of POSAF-II, which involved improved management of natural resources at the farm level by encouraging the adoption of sustainable technologies and practices (e.g., terracing, level curves, integrated pest management, and organic fertilization, among others) primarily in agroforestry and forestry management systems (IDB, 2001).

Natural resource management (NRM) integrates a variety of conservation technologies and management techniques within a production system aimed at protecting water, forests, and ecosystems. These conservation strategies can be applied to agricultural value chains, such as crops, forest products, livestock, and integrated aquaculture systems, in order to increase economic performance while ensuring the well-being of farm households and protecting the ecosystem and its natural resources (Cocchi & Bravo-Ureta, 2007; Del Carpio & Maredia, 2011; Solís, Bravo-Ureta & Quiroga, 2007; Kassie et al., 2011).

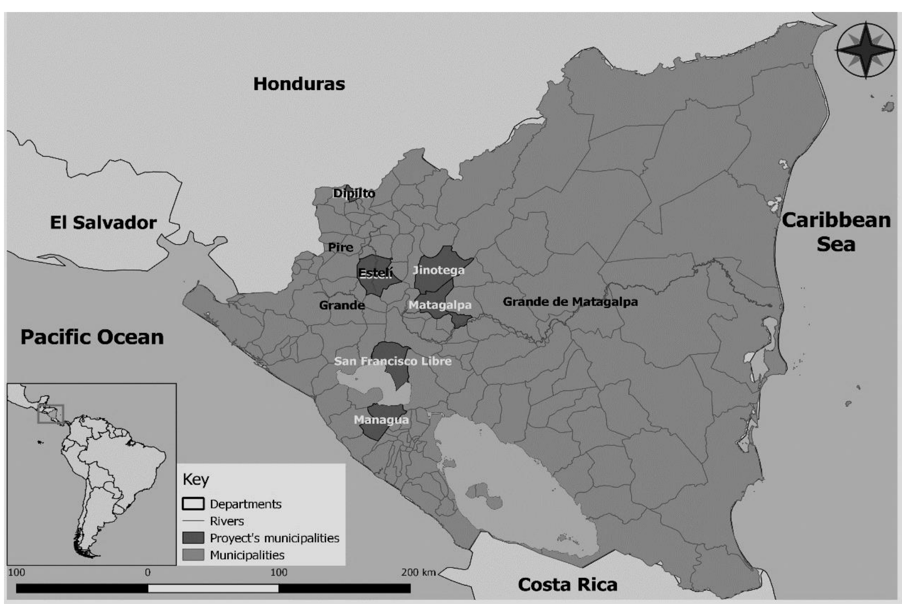

Figure 4.1 Area of influence of POSAF-II..

While impact evaluation (IE) studies of NRM technologies have shown positive effects on farm income, the role of managerial performance, commonly proxied by technical efficiency (TE), has been largely ignored (Bravo-Ureta, Greene, & Solís, 2012; Franzluebbers, Sawchik & Taboada, 2014). An even more striking gap is the dearth of IE work that focuses on TE and that utilizes counterfactual methods to correct for selection bias (González-Flores, Bravo-Ureta, Solís & Winters, 2014). Our study contributes to closing this gap in the literature by using data from treatment and control groups along with stochastic production frontier methods that correct for selection bias. This framework, based on Greene (2010) and Bravo-Ureta et al. (2012), allows us to obtain unbiased managerial (TE) and technological change (TC) effects attributable to POSAF-II.

3.3 Review of the literature

A robust body of research has analyzed the contribution of NRM programs to household well-being and farm income (Cocchi & Bravo-Ureta, 2007; Marenya & Barrett, 2007; Franzluebbers et al., 2014; Jaleta et al., 2016). However, the same level of attention has not been given to understanding the mechanism by which NRM technologies boost farm income, and this is an important issue in order to design and implement cost effective interventions (Pretty et al., 2006; Pretty, Toulmin, & Williams, 2011; Lutz, Pagiola, & Reiche, 1994). As mentioned earlier, the interest here is on understanding the role of managerial performance and technology in increasing farm income as a consequence of NRM interventions.

Attempts to gauge the impact of NRM on TE include the study by Odoul et al. (2011), who focused on the adoption of soil and water conservation technologies among smallholder farmers in sub-Saharan Africa. These authors did not find a significant impact on TE. Similar results were found by Ndlovu et al. (2014) when evaluating conservation technologies used by maize producers in Zimbabwe. To deal with possible biases, the authors used panel data for farmers using conservation or conventional farming. In contrast, Tien et al. (2011) concluded that the adopters of zero tillage and direct seeded rice had a higher level of TE than non-adopters. Frey et al. (2012) compared silvopastoral and conventional cattle ranching operations that simultaneously apply two or more silvopastoral technologies, and the authors claimed that they accounted for sample selection bias by using paired comparisons of technologies within the same farms. Their results suggested that farmers who used these technologies displayed higher TE than conventional cattle-ranchers. Krishna and Veettil (2014) evaluated minimum tillage, another NRM practice, by comparing villages with full adoption (> 90%) with non-full adopters in India. Their results showed that the TE for the two groups of villages was 0.92 and 0.88, respectively. In dealing with sample selection bias, the studies cited have ignored the fact that the stochastic production frontier (SPF) is a non-linear model, and this a clear shortcoming in their analyses. Sample selection bias is a frequent issue in impact evaluation analysis when the decision to participate in the program is not random, as is the case with POSAF-II. This problem typically arises because some participants choose to participate in the program while others do not, although the program is offered to all eligible individuals. As a result, the choice of participating may lead to differences between participants and non-participants. For this reason, we used the methodological framework mentioned above.

Published research focusing on the impact of NRM technologies on TE in Central America is limited. Among the few relevant articles, Solís et al. (2007) used a switching regression model to account for sample selection bias for high and low-level adopters of soil conservation technologies in El Salvador and Honduras. The authors concluded that farmers with adoption levels above the mean display higher TEs. More recently, Bravo-Ureta et al. (2012), based on Greene (2010), analyzed the NRM in Priority Watersheds Project in Honduras, combining propensity score matching (PSM) with the SPF methodology that addresses sample selection bias. These authors found that the TE level in the treatment group was higher than in the control group, and that selection bias was an issue. González-Flores et al. (2014) used the latter model to evaluate a technology and training program in Ecuador. Rahman et al. (2009) and Wollni and Brümmer (2012) have also applied the SPF corrected for sample selection, but without using PSM to remove biases coming from observables. The methodology used in these studies relies on separate SPF models for treatment and control groups; thus, a direct comparison of TE scores across these groups is not suitable. To address this issue, Villano et al. (2015) as well as Lakner, Brenes-Muños & Brümmer (2017) estimated meta-frontier models, making it possible to compare directly TE for different groups relative to a common benchmark.

3.4 Analytical framework and data

To assess productivity differentials between treatment and control groups, we use the SPF method that deals with sample selection bias as mentioned above. We first use PSM to match beneficiaries (BENF) and control (CONF) farmers with similar propensity scores to mitigate bias associated with observable variables. Propensity score matching (PSM) can be a reliable approach in cases in which panel data is not available, and an experimental design was not set before program implementation, as was the case for POSAF-II (Hirano & Imbens, 2001; Mendola, 2007; Khandker, Koolwal & Samad, 2010). Next, we estimate standard and sample selection SPFs, and then meta-frontier models to compare TE for BENF and CONF.

4.3.1 Econometric estimation and sample selection bias

Interventions promoted by POSAF-II can result in TC that represents a shift in the production frontier and/or changes in TE representing managerial performance. These two effects are estimated in this study using the SPF framework. To determine differences in productivity between treatment and control groups, it is necessary to address sample selection bias arising from both observable and unobservable variables. Here, both sources of bias are mitigated using PSM to deal with biases from observables and the stochastic production frontier model corrected for sample selection to cope with biases from unobservable variables.

The first step is to use PSM to construct a counterfactual group of farmers based on time-invariant observable characteristics. Propensity score matching (PSM) uses a Probit or Logit model to calculate the predicted probability of treatment based on a given set of predetermined covariates (Khandker et al., 2010). These probabilities, or propensity scores, are then used to match similar households in the treatment group with those from the control group. While different matching criteria are available, we use the 1-to-1 nearest neighbor matching (NNM) criterion without replacement, because this method is easy to interpret and reflects a clear match for individuals based on the assumption of common support1 (Caliendo & Kopeinig, 2008). Furthermore, this method is often used in applied research (Bravo-Ureta et al., 2011; Kassie et al., 2011; Villano et al., 2015).

The second step involves the estimation of SPF models. First, the estimation is done using the pooled (P) unmatched (U) sample of BENF and CONF groups. Next, we estimate two separate models using unmatched data, one for BENF and a second for CONF. Then, we perform a

[1] The region of common support represents the range where propensity scores for both treated and control observation are found (Angrist & Pischke, 2009).

likelihood ratio test (LR) for the equality of the last two models. If there is no difference, then the model using the pooled dataset is supported. The models are then re-estimated for BENF and CONF using the sample selection SPF framework. Subsequently, the process is repeated using the matched samples to estimate a pooled model. Then, two separate standard SPFs are estimated using the matched subsamples, one for BENF and another for CONF. Finally, we re-estimate these models for both BENF and CONF using the sample selection SPF. Thus, the models in this step incorporate corrections for biases from both observable and unobservable variables (Bravo-Ureta, et al. 2012).

The selection approach for estimating SPF is expressed as follows:

Sample selection: $d_i = 1[\alpha' \boldsymbol{z}_i + w_i > 0], w_i \sim N(0,1)$
(1)

Stochastic frontier model: $y_i = \beta' x_i + \varepsilon_i, \ \varepsilon_i \sim N[0, \sigma_\varepsilon^2]$
(2)

Error structure: $\varepsilon_i = v_i - u_i$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i|, \text{ where } U_i \sim N(0,1)$$

$$v_i = \sigma_v V_i, \text{ where } V_i \sim N(0,1)$$

$$(w_{i,} v_i) \sim N_2[(0,0), (1, \rho\sigma_v, \sigma_v^2)],$$

where d is a binary variable equal to 1 for BENF and 0 for CONF, y denotes the output variable, z is a vector of control variables, x is a vector of inputs in the production frontier, α and β are the parameters to be estimated, and the error structure corresponds to that in the stochastic frontier model. In this model, the parameter ρ captures sample selection bias. The full model and further details concerning its estimation are available in Greene (2010) and Bravo-Ureta et al. (2012).

As mentioned before, TE scores for beneficiary and control groups obtained from the estimation of separate models are not directly comparable; therefore, like Villano et al. (2015), we use a meta-frontier approach to estimate productivity differentials between the treatment and control groups. This framework makes it possible to compare the TE of different groups by estimating a meta-frontier, which is a function that envelopes separate SPF models for the beneficiary and control groups (Battese, Prasada Rao, & O'Donnell, 2004; O'Donnell, Rao & Battese, 2008). The meta-frontier production model is defined as follows:

$$y_i^* = f\left(x_{i,}\beta^*\right) = e^{x_i\beta},^* \tag{3}$$

$$x_i\beta^* \geq \ x_i\beta_{j.} \tag{4}$$

where β* is a vector of meta-frontier parameters subject to equation (4) for all i observations, β_j denotes the parameter vector of the SPF function for the treatment and control groups, and y^* denotes the meta-frontier output. Given the constraints, equation (3) can be estimated by solving the following optimization problem:

$$\min L \equiv \sum_{i=1}^{N}\left|(\ln f(x_i\, \beta^*) - (\ln f(x_i\, \hat{\beta}_{(j)})\right| \tag{5}$$

$$s.t\ \ \ln f(x_i\, \beta^*) \geq ln\ f\left(x_{i,}\hat{\beta}_{(j)}\right). \tag{6}$$

Since $\hat{\beta}_{(j)}$ is treated as fixed, the second term in the summation is constant with respect to the minimization. Therefore, the solution of equation (5) can be obtained by minimization of the objective function, $L^* \equiv \bar{x}\beta^*$, subject to equation (6); $\bar{x}$ is the row vector of means of elements of the x vector for all the observations in the dataset. After estimation of the meta-frontier parameters (β^*), we can calculate meta-technology ratios (MTRs), which fall between zero and one due to the restriction imposed by equation (4). The MTR is defined as the distance between the group frontier and the meta-frontier, and is calculated as follows (O'Donnell et al., 2008):

$$MTR = \frac{e^{x_i \beta_j}}{e^{x_i \beta^*}}. \tag{7}$$

After estimating the MTR, the meta-frontier TE (TE*) is estimated as:

$$TE^* = TE_j \times MTR_j. \tag{8}$$

4.3.2 Data and empirical model

In this study, we use cross-sectional data collected in 2012 from 1,201 farmers (475 BENF, 726 CONF). Treatment farmers were beneficiaries of POSAF-II, which was implemented between 2002 and 2008 by the MARENA. As indicated earlier, the aim of the program was to improve socio-economic conditions by boosting farm productivity among small and medium-sized farmers, primarily through the promotion and adoption of soil conservation and water management practices. POSAF-II incorporated two major production systems: i) agroforestry (SAGF), including the planting of fruit trees, introduction of soil conservation practices (stone barriers, terraces, and live barriers, among others) and silvopastoral sub-systems; and ii) forestry (SFOR), including forest planting and regeneration, and management of natural resources. Specific technology packages were defined for each system, and the program supported farms in the selection and adoption of specific packages by providing financial support and technical assistance (Bravo-Ureta, 2012).

The data collection started with the matching of treatment and control communities based on agro-ecological characteristics, such as altitude (ALT), temperature (TEMP), precipitation (PRECI), and the prevalence of canículas or short-term-drought (STD). Then, a random sample of the matched communities was used to draw random samples of beneficiaries and control farmers.

Further information about the data collection can be found in Bravo-Ureta (2012). To determine whether POSAF-II had an impact on the TE and TC of BENF, our model should yield a clear causal interpretation. Therefore, the first stage of data collection makes a first approximation on the construction of a counterfactual group. Since we used PSM to pair beneficiaries and control communities, both groups have similar time-invariant characteristics (Cameron & Trivedi, 2005; Khandker et al., 2010). In the second stage, we matched beneficiaries and controls from the selected communities. Table 4.1 presents the definitions of the variables used in the matching of communities and farmers, as well as in the estimation of the SPF models.

The NNM criterion produced 172 pairs of observations for SAGF and 302 pairs of observations for SFOR. In the former, one observation was discarded for BENF and 30 from CONF due to a lack of common support. In SFOR, four BENF and one CONF were discarded. The region of common support is the interval 0.01 and 0.82, and 0.14 and 0.98, respectively, for SAFG and SFOR, as presented in Figure 4.2. Along with the NNM, we used the Genetic Matching method, which is a generalization of the Mahalanobis metric, which includes an additional weight matrix to find a distance that optimizes post-matching covariate balance (Diamond & Sekhon, 2013). Following Ho et al. (2011), we ran a balance test to check the distribution of the covariates in the two groups, as well as to compare which of the matching processes led to the best balance. This exercise revealed that the NNM generated the best covariate balance, i.e., the smallest distance between the control and treated groups. Thus, our analysis is based on the matched sample generated by the NNM procedure.

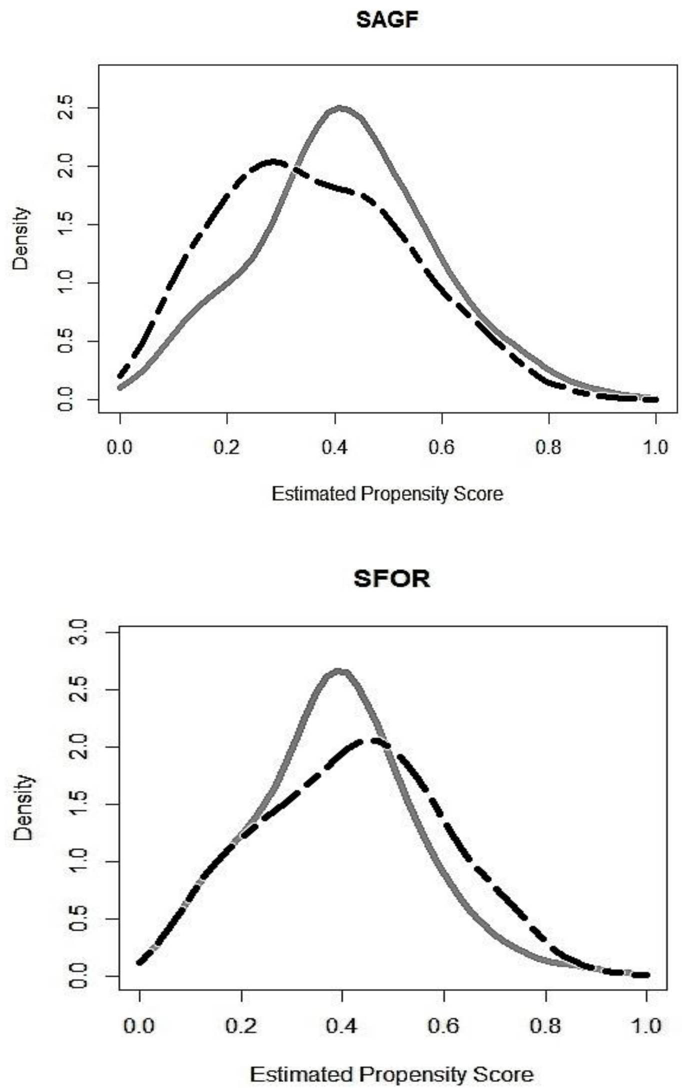

Figure 4.2 Kernel distribution of propensity scores for BENF (broken black line) and CONF (continuous gray line).

Now we move to the estimation of the SPF corrected for sample selection bias based on Greene (2010). This method first requires the estimation of another Probit model of program participation, which enables the sample selection feature of the model. This Probit is expressed as follows:

$$P_i = \alpha_0 + \sum_{j=1}^{10} \alpha_j \boldsymbol{Z}_{ji} + w_i, \tag{9}$$

where Pi is a dichotomous variable equal to 1 for BENF and 0 otherwise, Z is a vector of exogenous variables that explain participation in the Program, $\boldsymbol{\alpha}$ are the unknown parameters to be estimated, and w is the error term. The Z variables used are AGE, SCHOOL, DIST, NET, TEMP, PRECI, STD, and ACCE (see Table 4.1).

Table 4.1. Definition of variables used in the SPF and Probit models

Variables	Unit	Definition
SPF model		
TVAP	US$/hectare	Total value of agricultural production
LAND	Hectares	Total land devoted to agricultural production
PINP	US$	Purchased inputs presents the production costs, excluding labor
LABOR	US$	Total value of family and hired labor
BENF	Dummy	1 if the household is a beneficiary of POSAF-II
Probit models		
AGE	Years	Age of the household head
SCHOOL	Years	Years of schooling of the household head
NET	Dummy	1 if the farmer is a member of an organization focused on social activities or agricultural production
DIST	Kilometers	Plot distance to main town
ALT	Meters	Meters above sea level
TEMP	Celsius	Average temperature in the region
PRECI	Millimeters	Annual rainfall
STD	Days	Number of drought days during the rainy season
ACCE	Dummy	1 if the farm is accessible all year

After estimation of the participation in equation (9), we used a Cobb-Douglas (CD) SPF model to estimate efficiency. The CD model can be formally expressed as follows:

$$LnY_i = B_0 + \sum_{j=1}^{n} \beta_j \, Ln\left(X_{ij}\right) + (v_i - u_i) \qquad iff \;\; B = 1, \tag{10}$$

where Yi refers to the output of the ith farmer, measured as the total value of agricultural production (TVAP) in US dollars. The total value of agricultural production (TVAP) is equal to the sum of the value of the different outputs produced by each farm using constant average prices calculated from the data collected in the surveys conducted during the study. This kind of monetary indicator is often employed in the impact evaluation and the applied production economics literature to measure output when the use of physical units is not possible. It is important to emphasize that monetary figures must be valued at constant prices to avoid possible market effects (e.g. Battese, Prasada Rao, & O'Donnell, 2004; Frey et al., 2012; Ghebru & Holden, 2015; González-Flores, Bravo-Ureta, Solís, & Winters, 2014; Odoul, Binam, Olarinde, Diagne, & Adekunle, 2011; Solís, Bravo-Ureta, & Quiroga, 2009). In addition, the program analyzed is relatively small, so there is no expectation of price effects that could result from supply shifts that could be attributed to the program itself. The vector X are traditional inputs, LAND, PINP, and LABOR, and we add altitude, precipitation, temperature, and drought to account for environmental conditions as done by Sherlund et al. (2002), Rahman and Hasan (2008), and Bravo-Ureta et al. (2012), among others. The recent literature argues that these types of variables allow for strong identification in production models, and their exclusion is likely to lead to omitted variables bias (Burke and Emerick 2016; Dell, Jones, and Olken 2014; Njuki, Bravo-Ureta, and Mukherjee 2016; O'Donnell 2016). Moreover, technological choices made by farmers are influenced by environmental conditions, and failure to account for these factors can bias technical efficiency estimates (Sherlund et al., 2002). Finally, β are unknown parameters to be estimated; v is the standard error that follows a two-sided normal distribution; and u is the inefficiency term with a half-normal distribution.

4.3.3 Descriptive analysis

Tables 4.2 and 4.3 present descriptive statistics for the variables included in the SAGF and SFOR models before and after matching. The data shows that for SAGF and SFOR, BENF display a higher TVAP (SAGF \$1168.69, SFOR \$7256.88) compared to the CONF. This conforms to expectations since the technologies offered to program beneficiaries were intended to increase farm productivity and income. For SAGF, the variables AGE, DIST, ALT, and TEMP are statistically different from the CONF at the 1% significance level. Once matching is done, the mean value of AGE is the only one that remains different for the CONF group. The mean value of PINP does not exhibit any statistical difference between BENF and CONF, although the former were advised to use integrated pest management and to fertilize their farms. This is consistent with Mauceri et al. (2007), who argue that improved practices are likely to decrease the use of purchased inputs. In sum, the balance condition indicates that matching generated a suitable counterfactual group for our analysis.

Table 4.2. Summary statistics of variables used in the matching and production models in SAGF

	Pooled		BENF		CONF		
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	t-test
Unmatched sample							
TVAP	973.93	1850.31	1168.69	1744.57	883.84	1892.72	0.085
LAND	13.24	27.87	15.77	38.46	10.28	19.69	0.033
LABOR	762.35	1270.87	633.35	1172.57	822.02	1311.07	0.093
PINP	781.25	1263.47	672.43	1335.77	831.59	1227.16	0.185
AGE	48.59	15.45	53.48	14.53	45.78	15.29	**0.000**
SCHOOL	4.64	4.52	4.19	4.53	4.60	4.35	0.786
NET	0.17	0.38	0.21	0.40	0.16	0.37	0.189
DIST	32.88	24.86	44.07	29.45	32.78	24.59	**0.008**
ALT	635.83	304.59	492.89	317.09	646.64	305.71	**0.000**
TEMP	22.93	2.54	24.01	2.55	22.97	2.62	**0.000**
PRECI	1307.86	282.83	1284.52	266.25	1301.34	288.11	0.909
STD	19.91	20.53	23.62	17.48	21.72	21.91	0.405
Observations	547		173		374		
Matched Sample							
TVAP	943.43	1523.31	1172.26	1749.02	714.59	1220.69	**0.005**
LAND	16.02	34.01	15.76	38.57	12.85	25.44	0.333
LABOR	626.63	1126.47	636.95	1175.03	616.32	1079.07	0.865
PINP	663.71	1186.10	676.18	1338.76	651.24	1014.55	0.846
AGE	52.70	14.71	53.35	14.40	52.22	13.94	0.336
SCHOOL	4.71	4.81	4.21	4.53	4.05	4.16	0.646
NET	0.21	0.41	0.21	0.40	0.21	0.41	0.693
DIST	36.21	27.65	43.88	29.26	43.02	32.25	0.523
ALT	558.14	293.15	494.11	316.95	499.16	319.71	0.304
TEMP	23.35	2.56	24.00	2.56	24.01	2.76	0.470
PRECI	1316.28	270.56	1284.03	266.94	1302.52	272.82	0.633
STD	17.96	17.98	23.63	17.53	21.76	19.92	0.330
Observations	344		172		172		

Notes: "in bold" the difference between the mean of BENF and CONF is statistically significant at least at the 1% level.

Table 4.3. Summary statistics of variables used in the matching and production models in SFOR

	Pooled		BENF		CONF		
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	t-test
Unmatched sample							
TVAP	5850.76	13791.05	7256.88	18655.35	4628.39	7097.04	0.023
LAND	18.23	43.26	24.50	48.14	12.78	37.75	**0.000**
LABOR	8091.35	19307.14	6437.57	16989.93	9528.99	21034.64	0.043
PINP	4404.12	9039.67	4799.56	10482.23	4060.35	7564.58	0.008
AGE	49.30	15.39	54.47	14.29	44.81	14.91	**0.000**
SCHOOL	4.66	4.52	4.79	4.70	4.54	4.35	0.081
NET	0.178	0.38	0.17	0.38	0.18	0.38	0.589
DIST	39.71	30.28	42.58	32.07	37.21	28.44	0.03
ALT	568.39	315.94	526.79	313.83	604.54	313.75	0.851
TEMP	23.50	2.57	23.84	2.55	23.21	2.55	0.001
PRECI	1286.93	239.44	1279.74	215.27	1293.18	258.77	0.5325
STD	21.37	20.14	21.54	19.07	21.23	21.06	0.9636
Observations	658		306		352		
Matched Sample							
TVAP	5792.80	13922.83	6999.05	18399.87	4586.55	6845.39	**0.000**
LAND	15.76	25.74	20.43	29.59	11.09	20.19	0.029
LABOR	7547.10	19042.14	6519.86	17087.24	8574.34	20792.30	0.185
PINP	4407.46	9148.04	4755.09	10518.83	4059.84	7534.14	0.351
AGE	50.65	14.79	54.410	14.22	46.894	14.42	**0.000**
SCHOOL	4.614	4.48	4.72	4.63	4.51	4.33	0.556
NET	0.18	0.38	0.18	0.38	0.19	0.39	0.676
DIST	41.11	30.97	42.76	32.22	39.46	29.63	0.191
ALT	551.66	315.93	524.50	312.95	578.81	317.09	0.094
TEMP	23.66	2.56	23.86	2.56	23.46	2.55	0.066
PRECI	1283.44	237.57	1280.79	215.27	1286.09	258.29	0.784
STD	21.42	19.83	21.43	19.03	21.41556	20.63	0.992
Observations	604		302		302		

Notes: "in bold" the difference between the mean of BENF and CONF is statistically significant at least at the 1% level.

3.5 Results and Discussion

Now we proceed to discuss the results of the estimation of the sample selection corrected SPF model and subsequent analysis. First, we consider the results of the Probit model, which are presented in Table 4.4. A statistically significant Chi-Square of 73.3 and 130.2 for SAGF and SFOR, respectively, rejects the null hypothesis that all parameters in the POSAF-II participation equation are equal to zero. Furthermore, we find that for both SAGF and SFOR, AGE plays a significant role in the decision to participate in POSAF-II, and that this effect is non-linear. Similar results were obtained by Bravo-Ureta et al. (2012) and by Mendola (2007), who argue that this characteristic influences the adoption of new technologies, but that there is a threshold beyond which farmers are less receptive to such technologies. The parameter for schooling of household heads is statistically significant and positive for SFOR, while negative but not significant for SAGF. Weber et al. (2011) reported similar results regarding the role of schooling on the decision to adopt NRM technologies in a forestry intervention in Brazil. Furthermore, the estimated model suggests that farmers located close to the center of the town were more likely to be beneficiaries of the SAGF. Since SAGF farmers produce perishable goods, being located close to the center of town favors the commercialization of such goods. In contrast, forestry activities are more likely to occur in places with high elevation, and the commercialization of the associated output often takes place on the farm (Admasu et al., 2013).

Table 4.4. Estimate of the Probit selection equation for SAGF and SFOR

	SAGF		SFOR	
	Coeff.	S.E	Coeff.	S.E
Constant	5.309[a]	1.000	5.604 [a]	0.919
AGE	-0.072 [a]	0.025	-0.099 [a]	0.021
AGE^2	0.000 [b]	0.000	0.001 [a]	0.000
SCHOOL	-0.049	0.039	0.072 [b]	0.035
$SCHOOL^2$	0.002	0.002	-0.002	0.002
LAND	-0.003	0.002	-0.003 [b]	0.001
DIST	-0.007 [a]	0.003	0.008 [a]	0.002
NET	-0.182	0.155	0.010	0.139
TEMP	-0.125 [a]	0.028	-0.124[a]	0.027
PRECIP	0.000	0.000	0.001 [a]	0.000
STD	0.014[a]	0.005	0.015 [a]	0.004
ACCE	0.028	0.146	-0.230 [c]	0.128
Log likelihood	-304.69		-389.36	
Chi-squared	73.29 [a]		130.24[a]	
N	547		658	

Note: [a], [b], [c] => Significance at 1%, 5%, 10% level.

Farmers located in areas with high temperatures and low levels of precipitation were less likely to join the program (SAGF and SFOR), and this is consistent with the environmental requirement of the crops produced by beneficiaries. For instance, coffee plantations require more than 1000 mm of precipitation per year, and temperatures between 18-21º Celsius to perform well (Jaramillo et al., 2011). Furthermore, farmers located in areas with higher precipitation experience relatively higher levels of soil degradation; thus, adopting NRM technologies seems appropriate. In addition, POSAF-II sought to alleviate some of the effects of Hurricane Mitch on the rainforest areas of Nicaragua; hence, beneficiaries likely perceived POSAF-II as a mechanism to deal with lingering effects from the hurricane. These results are generally in line with Kassie et al. (2008), who found that farmers located in areas with high precipitation were more likely to adopt soil conservation technologies in Ethiopia.

We next estimate separate and pooled SPF models for the unmatched samples for BENF and CONF for each of the two production systems. Preliminary comparisons led to the acceptance of the CD functional form over the Translog (TL), and thus we use the former throughout. To compare the separate versus the pooled models, we use a likelihood ratio test based on Greene (2007), which can be expressed as:

$$LR = 2\big((lnLp - (lnL_B + lnL_c)\big) \tag{11}$$

where $lnLp$, lnL_B, and lnL_c represent the log-likelihood function values obtained from the pooled (unrestricted model), and beneficiary and control subsamples (restricted), respectively. The LR tests confirm that beneficiaries and controls display different technologies for both the SFOR and SAGF systems. In the case of SAGF, this is also indicated by the significance of the BENF parameter (Table 4.5).

Table 4.5 shows that LAND, LABOR, and PINP (purchased inputs) are positively related to TVAP, as expected. The estimated parameters are (partial) production elasticities, which measure the contribution (%) of each input to output change (%). The results show that cultivated land (LAND) makes the highest contribution to TVAP; i.e., a one percent change in cultivated area produces a larger percent growth in output compared to the other two inputs. In addition, the effects of labor (LABOR) and purchased inputs (PINP) differ between BENF and CONF for SGAF. For BENF, LABOR exhibits the second highest contribution to TVAP. Solís et al. (2007) report similar results in their analysis of soil conservation practices in Honduras. As reported by Marenya and Barrett (2007) and Abdulai and Huffman (2014), the implementation of NRM practices relies heavily on the use of labor, which may explain the weight of this input in the production frontier among BENF. In the case of CONF, labor might not be a constraint, so we would expect a lower contribution from this input to production. For SFOR, PINP makes the second largest contribution to the TVAP. This result is in line with Bravo-Ureta et al. (2012) and González-Flores et al. (2014), who find that purchased inputs play an important role in farm production.

Tables 4.5 and 4.6 also report the values for γ, used to test for the presence of technical inefficiency (TI). We reject the underlying hypothesis of $\gamma = 0$, or no inefficiency with a probability value of less than 1%. Therefore, a substantial amount of variation in TVAP can be attributed to technical inefficiency for both BENF and CONF. As previously mentioned, the reason for following Greene (2010) is to estimate an unbiased TE for beneficiary and control farmers, and this depends on the significance of the ρ parameter (see Table 4.5 and 4.6). The results show no selection bias for beneficiaries of SAGF and SFOR, and this is consistent across the unmatched and matched samples. One exception is for the control unmatched sample for SAGF, but matching removed the presence of sample selection bias. Thus, we can conclude that unobservable factors (e.g., managerial skills, motivation) do not account for differences in the performance of beneficiary vis-a-vis control groups for both the SFOR and SAGF systems in POSAF-II. Methodologically, these results imply that the matching performed at the community and farm levels yielded a counterfactual that mitigates biases from both observable and unobservable variables. We should note that Cavatassi et al. (2011) used a similar procedure to define their control group, and also found that biases were alleviated.

Table 4.5. Parameter estimates for the conventional and sample selection SPF models: unmatched and matched sample for SAGF

Variables	**Unmatched sample**					**Matched sample**				
	Conventional SPF			Sample selection corrected SPF		Conventional SPF			Sample selection corrected SPF	
	PF-U	BF-U	CF-U	BF-US	CF-US	PF-M	BF-M	CF-M	BF-MS	CF-MS
Land	0.457^{a}	0.412^{a}	0.493^{a}	0.388^{a}	0.522^{a}	0.499^{a}	0.412^{a}	0.575^{a}	0.404^{a}	0.400^{a}
Labor	0.120^{c}	0.225^{b}	0.051	0.219^{c}	0.023	0.155^{b}	0.225^{b}	0.026	0.229^{b}	0.230^{b}
PINP	0.191^{a}	0.115	0.273^{a}	0.121	0.279^{a}	0.159^{b}	0.115	0.273^{b}	0.111	0.109
ALT	0.027	-0.018	0.026	-0.018	0.029	0.048	-0.018	0.063	-0.012	-0.014
DROUGHT	-0.006	-0.001	0.000	0.002	-0.004	-0.001	-0.001	0.007	-0.001	-0.001
PRECI	0.0001	-0.0001	0.0003	0.0005	0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001
Temp.	-0.014	-0.071	-0.0189	-0.081	0.170	-0.008	-0.071	0.009	-0.060	-0.062
BENF	0.576^{a}					0.624^{a}				
Constant	4.384^{a}	6.874^{a}	4.033^{a}	7.196^{b}	3.792^{a}	4.432^{a}	6.854^{a}	3.925^{a}	6.721^{b}	6.828^{b}
γ	1.648^{a}	2.493^{a}	1.491^{a}	-	-	2.313^{a}	2.481^{a}	2.476^{a}	-	-
σ^2	1.572^{a}	1.521^{a}	1.599^{a}	-		1.595^{a}	1.524^{a}	1.680^{a}	-	-
L. Likelihood	846.8	- 244.0	-595.4	-419.8	-724.5	-507.9	-243.1	-260.2	-359.9	-234.4
$\sigma(u)$	-		-	1.448^{a}	1.359^{a}				1.376^{a}	1.370^{a}
$\sigma(v)$	-		-	0.610^{a}	0.969^{a}				0.601^{a}	0.617^{a}
$\rho(w,v)$	**-**		**-**	**-0.301**	**-0.605^{b}**				**-0.252**	**-0.358**
N	547	173	374	174	374	344	172	172	172	172

^{a} p<0.010; ^{b} p<0.05; ^{c} <0.01.

Table 4.6. Parameter estimates for the conventional and sample selection SPF models: unmatched and matched sample for SFOR

	Unmatched sample					Matched sample				
Variables	Conventional SPF			Sample selection corrected SPF		Conventional SPF			Sample selection corrected SPF	
	PF-U	BF-U	CF-U	BF-US	CF-US	PF-M	BF-M	CF-M	BF-MS	CF-MS
Land	0.572 [a]	0.553[a]	0.616 [a]	0.512 [a]	0.621 [a]	0.586[a]	0.562 [a]	0.658 [a]	0.537[a]	0.653[a]
Labor	0.096 [a]	0.090[a]	0.057[a]	0.089 [a]	0.053	0.091 [a]	0.086[a]	0.053	0.085[a]	0.053
PINP	0.206[a]	0.188 [a]	0.297[a]	0.196 [a]	0.305[a]	0.202 [a]	0.185 [a]	0.304[a]	0.188 [a]	0.305[a]
ALT	0.055[c]	0.011	0.065 [c]	-0.005	0.055	0.048	0.039	0.034	0.036	0.026
DROUGHT	-0.003	-0.004	-0.002	-0.002	-0.003	-0.005[c]	-0.005	-0.004	-0.004	-0.005
Temp.	-0.0132	-0.092	-0.015	-0.119	-0.014	-0.023	-0.064	-0.011	-0.079	-0.013
BENF	-0.008	-	-	-	-	-0.020				
Constant	5.792[a]	8.117[a]	4.667 [a]	8.918 [a]	4.706[a]	6.070[a]	7.245 [a]	5.435[a]	7.889 [a]	5.421[a]
γ	1.442[a]	1.482[a]	1.410[a]			1.351[a]	1.276 [a]	1.413 [a]		
σ^2	1.331[a]	1.453 [a]	1.208[a]			1.295[a]	1.344 [a]	1.223[a]		
L. Likelihood	-932.11	-457.90	-466.68	-658.07	-661.50	-849.811	-440.61	-404.05	-626.49	-593.23
σ(u)	-			1.073 [a]	0.831 [a]				1.125[a]	0. 819[a]
σ(v)	-			0.903[a]	0.786[a]				0.822[a]	0. 797 [a]
ρ(w,v)	**-**			**-0.207**	**-0.149**				**-0.283**	**0.45**
N	658	306	352	306	352	604	302	302	302	243

[a] p<0.01; [b] p<0.05; [c] <0.10.

Tables 4.7 and 4.8 present a summary of average TE scores coming from the SPF and the meta-frontier models, as well as the MTRs for SAGF and SFOR, respectively. In both tables, we present results obtained from unmatched and matched samples, as well as for conventional and sample selection corrected SPFs for BENF and CONF. Table 4.7 shows that the beneficiaries of the SAGF system display an average TE of 40%, a value that is consistent across all specifications, including when the sample selection framework is used. Similar TE scores have been reported by Bravo-Ureta et al. (2007), Frey et al. (2012), Ghebru and Holden (2015), and González-Flores et al. (2014). For SAGF controls, the TE scores range from 39% to 36%. For SFOR, the average TE for unmatched beneficiaries is 43% vs. 49% for unmatched controls, and these results are very similar to those obtained from the matched sample selection framework. It is important to remember, as mentioned earlier, that these results are only relevant for comparisons within groups, and not across groups.

In order to make a meaningful comparison of TE across different groups, we need to use a common benchmark technology, which is the reason why we estimate meta-frontiers. In addition, meta-frontiers make it possible to examine MTRs, a measure of the distance of the group frontier (BENF frontier or CONF frontier) with respect to the meta-frontier (O'Donnell et al., 2008).

On average, the results in Tables 4.7 and 4.8 show that, using the matched samples along with the sample selection SPF model, the estimated meta-technology ratios for BENF are significantly higher (98% for SAGF and 99% for SFOR) than for CONF (31% for SAGF and 56% for SFOR). Hence, TE with reference to the meta-frontier, which allows for a meaningful comparison between beneficiaries and controls, is considerably higher for BENF (40% for SAGF and 44% for SFOR) than for CONF (11% for SAGF and 27% for SFOR). These results are evidence that participation in POSAF-II has led to a significant increase in the productivity of beneficiaries relative to controls; however, both groups exhibit relatively low levels of TE compared to what has been reported in the literature (e.g., Bravo-Ureta et al., 2007).

The TE estimates reported here are relatively low when compared to the available evidence for Latin America (Bravo-Ureta et al., 2007; Lachaud et al., 2015). However, it is important to keep in mind that POSAF-II was implemented in areas that were severely damaged by Hurricane Mitch in October 1998. This natural disaster produced massive and lasting soil losses with profound adverse effects on productivity, posing severe management challenges to farmers (Menéndez-Duarte et al., 2003). Nevertheless, our findings convey the need to implement policies designed to provide tailored technical assistance over a suitable time frame. The intention is for farmers to improve their knowledge and managerial performance in order to achieve the full benefits of the NRM technologies adopted.

Table 4.7. Descriptive statistics of TE scores from alternative models for SAGF

Item	BENF		CONF		
Conventional SPF (SPF-C)	Mean	St.Dev	Mean	St.Dev	Test of Means
TE-group [a]	0.40	0.20	0.39	0.16	***
Meta-technology ratio (MTR) [b]	0.98	0.06	0.47	0.11	***
TE-meta-frontier [c]	0.39	0.20	0.18	0.09	***
TE-sample selection SPF (SPF-USS)					
TE-group [a]	0.40	0.20	0.39	0.17	***
Meta-technology ratio (MTR) [b]	0.89	0.07	0.47	0.13	***
TE-meta-frontier [c]	0.35	0.18	0.18	0.10	***
Matched sample (SPF-M)					
TE-group [a]	0.40	0.20	0.36	0.20	***
Meta-technology ratio [b]	0.94	0.03	0.51	0.16	***
TE-meta-frontier [c]	0.37	0.19	0.18	0.12	***
Matched sample with sample selection(SPF-MSS)					
TE-group [a]	0.40	0.20	0.36	0.20	***
Meta-technology ratio (MTR) [b]	0.98	0.06	0.31	0.11	***
TE-meta-frontier [c]	0.40	0.20	0.11	0.08	***

[a] Technical efficiency with respect to the group frontier.[b] Meta-technology ratio [c] Technical efficiency with respect to the meta-frontier.

Table 4.8. Descriptive statistics of TE scores from alternative models for SFOR

Item	BENF		CONF		
Conventional SPF (SPF-C)	Mean	St.Dev	Mean	St.Dev	Test of Means
TE-group [a]	0.43	0.17	0.49	0.15	***
Meta-technology ratio (MTR) [b]	0.94	0.16	0.56	0.11	***
TE-meta-frontier[c]	0.40	0.17	0.28	0.10	***
TE-sample selection SPF (SPF-USS)					
TE-group [a]	0.47	0.15	0.54	0.12	***
Meta-technology ratio (MTR) [b]	0.93	0.19	0.47	0.11	***
TE-Meta-frontier[c]	0.43	0.16	0.25	0.09	***
Matched sample (SPF-M)					
TE-group [a]	0.46	0.15	0.52	0.13	***
Meta-technology ratio (MTR) [b]	0.99	0.01	0.87	0.10	***
TE-meta-frontier [c]	0.46	0.15	0.46	0.13	***
Matched sample with sample selection(SPF-MSS)					
TE-group [a]	0.44	0.16	0.49	0.15	***
Meta-technology ratio (MTR) [b]	0.99	0.09	0.56	0.10	***
TE-meta-frontier[c]	0.44	0.16	0.27	0.10	***

[a] Technical efficiency with respect to the group frontier.[b] Meta-technology ratio [c] Technical efficiency with respect to the meta-frontier. Notes*** p<0.01; ** p<0.05; * 0.01.

In addition to comparing the managerial performance (i.e., TE) between BENF and CONF, we are also interested in quantifying the impact of POSAF-II on TVAP assuming full efficiency, i.e., that all farmers operate on their respective frontiers. We do this by calculating frontier output for beneficiaries and controls for SFOR and SAGF separately, using the results from the models estimated with matched sample and selectivity. Thus, any differentials in TVAP measured in this part of the analysis are technological gaps or distances between the respective production frontiers of the BENF and CONF groups. These differentials represent unbiased indication of technological change (shift in the frontier) attributable to POSAF-II since we control for biases from both observable and unobservable characteristics.

Table 4.9 shows that the average annual predicted frontier output (TVAP) for the beneficiaries of the SAGF system is US $76.3 per hectare, compared to US $47.2 per hectare for the respective controls. This is an increase of US $29.1, or 38.1%. The corresponding figures for SFOR are US $139.1 (BENF) and US $102.0 (CONF), which amounts to a US $39.8 gain per hectare, or a 28.6% increase. As also shown in Table 4.9, these differences are highly statistically significant. Now, if we multiply the per hectare increases in TVAP by the average farm sizes for each group and production system, we obtain household level benefits. Thus, the impact of POSAF-II resulted in an average annual benefit of US $457 for SAGF and US $980 for SFOR households given an average farm size equal to 15.8 and 24.5 hectares (see Table 4.2), respectively. The magnitude of this impact is significant considering that the Nicaraguan gross domestic product per capita in 2015 reached US$ 2,087 (World Bank, 2017). Therefore, the economic impact derived from being a beneficiary of POSAF-II is equivalent to approximately 25% and 50% of the GDP per capita for SAGF and SFOR, respectively. In sum, we note that beneficiaries of both systems have experienced a significant shift in their production frontier and incomes relative to the respective control groups, holding all inputs constant, and that this shift is a causal effect of POSAF-II.

Finally, we use the bounding approach suggested by Rosenbaum (2002) to verify if the difference in TVAP between beneficiary and control groups is affected by selection bias. Our results show that the TVAP differentials estimated are robust to effects in unobservable factors (such as managerial skills) larger than 100%. More details are provided in Appendix Table 4.A1.

Table 4.9. Average annual productivity increase per hectare from technical change (TC) attributable to POSAF-II (US$)

System	TVAP			Std. Err.[a]	T-test [b]
	BENF	CONF	TC		
SAGF	76.3	47.2	29.1	3.3	***
SFOR	139.1	102.0	39.8	6.2	***

[a] Tests are for differences in means with respect to treated farmers
[b] Bootstrap Std. Err with 1000 repetitions
*** $p<0.01$.

3.6 Summary and conclusions

In this paper, we analyze the impact of POSAF-II on technical efficiency (TE) and technological change (TC), and thereby on household income. POSAF-II is a natural resource management (NRM) program that was implemented in Nicaragua between 2002 and 2008. We use cross-sectional data for beneficiary and control farmers along with a method that combines propensity score matching (PSM) and sample selection corrected stochastic production frontiers (SPF). The former approach addresses possible bias from observable variables, while the latter mitigates biases from unobservable variables. The econometric results show that sample selection bias was not present, which implies that the matching procedures implemented were adequate to mitigate bias from both observable and unobservable variables. In order to check for the robustness of our results, we run a sensitivity analysis to test for the effect of unobservable variables on the estimated impact of POSAF-II on the total value of agricultural production (TVAP), and this further confirms that bias is not an issue in our analysis.

Beneficiaries received financial and technical support to facilitate the adoption of technologies associated with an agroforestry (SAGF) or a forestry (SFOR) production system. Our results reveal that average TE with reference to the meta-frontier is consistently higher for beneficiary farmers (40 % for SAGF and 44% for SFOR) compared to their respective controls (11% for SAGF and 27% for SFOR). These significant differences reveal that the location of the frontier for beneficiaries in both production systems is much higher than the location for control farmers with respect to the common benchmark. Furthermore, these differences are due to the fact that beneficiaries of both the SAGF and SFOR systems have experienced a significant shift in their production frontier, relative to the respective control groups, and this shift is a causal effect of POSAF-II. Consequently, the change in productivity among beneficiaries was driven by an upward shift in the production frontier as a result of technological change induced by the program.

The analysis presented in this study clearly shows that NRM projects, like POSAF-II, designed to promote environmentally-friendly technologies, can also have positive effects on the income and well-being of small and medium-sized farms. Furthermore, our findings indicate that POSAF-II induced a significant increase in productivity due to an upward shift in the production frontier and to a moderate improvement in the TE of beneficiaries relative to controls. These findings support the notion that to ensure that NRM technologies reach their potential, it is essential that those who design and implement these interventions pay particular attention to the technical assistance provided to farmers to encourage better managerial performance, and thus enhance utilization of the technologies promoted. In sum, our results justify the implementation of well-designed and carefully implemented NRM interventions as an instrument to increase farm income while promoting the adoption of technologies that are friendly to the environment. From a broader perspective, our findings suggest that NRM programs can contribute to the achievement of the economic and environmental dimensions of the Sustainable Development Goals (SDGs).

Finally, we point out that the present study was conducted in the absence of baseline data. Nevertheless, our results suggest that appropriate program design and careful choice of the methodology applied to define a proper counterfactual situation can provide robust results, even when the analysis is based only on endline data. Although this study generated robust results using cross-sectional data, the timely collection of baseline data remains an important undertaking in order to enrich studies of this type, and thus generate even more reliable results. Under ideal circumstances, a follow up survey would be undertaken 10 or 15 years after the end of a NRM project to allow for a more comprehensive assessment of benefits and of the long-term sustainability and learning effects of such projects.

3.5 References

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Appendix 1.

As explained in the text, the methodological framework used in this study- the participation Probit along with the sample selection SPF model- corrects for biases from observable and unobservable characteristics that, if not appropriately dealt with, can lead to misleading results. In addition, we examined the extent to which the null hypothesis of no difference in TVAP between BENF and CONF can be rejected. To this end, we use the bounding approach suggested by Rosenbaum (2002) to perform a sensitivity analysis. Since TVAP is a continuous variable, we used the ado-file (rbounds) in Stata proposed by Diprete & Gangl (2004). This method is characterized by using an arbitrary Gamma value to specify the level of bias. In lieu of an arbitrary value, we use the ρ from the sample selection estimate from Tables 4.5 and 4.6 to perform the sensitivity analysis. Therefore, the size of the bias is equal to one plus 0.60 and 0.15 for SAGF and SFOR, respectively.

Table 4.A1 displays the results of the sensitivity analysis for both production systems. A critical p-value larger than 0.05 would lead to the questioning of the impact of POSAF-II on TVAP. As shown in Table 4.A1, our results remain robust, even in cases when changes exceed 100% of the Gamma values (2.2 for SAGF and 1.30 for SFOR). In order to detect a change in the estimated impact of POSAF-II, the effect of unobservable variables should be significantly larger than 100%. This is very unlikely since the estimation process accounts for several variables that play a significant role in the decision to participate in POSAF-II. Thus, we conclude that the confidence intervals for TVAP differentials between beneficiaries and controls do not include zero or negative values.

Table 4.A1. Estimation of Rosenbaum bounds to check the sensitivity of results to unobservable bias

SAGF			SFOR		
Gamma* (ρ)	sig+	sig-	Gamma* (ρ)	sig+	sig-
1	0	0	1	0	0
1.6	**<0.001**	**0**	**1.1**	**<0.001**	**0**
2.2	**<0.001**	**0**	**1.3**	**<0.001**	**0**
2.8	<0.001	0	1.4	<0.001	0
3.4	<0.001	0	1.6	<0.001	0
4.0	<0.001	0	1.7	<0.001	0
4.6	<0.001	0	1.9	<0.001	0
5.2	<0.001	0	2.0	<0.001	0

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
"in bold" significance level of the Gamma values

Chapter 5 Key conclusions

By 2050 the world population is expected to reach 9 billion and producing enough food and fiber to feed all these people represents a significant challenge. In addition, complications derived from increasing unpredictable weather will make agricultural systems more vulnerable to extreme conditions, such as extended droughts, flooding, and heat waves. These processes impose a significant burden on natural resources and the higher demand for food implies the need to increase agricultural production, which leads to added pressure on soil, water and other resources. The increased exploitation of natural resources reduces soil productivity, which may lead to an expansion of land under cultivation to offset the lower productivity. Extreme weather, such as hurricanes and downpour events (i.e., flash-flooding), will produce substantial soil erosion and forest destruction, which will have a significant impact on overall soil productivity. In addition, a reduction in agricultural research and development (R&D) expenditures has made it more difficult to generate technologies to address these challenges. Generally, these challenges will pose a significant threat to the 1.2 billion people living below the poverty line, 70% of whom live in rural areas with most making their living from agricultural or other related activities.

Against this background, this dissertation analyzes the nexus between natural resource management (NRM) programs, productivity, and farmer well-being. NRM technologies comprehend the use of conservation agriculture, improved soil and water management, integrated pest management, as well as the implementation of agroforestry and silvopastoral practices (Food and Agriculture Organization of the United Nations [FAO], 2017). The underlying hypothesis is that NRM programs can address the vicious circle of low farm productivity, increased poverty, exploitation of natural resources, resource degradation and further reduced productivity. To validate this hypothesis, the evidence available in the resource economics literature concerning the impact of NRM programs on agricultural production and poverty alleviation in developing countries is examined.

Meta-regression methods are used to analyze 75 studies of NRM program effects with a total of 215 observations. Based on these data we compare the results of several econometric approaches that include fitting ordered probit, probit, ordinary least squares regression, and Bayesian regression models. Our results indicate that NRM programs are more likely to have positive effects in Asia and Africa. However, our results also indicate that the magnitude of the effect is relatively lower on these two continents. Likewise, the inclusion of training and participatory extension methods appears to increase the likelihood of finding a positive effect. Both characteristics also matter when it comes to finding a larger average treatment effect. Our results further suggest that the likelihood of a positive treatment effect decreases when NRM programs are implemented by governments. This indicates that government agencies involved in the implementation of NRM programs need to enhance their managerial performance to deliver better results. Furthermore, in the short run, governments should work closely with NGOs and international agencies on the delivery and the implementation of NRM technologies.

Our results show that the use of yield or a monetary outcome as dependent variables, relative to the use of technical efficiency (TE), decreases the likelihood of observing a positive treatment effect. It is commonly argued that NRM leads to a more efficient use of natural resources, specially fertilizer; thus, our finding supports such argument.

Just as other studies show that NRM technologies need an appropriate amount of time to generate significant effects, our results indicate that there is a positive association between years elapsed between the end of program and when the evaluation is undertaken. This opens the door to reconsider impact evaluations that show insignificant or negative effects in the short term.

Furthermore, development agencies should contemplate this point when determining the timing of impact evaluations. Econometric methods, the type of data, and sample size do not play a significant role for program effectiveness.

After studying the accumulated evidence in the literature, we proceed to provide our own evaluation of a specific NRM intervention, the Socio-Environmental and Forestry Development Program-II (POSAF-II) implemented in Nicaragua, between 2002 and 2008. The goal of POSAF II was to promote economic development and environmental sustainability. Results based on propensity score matching (PSM), ordinary least squares (OLS), weighted least squares (WLS) and instrumental variables (IV) indicate that POSAF-II has had a positive and significant impact on the total value of agricultural production, thus increasing agricultural income and household wealth. Furthermore, the positive benefit accrued by beneficiary farmers led neighbors to adopt NRM technologies, which produced a spillover effect of approximately half the size that beneficiary farmers received themselves. These results show that a well-designed NRM program can produce additional welfare gains for those who do not receive an incentive to adopt the technologies offered by the program.

Furthermore, our results show that the combination of direct and indirect effects of NRM programs yield a high payoff. A 35% internal rate of return obtained from our estimation illustrates that investments in NRM technologies like those delivered by POSAF-II for agroforestry (SAGF) and forestry (SFOR) have a positive economic return. However, due to data constraints it was not possible to disentangle the contribution of specific technologies to the economic results; yet, it does appear that the combination of technologies for the SAGF and SFOR systems was appropriate. Nevertheless, in formulating similar projects, it would be informative to examine alternative bundling of technologies to see if the performance of recommended systems could be improved. This is a matter that deserves further study.

Our analysis suggests that the design of NRM programs should include a proper strategy to deliver agricultural technologies, and the length of time that technical assistance is provided should be sufficient to allow the full adoption of the technologies. POSAF-II provided an initial training phase that led farmers to choose the technologies that best fit their needs; thus, the demand for a specific package came from a knowledge base delivered to farmers as part of the intervention. In contrast, development projects often deliver technologies that extension agents or researchers deem suitable without much or even any farmer input; this approach is likely to lead to a low level of empowerment and interest from potential beneficiaries in the technologies promoted. In addition, three years of extension support with an average contact of two visits per month seems to be appropriate to induce the adoption of the technologies offered by POSAF-II. These factors plus an implementation scheme compatible with the constraints faced by different types of beneficiaries can be considered crucial for the success of an NRM program like POSAF-II.

It has been argued that more efficient farmers make better use of natural resources and the implementation of NRM technologies increase the efficiency of external inputs, such as fertilizers and pesticides. Our results confirm these effects based on a method that combines propensity score matching (PSM), sample selection corrected stochastic production frontiers (SPF), and a meta-frontier analysis. Our analysis of technical efficiency (TE) and technological change (TC) shows a positive impact of NRM technologies. The results reveal that the frontier for beneficiaries in both SAGF and SFOR is much higher than the function for control farmers with respect to the common benchmark. Furthermore, these differences are due to the fact that beneficiaries of both production systems have experienced a significant shift in their production frontier, relative to the respective control groups, and this shift is a causal effect of POSAF-II. Consequently, the change in productivity among beneficiaries was driven by an upward shift in the production frontier as a result of technological change induced by the program.

The analysis presented in this study clearly shows that NRM projects, such as POSAF-II, designed to promote environmentally-friendly technologies, can also have positive effects on the income and well-being of small and medium-sized farms. Furthermore, our findings indicate that POSAF-II induced a significant increase in productivity due to an upward shift in the production frontier and to a moderate improvement in the TE of beneficiaries relative to controls. These findings support the notion that to ensure that NRM technologies reach their potential, it is essential that those who design and implement these interventions pay particular attention to the technical assistance provided to farmers to encourage better managerial performance, and thus enhance utilization of the technologies promoted.

The promotion of NRM programs to tackle natural resource degradation and to increase productivity is a win-win public policy. Overall, NRM programs increase monetary outcomes by 8%, on average, and the effect on productivity ranges between 9.15% and 16.5%, which leads to substantial welfare gains for farmers. This indicates that its implementation leads to a better use of natural resources and induces a more efficient use of external inputs. NRM technologies aim at achieving a suitable and profitable agricultural production; our results indicate that this goal has been clearly accomplished by POSAF_II and other sumilar programs. Overall, our findings suggest that NRM technologies can effectively address the "triangle of poverty," and are relevant when considering the achievement of economic and environmental dimensions of the sustainable development goals (SDGs).

Finally, it is important to briefly consider limitations of this study and ideas for future research. A clear shortcoming is that the available data did not make it possible to disentangle the effect of individual technologies delivered by POSAF-II. We do recognize that the design of policies could benefit from more precise information concerning separate technologies. Thefore, an avenue for future research is to generate more disaggregated data so that the analysis can then focus on individual technologies and on the asessment of the optimal budling of technologies.

Furtheremore, the implementation of NRM technologies has focused primarily on farm and technology characteristics but has neglected detailed consideration of individual farmer characteristis, both productive and socio-economic, to shed light on what beneficiaries are more likely to adopt in a sustainable basis beyond the end of the project (Lalani et al. 2016; Zeweld et al. 2017). Most impact evaluation studies assume that farmers are expected profit maximizers and thus the adoption of new technologies becomes more likely if the associated expected profits exceeds the prevailing situation. However, this process is not well understood and is neccesary to develop a stronger link between behavioral economics and impact evaluation methods in order to have a more clear understanding of the adoption of NRM technologies.

Another feature that deserves attention is the link between climate change perceptions, farm efficiency and the adoption of NRM technologies. Up to now, the degree to which technical efficiency (TE) is affected by climate change perceptions has not been investigated. Most of the studies that examine the effects of climate on TE have focused on the connection between climatic variables and TE scores. However, these studies fail to account for the role that farmers perceptions may play in the adoption of NRM technologies.