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Impacts of an Agricultural Development Program for Poor Coconut Producers in the Philippines: An Approach Using Panel Data and Propensity Score Matching Techniques

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Using panel data econometric techniques and propensity score matching procedures, this study evaluates the impact of the MAUNLAD agricultural development program—a program designed to help alleviate poverty in Philippine coconut-producing communities. Our results indicate that the program had a significant positive mean effect on the recipients' total net farm income. Moreover, the probability of being in poverty is shown to decrease when a poor coconut producer participates in the program. The program's emphasis on training, intercropping, and livestock integration, as well as the more participatory approach taken, contributed to the strong positive impact of the program.

Key words: coconut farmers, panel data econometric techniques, poverty alleviation program, propensity score matching (PSM)

Introduction

A major problem facing the Philippine coconut industry is the high incidence of poverty among coconut farm families. Statistics show that about 90% of Filipino coconut farmers live below the poverty line (Castillo and Quebral, 1996). In fact, the Philippine Coconut Authority (PCA)[1] reports that more than two million coconut farmers in the Philippines continue to live in poverty [PCA-Agricultural Research and Development Branch (ARDB), 1998]. Previous studies on this issue have found that the low income of coconut farm households can be attributed to one or a combination of the following factors: (*a*) low coconut yields, (*b*) low prices of farm produce, (*c*) a limited market, (*d*) underutilization of coconut lands, and (*e*) high cost of farm inputs (Magat, 1990).

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[1] The Philippine Coconut Authority (PCA) is one of the agencies within the Philippines' Department of Agriculture whose primary mandate is to promote the rapid vertical integrated development and growth of the coconut and other oil palm industries, in all its aspects, to ensure the coconut farmers become direct participants in, and beneficiaries of, such development and growth (P.D. 232, as amended by P.D. 1468).

The concern about poverty in coconut-based farmer communities resulted in the implementation of various government agricultural programs aimed at improving the productivity and incomes of these poor households. However, the majority of these programs focused simply on the transfer of particular technologies as a means to improve farm incomes and alleviate poverty among coconut-producing households. These narrow technology transfer programs had limited success due to the lack of planning and consultation with farmer-recipients and other stakeholders in the industry (Aragon, 2000). The absence of a monitoring and evaluation system, as a feedback mechanism for producers and/or stakeholders, also contributed to these past programs' lack of success (PCA-ARDB, 1998). In particular, these programs did not make it a priority to obtain socioeconomic baseline data as a means to evaluate and, consequently, adjust the program to better meet the needs of coconut farmer recipients.

In light of these past failures, the PCA launched a more comprehensive and participatory program in 1999 called "Maunlad na Niyugan Tugon sa Kahirapan," which is translated in English as "Progressive Coconut Farming to Address Poverty," and is more commonly known as the "MAUNLAD program."[2] The goal of this program is to help poor coconut farmers attain self-sufficiency in basic food supply and to increase their average gross income from 10,000 to 20,000 Philippine pesos (PhP) per year (or approximately US$200 to $400 per year).[3] The MAUNLAD program is "comprehensive" in the sense that it includes several different components to assist poor coconut producers, aside from pure transfer of technology (i.e., seeds, fertilizer, etc.). For example, improved credit access and training services (among others) are important aspects of the program. It is also important to note that this program explicitly emphasized the importance of farmer participation (i.e., a participatory approach) in its development and implementation, and advocated extensive monitoring and evaluation.

The objective of this article is to assess the ex post impact of the MAUNLAD agricultural development program and recommend strategies to improve/sustain its performance. A two-period panel data set of program recipients and nonrecipients, purposely collected as a means to evaluate the program, is utilized to achieve this objective. Panel data econometric techniques [using difference-in-difference (DID) approaches] and propensity score matching (PSM) techniques (to control for selection problems) are employed to more accurately measure program impacts. Insights from a more accurate assessment of program impacts have important implications for designing effective agricultural development programs in the Philippines and in helping assure continued government support in the future.

A number of impact evaluation studies using panel data DID, and/or PSM techniques appear in the anti-poverty and the active labor market literatures. [For examples of anti-poverty studies, see Schultz (2004); Skoufias (2005); and Ravallion and Chen (2005). For examples of the active labor market literature, see Heckman, LaLonde, and Smith (1999); Benus, Grover, and Varcin (1998); and Benus et al. (1998).] However, only a few studies have used these so-called "new-generation" impact evaluation techniques in the context of agricultural development programs or policies. For instance, Baker (2003) discussed a number of development studies that employed all or some of these newer impact evaluation techniques, and, among those studies she examined, only one

[2] Hereinafter, the poverty alleviation program of interest in this article is referred to as the "MAUNLAD program."

[3] The exchange rate during the period under consideration is around PhP50 to one U.S. dollar.

(World Bank, 1999) was related to an agricultural development project (i.e., an extension program in Kenya).

In fact, in the context of an agricultural development program, a majority of the "new-generation" impact evaluation studies involve assessment of extension-type programs like Farmer Field Schools (FFSs) and Training-&-Visit (T&V) systems (see Bindlish, Evenson, and Gbetibouo, 1993; World Bank, 1999; Godtland et al., 2004; Feder, Murgai, and Quizon, 2004). One exception is Sadoulet, de Janvry, and Davis (2001) where panel data DID techniques were used to analyze the PROCAMPO program—a program that compensates Mexican farmers due to the anticipated negative effects of the North American Free Trade Agreement (NAFTA). Although there have been a number of studies employing the new-generation impact evaluation techniques in agriculture, no previous investigation has carefully applied a combined panel data DID and PSM approach to analyze an agricultural development project like the MAUNLAD program. This paper contributes to the agricultural economics/development literature in this regard. As Ravallion (2005) argues, good ex post impact evaluations may require the use of multiple new-generation impact evaluation techniques.

Description of the Program and the Data

Program Components

As discussed above, the MAUNLAD program aims to improve farm income of poor coconut producers and, consequently, alleviate poverty in coconut-producing communities in the Philippines. From past experience, the Philippine government has learned that a well-planned, participatory, and multi-faceted agricultural development program may be more effective in addressing poverty in coconut farm communities. Accordingly, to create this type of development program, the Philippine government invested approximately PhP10 million in the MAUNLAD program (Aragon, 2003) and the program was designed with the following components: (*a*) training services; (*b*) technology assistance; (*c*) promotion of intercropping; (*d*) promotion of livestock integration; (*e*) credit support; (*f*) irrigation and infrastructure support; (*g*) market assistance; (*h*) information support; (*i*) institutional networking support; (*j*) planning, policy, and project development support; (*k*) program monitoring and evaluation; and (*l*) research and development support.

Among the 12 components of the program, however, promotion of intercropping, promotion of livestock integration, training services, credit support, and technology assistance were the areas of emphasis in the initial implementation of the program. Promotion of intercropping and promotion of livestock integration are areas of emphasis because about 2.1 million hectares of coconut area are typically not utilized due mainly to the predominance of traditional coconut mono-cropping in the Philippines. This underutilization of land occurs in a mono-cropping system because a pure stand coconut farm typically utilizes only 22% of the area at a spacing of 7.5 × 7.5 meters, leaving nearly 78% of the area not effectively utilized (Suharto, 1996). Utilizing these unused areas (between palms of the coconut trees) for growing additional high-value crops and/or raising livestock was seen as a means for poor producers to gain more income and receive some degree of risk protection (through diversification) in the event of a total coconut crop loss (Batugal, 1996; Reynolds, 1995). The intercrops used by coconut producers are mainly fruit trees (i.e., jackfruit and mangoosteen), vegetables (e.g., bittergourd, mungbean), root crops (e.g., cassava), and/or other annual crops. The livestock typically integrated into coconut farms are cattle, swine, and/or poultry.

The training aspect of the MAUNLAD program was emphasized because it was viewed as a means for producers to develop their analytical skills, thereby enabling them to make better decisions and improve their productivity. The training involved in the MAUNLAD program typically includes topics about the proper use of fertilizers/pesticides/herbicides, proper intercrop choices, and coconut processing methods (among others). Credit support was also seen as an important element to alleviate poverty among coconut producers because increased capital availability is believed to improve access to necessary inputs and technical support. Finally, the technology assistance aspect of the MAUNLAD program is the traditional technology transfer approach where planting materials (i.e., improved coconut varieties) are simply provided free of charge to the program recipients.

Selection of MAUNLAD Program Sites and Recipients

Four program sites—Batangas, Davao City, Davao del Sur, and Biliran—were selected as the general areas for implementation of the program (see figure 1). Note that these sites were selected because they are the major coconut-producing areas in the Philippines. Once these areas were selected, the particular towns (within each area) for program implementation were then chosen based on the density and contiguity of coconut farms in the selected program site. The towns selected for the program have dense clusters of small but contiguous farms owned and/or operated by small coconut farmers, with an aggregate total of at least 15 hectares.

After the selection of program towns, the MAUNLAD program participants were then selected by the PCA based on the following two criteria. First, the participant coconut farmer must be willing to be a vital member of the program; and second, the farm owned and/or cultivated by the farmer must be at least one hectare, planted with coconut trees, and suitable for intercropping and livestock raising. Eventually, there were 48 coconut producers who participated in the MAUNLAD program in all sites (see table 1). A random sample of producers within the MAUNLAD program towns who were not willing to participate (but were willing to provide data) were then designated as part of the nonparticipant control group. A total of 107 nonparticipants were selected as control producers from within the MAUNLAD towns.

Additional nonparticipant control producers were selected by picking another coconut-producing town within each area having very similar characteristics to the MAUNLAD program towns.[4] For comparability purposes, the PCA made the effort to choose nonparticipant control towns with topography, climate, markets, and socio-demographic characteristics similar to the selected MAUNLAD towns. Within the selected nonparticipant control town, a random sample of 104 coconut producers were chosen to serve as a control group. The frequency distribution of observations for both the MAUNLAD and non-MAUNLAD sites is reported in table 1.

[4] Additional control observations from non-MAUNLAD towns were selected to mitigate potential bias from "diffusion effects" in the MAUNLAD towns (Ravallion, 2005). "Diffusion effects" are present when the program has inadvertent impacts felt by the control group within the program site. In the presence of positive "diffusion effects," comparing program recipients with nonrecipients may likely underestimate program impact.

Figure 1. Program sites of the MAUNLAD program, Philippines

Table 1. Distribution of Farmer-Respondents by Program Site and Type

	Classification of Farmer-Respondents					
	MAUNLAD		Non-MAUNLAD		Total	
Site	Number	Percent	Number	Percent	Number	Percent
Batangas						
Quipot [a]	4	8	40	19	44	17
Maraykit	—	—	40	19	40	15
Biliran						
Burabod [a]	29	60	17	8	46	18
Busali	—	—	29	14	29	11
Davao City						
Balengaeng [a]	7	15	20	9	27	10
Tagakpan	—	—	35	17	35	14
Davao del Sur						
Darong [a]	8	17	30	14	38	15
All Sites	48	100	211	100	259	100

[a] Selected MAUNLAD town

Two sets of data were collected from both the selected program recipients and non-recipients. The first set is the baseline data, gathered prior to the start of the MAUNLAD program. The second set is comprised of the impact evaluation data which were gathered after implementation of the program. Due to budget and coordination constraints, the baseline data were collected over several years (rather than in one single year). The baseline data from producers in Batangas Province were collected in 1999. The baseline data for Davao City and Davao del Sur were collected in early 2000 prior to implementation. The baseline data for Biliran were collected in early 2001. The MAUNLAD program was then officially implemented in late 2000 for three program areas—Batangas, Davao City, and Davao del Sur—and data for this year were subsequently collected. For the Biliran area, the MAUNLAD program officially commenced in late 2001, and data were collected for this year. Although the timing of data collection varies for the different locations, the data can be classified as either "before" or "after" program implementation. Note that the two-period data used in this study come from the same individual farmer, which means we have a panel or longitudinal data set to evaluate the impact of the MAUNLAD program.

The farm-level data used in this study include information about input utilization, production, expenses, and income from the production of coconut, other agricultural crops, livestock, and processing enterprises. In addition, information was also collected about the household size of coconut farmers, membership in cooperatives, amount of credit utilized by the farmer, amount of rainfall, and the trainings attended by coconut farmers.

Empirical Approach

Estimation Strategies

To obtain an accurate assessment of the program effect, one would ideally look at the difference between the outcomes for MAUNLAD producers and the outcomes from the same producers had they not participated in the program. Clearly, however, it is impossible to obtain data on MAUNLAD producers had they *not participated*; data are available only for producers who participated. The missing data for this type of program evaluation are called the "counterfactual" in the literature—What would have been the outcome if the MAUNLAD program recipients had not participated in the program?

More formally, let Y_i be an outcome variable for coconut producer i in a sample of size n. The outcome of interest in our case is total net farm income of the coconut farmer. As described in the previous section, some producers in the sample participated in the MAUNLAD program and some did not. Thus, let M_i be a dummy variable representing program participation when $M_i = 1$, and zero otherwise. Given the missing counterfactual alluded to above, we are restricted to estimating only the outcome difference between the MAUNLAD participants and nonparticipants (instead of the outcome difference between MAUNLAD participants and these same participants had they not participated). Hence, in applied work, economists utilize data on the participant and nonparticipant groups to estimate a regression of outcomes (Y_i) on a participation dummy (M_i) and a vector of control covariates ($\mathbf{X}_i$):

$$Y_i = \delta M_i + \mathbf{X}_i\beta + \varepsilon_i \quad \text{for } i = 1, \ldots, n, \tag{1}$$

where δ is simply the estimate of the program impact.

The estimator δ is unbiased only if the *observed* mean counterfactual (i.e., the observed outcome from the nonparticipant group) is truly equal to the *unobserved* mean counterfactual (i.e., the outcome for the participant group had they not participated). This condition means that the observed nonparticipant group is, on average, a good surrogate for the unobserved counterfactual outcome. This condition can be met only if the assignment of participant and nonparticipant groups in the sample is truly exogenous. Specifically, there is no selection bias where the selection of the participant and nonparticipant groups is invariant to the outcome of interest.

In practice, however, this condition is typically not met because observed or unobserved characteristics that influence selection also typically influence the outcome of interest. For example, it is possible that poor coconut producers with relatively higher incomes (than their peers) are more willing to participate in the program due to their higher (unobserved) managerial ability. Consequently, we would expect these producers to have had higher incomes regardless of their participation in the program. In this case, the impact estimate in (1) may just be due to the difference in the distribution of unobserved managerial ability between program participants and nonparticipants. Hence, if the distribution of observed and unobserved characteristics differs between participants and nonparticipants (and these characteristics also influence the outcome variable and selection), then selection problems will occur and our regression-based impact estimate in (1) may not be accurate. The selection problem due to observable characteristics is commonly known in the literature as the "selection on observables" problem, and the selection problem due to unobservable characteristics is denoted the "selection on unobservables" problem.

The regression in equation (1) implicitly assumes a single cross-sectional data set where the impact measure is essentially a "single-difference" calculation. Availability of a two-period panel data set allows us to calculate a "double difference" or "difference-in-difference" (DID) estimator of program impact (Wooldridge, 2002; Ravallion, 2005).

In essence, the DID approach compares the difference between the outcomes of the participant and nonparticipant groups during a pre-intervention baseline period (i.e., "before" implementation) versus the difference in the outcomes "after" program implementation. For a two-period panel where program participation is only in the second period, the DID estimator can be estimated by first taking the panel data analogue of the specification in (1):

(2) $$Y_{it} = \delta M_{it} + \mathbf{X}_{it}\beta + \varepsilon_{it} \quad \text{for } i = 1, \ldots, n;\ t = 1, 2,$$

where ε_{it} is defined as having both a time-invariant component (α_i) and a time-varying component (v_{it}) such that $\varepsilon_{it} = \alpha_i + v_{it}$. In this specification, the vector of control covariates $\mathbf{X}_{it}$ also includes a "before and after implementation" dummy variable.

If the unobservable characteristics that cause selection bias are time-invariant, then first-differencing or a fixed-effects transformation of the variables in equation (2) can help alleviate this problem:

(3) $$\Delta Y_i = \delta M_i + \Delta\mathbf{X}_i\beta + \Delta v_i \quad \text{for } i = 1, \ldots, n,$$

where the deltas (Δs) represent either: (*a*) differencing out the first time period value from the second period value (if we use a first-differencing transformation), or (*b*) a time-demeaning or mean-differencing transformation where each value is subtracted by the mean value (over time) for each cross-sectional unit (if we use a fixed-effects transformation) (see Wooldridge, 2002). Although we used both procedures in our analysis and verified that the results from both approaches are the same, only the results from the fixed-effects approach are presented here.

The fixed-effects approach works well in helping to mitigate selection problems if the selection of participants is based roughly on time-invariant variables (regardless if these are observable or unobservable). The correlation between unobserved time-invariant factors and the independent variables (due to omitted variable or selection bias) is taken into account in the fixed-effects approach. In our case, we know that the selection of MAUNLAD recipients is primarily based on farmers with relatively smaller farm size and their willingness to participate in the program. We can argue that farm size is a roughly time-invariant variable that may partly be swept away in the fixed-effects approach if it really did cause nonrandom selection and consequently the endogeneity problems. In addition, we can argue that the willingness of producers to participate is linked to unobserved time-invariant variables associated with each producer (i.e., management ability). Given these arguments, we feel that a fixed-effects approach helps alleviate some of the selection problems (i.e., it sweeps away time-invariant sources of heterogeneity) and is a logical initial approach for estimating the impact of the MAUNLAD program.

Notwithstanding the first-differenced/fixed-effects transformations, there still may be selection problems if the subsequent outcome *changes* (ΔY) are a function of the producers' initial (pre-intervention) time-varying characteristics and these initial characteristics also influence assignment between participant and nonparticipant groups. In our case, the MAUNLAD program was targeted for coconut farms with roughly smaller farm sizes, and this targeting criterion may also influence subsequent income *changes*, if they are truly time-varying (Jalan and Ravallion, 1998; Ravallion, 2005).[5] Here, we are again confronted with the problem of finding comparable participant and nonparticipant groups having very similar pre-intervention characteristics.

To address the observable time-varying characteristics that cause initial heterogeneity in the sample (and the consequent selection problem discussed in the previous paragraph), we adopt the propensity score matching (PSM) technique introduced by Rosenbaum and Rubin (1983). The idea behind the PSM approach is to find control observations (i.e., non-MAUNLAD farmers) having initial observable characteristics similar to the program recipients, to serve as valid surrogates for the missing counterfactuals.

To outline the method in more formal terms, let $P(\mathbf{X}_i) = \Pr(M_i = 1 \mid \mathbf{X}_i)$ denote the propensity score for producer i, which represents the probability of producer i participating in the program conditional on pre-intervention control covariates $\mathbf{X}_i$. Rosenbaum and Rubin (1983) proved that if the M_i's are independent over all i, and the outcomes are independent of participation given $\mathbf{X}_i$ (i.e., unobserved differences do not influence participation), then outcomes are also independent of participation given $P(\mathbf{X}_i)$. Hence, PSM uses $P(\mathbf{X}_i)$ to select the non-MAUNLAD participants who "match" the MAUNLAD participant characteristics.

In this study, we follow common practice in the matching literature by using a parametric binary response model (a probit model in our case) to estimate the propensity score for each observation in the recipient and control groups (Sianesi, 2001; Becker and Ichino, 2002). Pre-implementation variables are used as the observable characteristics in the probit model to calculate the propensity score (see further discussion of this issue below). The "balancing property" of the probit specification is tested to ensure that the sample of program recipients and the sample of nonrecipients have similar mean propensity scores and observables at various levels of propensity scores.[6]

Using the calculated propensity scores from the probit model that satisfy the balancing property, the sample is then matched whereby the program recipients and nonrecipients share sufficiently similar values of their observed characteristics. Following standard practice in the PSM literature, we then use the 1-to-1 nearest neighbor matching approach (without replacement) and the kernel matching approach to identify the nonprogram recipients who match the program recipients (Sianesi, 2001; Becker and Ichino, 2002). Using both approaches enables us to determine whether our results are robust to changes in the matching criteria. A "common support" constraint is also imposed where program recipients to be matched are dropped from the sample when their estimated propensity score is either above the maximum or below the minimum propensity score for the comparison (nonparticipant) group. Imposing this common support restriction often improves the quality of the matches (Becker and Ichino, 2002). Standard t-tests are then conducted on the pre-intervention observed characteristics to verify that these are not statistically different between the eventual program recipients and nonrecipients. This allows us to confirm we have a matched sample that can provide

[5] Note that availability of a panel data set allows for the possibility of helping to alleviate selection problems arising from initial heterogeneity that influence both the assignment and the outcome *levels* (Y) (as described in the single-difference discussion above). However, the panel data double-difference approach may still have selection bias if the initial heterogeneity influences assignment as well as outcome *changes* (ΔY) over time.

[6] The Becker and Ichino (2002) approach for testing the balancing property is adopted here. Specifically, the treatment and control groups are divided into several strata based on the predicted propensity scores and, within each stratum, equality of means of the observable characteristics are tested.

a good surrogate for the unobserved counterfactual and an accurate program impact can be calculated.

The obvious disadvantage of PSM is the reduction in the number of control or treatment observations in the sample because there may be treatment or control observations without matches. Nevertheless, the PSM approach addresses selection problems due to observable time-varying factors that may not have been addressed in the fixed-effects transformation. Moreover, as Ravallion (2005, p. 40) intimated, cleaning out the observable initial heterogeneity using PSM prior to estimation employing a fixed-effects panel data technique helps in more accurately estimating the mean impact of anti-poverty and other development programs (see also Heckman, Ichimura, and Todd, 1997, 1998).[7]

Model Specification: Impact Model and Probit Model

The purpose of the estimation strategies discussed above is to more accurately measure the impact of the MAUNLAD program on the total net farm income of those who participated in the program. Thus, the dependent or outcome variable of interest is the total net farm income per year [in Philippine pesos (PhP)].[8] The total net farm income (*TFI*) consists of income derived from all farm sources such as coconut production, intercropping practices, and livestock production. *TFI* as the outcome variable also gives an indication of the poverty status of producers (when compared to the relevant poverty line at the time).

To properly estimate the impact of the MAUNLAD program on total net farm income, the control covariates used in the study are: (*a*) the number of years of farmer's education (*EDUC*), (*b*) household size (*HH_SIZE*), (*c*) nonfarm household income (*NFI*), (*d*) total coconut farm area utilization (*C_AREA*), (*e*) labor utilization (*LABOR*), (*f*) material expense (*MAT_EXP*), (*g*) membership in the farmer cooperatives (*COOP*), and (*h*) the amount of rainfall (*RAIN*). A "before and after" program implementation dummy variable (*D*2) was included in the model as a control variable. Since the data were collected over several years, we included actual-year dummy variables in the specification as well (i.e., *YR*2000–*YR*2003 dummy variables, with *YR*1999 as the base). These variables are observable characteristics serving as control variables to account for observable factors that may affect the outcome differential between participants and nonparticipants.

[7] Combining PSM and the double-difference panel data approach helps eliminate selection bias due to time-invariant factors (regardless if it is observable or unobservable), as well as bias due to observable time-varying factors. However, it can be argued that selection bias may not be totally eliminated if there are unobserved time-varying factors that affect both participation and outcome changes over time. Nevertheless, the anti-poverty evaluation literature regards the combined PSM and double-difference panel approach as one of the best methods for eliminating selection problems in general (Ravallion, 2005). In our case, we feel that the combined PSM and double-difference panel approach eliminates the majority of selection problems, and even if the selection problem due to unobserved time-varying factors is still present, it is negligible.

[8] Note that all the income and expense variables (in PhP) used in the study are real (rather than nominal) values, with the year 2000 as the base. In addition, total net farm income includes net returns from all coconut products sold, the intercrops, and livestock. Examples of coconut products sold are copra (the dried meat of coconut from which oil is extracted) and de-husked coconut. Examples of intercrops sold are vegetables (e.g., bitter gourd, mungbean, okra), other annual crops (e.g., corn, pineapple), rootcrops (e.g., cassava), and fruit trees (e.g., jackfruit and mangoosteen). Livestock sales included in the net income calculation are returns from the sale of poultry, cattle, and/or swine. Nonfarm income from other sources (e.g., day labor, construction work) is not included in the farm income calculation (see the variable *NFI*).

Table 2. Definitions of Variables

Variable	Definition
TFI	Total farm income (PhP) of farmer/year which comes from coconut production, intercropping practices, and livestock raising
EDUC	Number of years of farmer's education
HH_SIZE	Size of the farmer's household (number of persons)
NFI	Total nonfarm household income of the farmer (PhP)
C_AREA	Total land area utilization of coconut (ha)
IC_AREA	Total land area utilization of intercrops (ha)
LABOR	Amount of labor utilized by farmer in mandays (MD)
MAT_EXP	Amount of farmer's material expenses (e.g., fertilizer, feeds) (PhP)
RAIN	Amount of rainfall (mm)
COOP	Dummy variable = 1 if the farmer is a member of a cooperative/farmers' association; 0 otherwise
CREDIT	Amount of credit availed by the farmer (PhP)
TF_AREA	Total farm area owned by the farmer (ha)
M	Dummy variable = 1 for MAUNLAD program recipient; 0 otherwise
LVSTOCK	Dummy variable = 1 if the farmer is involved in livestock integration; 0 otherwise
TRAINING	Dummy variable = 1 if the farmer participated in the trainings conducted through the program; 0 otherwise
*D*2	Dummy variable = 1 after program implementation; 0 before implementation

As noted above, a probit model of MAUNLAD participation must be estimated to calculate the propensity scores for each farmer. This entails properly specifying the probit equation with independent variables that affect whether or not a farmer participates in the program. Aside from the independent variables satisfying the balancing property, there is little guidance available to researchers for selecting the set of independent variables needed to calculate the propensity score (Smith and Todd, 2005). Hence, we chose variables in our survey that on theoretical grounds may be associated with the probability of participating in the program.

The following variables are included in the probit specification: (*a*) a training participation dummy (*TRAINING*), (*b*) the amount of intercropped area utilized (*IC_AREA*), (*c*) the amount of credit utilized (*CREDIT*), (*d*) the number of years of farmer's education (*EDUC*), (*e*) household size (*HH_SIZE*), (*f*) total coconut farm area utilization (*C_AREA*), (*g*) labor utilization (*LABOR*), (*h*) material expense (*MAT_EXP*), (*i*) membership in the farmer cooperatives (*COOP*), (*j*) the amount of rainfall (*RAIN*), and (*k*) total farm area of the producer (*TF_AREA*). Using the balancing property test in Becker and Ichino (2002), all the independent variables included in the probit specification above satisfy the balancing property. (The detailed results of the balancing tests are not reported here, but are available from the authors upon request.)

Definitions of the main variables used in the study are provided in table 2, and the summary statistics for these variables are presented in table 3 (both before and after the implementation of the program). Note that table 3 divides the summary statistics into three panels (A, B, and C) to show the statistics for the three key groups in the sample: the MAUNLAD farmers in the selected MAUNLAD towns (panel A), the non-MAUNLAD farmers in the selected MAUNLAD towns (panel B), and the non-MAUNLAD farmers in the control (non-MAUNLAD) towns (panel C).

Table 3. Summary Statistics Before and After Program Implementation

Variable	Mean		Standard Deviation	
	Before	After	Before	After
A. MAUNLAD Program Recipients in the Selected Towns (n = 48):				
TFI (PhP)	22,973	30,097	43,056	38,796
TRAINING	0.06	1.00	0.24	0.00
LVSTOCK	0.31	0.63	0.46	0.49
IC_AREA (ha)	0.77	0.82	1.08	0.89
CREDIT (PhP)	10.41	17,481	72.17	70,152
EDUC (years)	8.10	8.10	3.78	3.78
HH_SIZE (no.)	5.31	5.45	2.04	2.41
NFI (PhP)	29,099	32,072	35,994	56,458
C_AREA (ha)	1.93	2.19	1.47	1.38
LABOR (mandays)	76.57	249.42	110.90	570.90
MAT_EXP (PhP)	3,977	10,490	12,714	23,574
COOP	0.54	0.79	0.50	0.41
RAIN (mm)	2,457	1,931	80.28	208
TF_AREA (ha)	2.48	2.52	1.44	1.41
B. Non-MAUNLAD Farmers in the Selected MAUNLAD Towns (n = 107):				
TFI (PhP)	34,108	18,652	46,737	26,251
TRAINING	0.02	0.46	0.14	0.50
LVSTOCK	0.38	0.50	0.49	0.50
IC_AREA (ha)	0.78	0.64	0.71	0.76
CREDIT (PhP)	10,862	0	38,750	0
EDUC (years)	8.44	8.44	3.38	3.38
HH_SIZE (no.)	4.46	4.45	2.15	2.25
NFI (PhP)	68,359	31,886	118,027	74,264
C_AREA (ha)	1.81	1.74	1.39	1.27
LABOR (mandays)	138.68	143.40	191.80	177.20
MAT_EXP (PhP)	4,320	13,175	15,135	26,662
COOP	0.48	0.48	0.50	0.50
RAIN (mm)	2,385	1,930	59.16	284.80
TF_AREA (ha)	2.40	2.46	1.60	1.59
C. Non-MAUNLAD Farmers in the Control Towns (n = 104):				
TFI (PhP)	20,242	16,562	28,283	23,032
TRAINING	0.02	0.42	0.17	0.50
LVSTOCK	0.36	0.35	0.48	0.48
IC_AREA (ha)	0.85	0.42	1.21	0.73
CREDIT (PhP)	1,806	0	6,189	0
EDUC (years)	8.87	8.87	3.56	3.56
HH_SIZE (no.)	4.42	4.38	2.07	2.06
NFI (PhP)	55,253	40,638	91,825	66,721
C_AREA (ha)	1.50	1.60	1.39	1.11
LABOR (mandays)	99.07	61.47	111.90	83.53
MAT_EXP (PhP)	3,874	1,620	17,081	3,829
COOP	0.38	0.38	0.49	0.49
RAIN (mm)	2,405	1,985	72.28	263.20
TF_AREA (ha)	2.30	2.36	1.59	1.61

Table 4. Probit Results for Participation in the MAUNLAD Program

Variable	Coefficient	Std. Error	p-Value
TRAINING	0.44	0.64	0.49
IC_AREA (ha)	0.02	0.15	0.92
CREDIT (PhP)	-0.002	0.001	0.06
EDUC (years)	-0.012	0.03	0.70
HH_SIZE (no.)	0.055	0.05	0.31
C_AREA (ha)	0.35	0.14	0.01
LABOR (mandays)	-0.001	0.001	0.55
MAT_EXP (PhP)	0.00001	0.00007	0.11
COOP	-0.032	0.25	0.89
RAIN (mm)	0.012	0.002	< 0.01
TF_AREA (ha)	-0.11	0.14	0.44
*YR*2000	1.23	0.46	< 0.01
Constant	-31.58	6.87	< 0.01

Log Likelihood =	-86.35	Akaike Information Criterion =	0.77
LR χ^2 Statistic [8 df] / (p-Value) =	75.61 / (< 0.001)	Bayesian Information Criterion =	-1,194
Pseudo-R^2 =	0.30	Number of Observations =	259
McFadden's R^2 =	0.30		

Notes: The dependent variable is whether or not the farmer participated in the MAUNLAD program during the year of implementation. The predicted values based on the above parameters are used in the propensity score matching techniques, and all independent variables satisfy the balancing property.

Results and Discussion

Propensity Score Matching Results

The parameter estimates of the probit model are reported in table 4. Results show the importance of the amount of credit used and total coconut area utilized in the MAUNLAD participation decision. The region of common support for this probit specification is between the interval 0.02 and 0.78. The balancing property is satisfied for the specification reported in table 4. Using the predicted propensity scores from the probit specification in table 4, we then use 1-to-1 nearest neighbor matching (without replacement) and kernel matching to find the matched participant and nonparticipant groups.

For the 1-to-1 nearest neighbor matching, a matched nonparticipant was found for all 48 members of the MAUNLAD participant group. No participant has a propensity score outside of the common support. Hence, we have a total of 96 farmers (48 MAUNLAD farmers and 48 matched non-MAUNLAD farmers) in the 1-to-1 matched sample, with 192 total observations (96 farmers times two years of data). For the kernel matching procedure, we use an epanechnikov kernel with a bandwidth at 0.06. Unlike the 1-to-1 nearest neighbor matching, the kernel matching method resulted in two MAUNLAD participants who are not within the common support (because of the smoothing procedure used in this approach). These two farmers not within the common support were dropped from the kernel matched sample. Thus, the kernel matched sample consists of only 92 farmers (46 MAUNLAD farmers and 46 matched non-MAUNLAD farmers) and a total of 184 observations (92 farmers times two years of data).

Once the 1-to-1 matched sample and the kernel matched sample were delineated, t-tests were undertaken to determine whether the mean observed characteristics of the MAUNLAD participants are significantly different from the non-MAUNLAD farmers. Note that t-tests were conducted for three main cases: (a) comparison of means between the MAUNLAD participants and *all* non-MAUNLAD participants (regardless of which town), (b) comparison of means between the MAUNLAD participants and the non-MAUNLAD participants in the selected MAUNLAD towns, and (c) comparison of means between the MAUNLAD participants and the non-MAUNLAD participants in the control non-MAUNLAD towns. Results of these t-tests are reported in appendix tables A1–A3, respectively.

The corresponding p-values of the t-tests for both the 1-to-1 and kernel matched samples reveal that the observed characteristics are not significantly different (at the 5% level of significance) between the MAUNLAD farmers and the different MAUNLAD control groups. As suggested by these t-test results, both PSM procedures generated a matched sample that can provide a good surrogate for the unobserved counterfactual, allowing for a more accurate estimate of the program impact.

Estimated Average Program Impacts

The parameter estimates of the impact model using the unmatched sample are presented in table 5. For comparison, we show the results from an OLS regression (only using the post-MAUNLAD implementation data) and the results from the panel data (fixed-effects) estimation methods. Without matching, the mean impact of the MAUNLAD program is estimated to be PhP 18,312.96 using OLS, while the estimated impact is PhP 17,262.53 under the fixed-effects approach. Both estimates of the program impact are statistically significant at the 1% level. In contrast, using the 1-to-1 matched sample, the mean impact of the MAUNLAD program is estimated at PhP 15,225.06 using the OLS procedure and PhP 20,918.02 using the fixed-effects approach (table 6). Both impact estimates are strongly significant (at the 1% level).

As observed from table 7, the OLS and fixed-effects estimates of the MAUNLAD program impact using the kernel matched sample (PhP 16,666.37 and PhP26,821.82, respectively) are slightly higher than the estimates using the 1-to-1 matched sample. The impact estimates using both matched samples are statistically significant (at the 1% level). Hence, the strong positive impact of the MAUNLAD program seems to be robust to the matching criteria (although the magnitudes of the effect are slightly different for the two methods). Based on these figures, the program appears to have achieved its goal of increasing MAUNLAD farmers' net income by PhP 10,000 to PhP 20,0000 per year (~$200–$400 per year).

The results from tables 5–7 also indicate that the average program impact tends to be underestimated when PSM matching procedures are not used. This finding suggests that alleviating some of the selection problems (due to time-invariant and observable time-varying factors) does have a significant effect on the accuracy of the estimated program impact. Overall, results from tables 5–7 suggest the MAUNLAD program has raised the net farm income of the coconut farmer recipients and may have helped to mitigate poverty in these communities.

In the fixed-effects results reported in tables 5–7, the two control covariates that tend to have a significant positive effect on total net farm income (in at least one of these

Table 5. Impact of the MAUNLAD Program on Total Net Farm Income: Unmatched Sample Results [dependent variable = *Total Net Farm Income*]

	Estimation Method			
	OLS[b] (n = 259)		Fixed Effects (n = 518)	
Independent Variable[a]	Coefficient	p-Value	Coefficient	p-Value
D2[b]	—	—	-35,951.59	< 0.01
M	18,312.96	< 0.01	17,262.53	0.04
EDUC (years)[c]	709.50	0.09	—	—
HH_SIZE (no.)	631.20	0.39	-1,993.62	0.18
NFI (PhP)	-0.03	0.14	-0.012	0.69
C_AREA (ha)	879.24	0.51	7,969.65	< 0.01
LABOR (mandays)	-1.47	0.85	-36.63	0.01
MAT_EXP (PhP)	-0.07	0.47	0.30	0.02
COOP	-3,706.56	0.33	-6,971.55	0.64
RAIN (mm)	-45.48	< 0.001	-53.52	< 0.01
Constant	103,308.30	< 0.01	158,522.30	< 0.01
R^2	0.317		0.186	

[a] In the interest of space, the parameter estimates associated with the actual year dummy variables are excluded in this table but are available from the authors upon request.
[b] As suggested by a reviewer, only the sample after implementation of the MAUNLAD program was used in all OLS estimations. As such, the *D*2 variable in the OLS estimation was dropped.
[c] The *EDUC* variable is dropped in the fixed-effects estimation because it is time-invariant in the sample.

Table 6. Impact of the MAUNLAD Program on Total Net Farm Income: Matched Sample Results Using 1-to-1 Nearest Neighbor Matching [dependent variable = *Total Net Farm Income*]

	Estimation Method			
	PSM-OLS[b] (n = 96)		PSM-Fixed Effects (n = 192)	
Independent Variable[a]	Coefficient	p-Value	Coefficient	p-Value
D2[b]	—	—	-20,474.19	0.25
M	15,225.06	< 0.01	20,918.02	0.01
EDUC (years)[c]	135.69	0.81	—	—
HH_SIZE (no.)	601.39	0.64	-1,006.13	0.63
NFI (PhP)	-0.08	0.08	0.001	0.99
C_AREA (ha)	-6,533.02	< 0.01	4,799.54	0.17
LABOR (mandays)	-35.01	< 0.01	-96.75	< 0.01
MAT_EXP (PhP)	1.07	< 0.01	0.95	< 0.01
COOP	-2,745.42	0.56	-10,641.31	0.37
RAIN (mm)	-73.56	< 0.01	-41.03	0.12
Constant	182,514.00	< 0.01	124,999.00	0.07
R^2	0.677		0.187	

[a] In the interest of space, the parameter estimates associated with the actual year dummy variables are excluded in this table but are available from the authors upon request.
[b] As suggested by a reviewer, only the sample after implementation of the MAUNLAD program was used in all OLS estimations. As such, the *D*2 variable in the OLS estimation was dropped. The matched sample used here consists of 96 observations (48 participants and 48 matched nonparticipants).
[c] The *EDUC* variable is dropped in the fixed-effects estimation because it is time-invariant in the sample.

Table 7. Impact of the MAUNLAD Program on Total Net Farm Income: Matched Sample Results Using Kernel Matching [dependent variable = *Total Net Farm Income*]

	Estimation Method			
	PSM-OLS[b] (n = 92)		PSM-Fixed Effects (n = 152)	
Independent Variable[a]	Coefficient	p-Value	Coefficient	p-Value
D2[b]	—	—	-48,234.59	0.05
M	16,666.37	< 0.01	26,821.82	0.01
EDUC (years)[c]	-195.49	0.76	—	—
HH_SIZE (no.)	-232.42	0.82	-2,578.35	0.28
NFI (PhP)	-0.10	0.05	-0.001	0.97
C_AREA (ha)	-5,523.94	< 0.01	6,399.59	0.16
LABOR (mandays)	-38.38	< 0.01	-101.27	< 0.01
MAT_EXP (PhP)	1.12	< 0.01	1.53	< 0.01
COOP	-1,384.20	0.78	-13,718.92	0.35
RAIN (mm)	-68.52	< 0.01	-64.33	0.07
Constant	153,986.00	< 0.01	197,545.00	0.04
R^2	0.677		0.470	

[a] In the interest of space, the parameter estimates associated with the actual year dummy variables are excluded in this table but are available from the authors upon request.
[b] As suggested by a reviewer, only the sample after implementation of the MAUNLAD program was used in all OLS estimations. As such, the *D*2 variable in the OLS estimation was dropped. The matched sample used here consists of 92 observations (46 participants and 46 matched nonparticipants). Two MAUNLAD participants were not within the common support (because of the smoothing procedure used in the kernel matching) and were dropped from the matched sample.
[c] The *EDUC* variable is dropped in the fixed-effects estimation because it is time-invariant in the sample.

tables) are the size of the coconut farm area utilized (*C_AREA*) and the farm material expense (*MAT_EXP*). These results are consistent with our theoretical expectation of their effects. However, note that the magnitude of the material expense parameter (in most cases) is practically negligible, even though it is statistically significant. In contrast, the "before and after implementation" dummy (*D*2), the farm labor employed (*LABOR*), and the amount of rainfall (*RAIN*) tend to have a statistically significant negative effect on total net farm income. The negative sign of the *D*2 dummy reflects the general decrease in mean net farm income observed for the entire sample after implementation. As discussed in Wooldridge (2002), this simply serves as a control for secular trends in the outcome variable. Note that the negative labor impact is contrary to our a priori expectations since we would expect labor inputs to positively affect income. The statistically significant negative effect of rainfall is expected because coconuts are sensitive to rainfall levels—i.e., excess amounts can easily harm the coconut palms/nuts and the intercrops. This negative estimate may be picking up the adverse effects of tropical typhoons, which are common in the program sites. The remainder of the control covariates tend to have statistically insignificant signs.

Sensitivity Analysis: Accounting for Outliers

In this section we investigate the sensitivity of our results to outliers. The Grubbs' outlier test (Grubbs, 1969) is used to identify the outliers in the sample. Based on the outlier test, a total of 12 farmers with total net farm income above PhP 119,859 and below

Table 8. Sensitivity Analysis: Impact of the MAUNLAD Program on Total Net Farm Income when Outliers Are Dropped from the Sample Using the Grubb's Outlier Test [dependent variable = *Total Net Farm Income*]

	Unmatched Sample (n = 92)				1-to-1 Matched Sample (n = 86)				Kernel Matched Sample (n = 86)			
	OLS[b]		Fixed Effects		PSM-OLS[b]		PSM-Fixed Effects		PSM-OLS[b]		PSM-Fixed Effects	
Independent Variable[a]	Coeff.	*p*-Value	Coeff.	*p*-Value	Coeff.	*p*-Value	Coeff.	*p*-Value	Coeff.	*p*-Value	Coeff.	*p*-Value
D2[b]	—	—	-14,708	< 0.01	—	—	-15,499	0.15	—	—	-23,179	0.07
M	15,165	< 0.01	13,678	< 0.01	18,784	< 0.01	21,467	< 0.01	18,513	< 0.01	20,430	< 0.01
EDUC (years)[c]	658	0.09	—	—	64	0.92	—	—	-212	0.73	—	—
HH_SIZE (no.)	451	0.50	-671	0.47	561	0.59	671	0.61	-197	0.85	51	0.97
NFI (PhP)	-0.01	0.48	-0.004	0.84	-0.06	0.35	-0.08	0.15	-0.04	0.53	-0.09	0.17
C_AREA (ha)	1,762	0.15	1,478	0.38	-3,056	0.15	1,974	0.40	-2,650	0.24	2,632	0.29
LABOR (mandays)	17	0.05	14	0.10	-32	0.01	-35	< 0.01	-33	0.01	-32	0.01
MAT_EXP (PhP)	-0.03	0.76	-0.04	0.72	1.1	< 0.01	0.74	< 0.01	1.17	< 0.01	0.71	< 0.01
COOP	-3,402	0.32	-7,591	0.41	-5,330	0.28	-11,839	0.13	-6,376	0.20	-11,170	0.14
RAIN (mm)	-42	< 0.01	-27	< 0.01	-65	< 0.01	-27	0.09	-71.82	< 0.01	-40	0.03
Constant	92,841	< 0.01	87,296	< 0.01	137,579	< 0.01	81,488	0.06	157,150	< 0.01	116,636	0.02
R^2	0.35		0.18		0.62		0.26		0.63		0.37	

[a] In the interest of space, the parameter estimates associated with the actual year dummy variables are excluded in this table but are available from the authors upon request.
[b] As suggested by a reviewer, only the sample after implementation of the MAUNLAD program was used in all OLS estimations. As such, the *D2* variable in the OLS estimations was dropped. In the fixed-effects estimations, two years of data (before and after implementation) were utilized.
[c] The *EDUC* variable is dropped in the fixed-effects estimations because it is time-invariant in the sample.

PhP-96,811 are dropped from the sample, and this "outlier-free" sample is then used to check whether the above results are sensitive to outliers. Estimation results using the "outlier-free" sample are presented in table 8.

Overall, the MAUNLAD program impact without outliers is still in the neighborhood of the magnitudes estimated using the sample with outliers. Furthermore, the program impact magnitudes using the 1-to-1 matching approach and the kernel matching approach are now very similar, and still strongly significant. For example, the estimates of the MAUNLAD program impact using fixed effects are PhP 21,467 and PhP 20,430 for the 1-to-1 matching and kernel matching, respectively. These values are very similar to the ones reported in the previous subsection for the full sample using both methods. Based on these results, the estimated MAUNLAD program impact appears to be robust to outliers in the sample.

Poverty Status Analysis

To initially assess if the MAUNLAD program has helped alleviate poverty, we calculated the proportion of farmer-respondents who are below or above the poverty line. The poverty line used is the average poverty line (in real terms) for the particular period of interest, before and/or after program implementation.[9] Before the implementation of the MAUNLAD program, 58% of the MAUNLAD farmer-respondents were considered to be poor since their total net farm income fell below the poverty threshold of PhP 11,605. After implementation of the program, however, the number of poor farmers decreased by 12%, with the new poverty threshold at PhP 11,259. In contrast, the number of poor non-MAUNLAD farmer-respondents increased, from 39% before the program to 52% after the program. In particular, the number of non-MAUNLAD farmers below the poverty line increased from 28% to 44% for those within the selected MAUNLAD towns and, in the control non-MAUNLAD towns, the non-MAUNLAD farmers below the poverty line also increased, from 51% before the program to 53% after the program.

Note that the above statistics are based on the actual net farm income of the MAUNLAD program recipients and nonrecipients. Thus, even though it seems the program had a positive impact due to the reduction in the proportion of program recipients in poverty, this is not necessarily true because we did not control for other factors that could have affected the net farm income differential between recipients and non-recipients. Therefore, in figure 2 we show the kernel density of the *predicted* total net farm income of both the MAUNLAD and non-MAUNLAD farmers based on the estimated parameter estimates from the PSM-fixed effects using the 1-to-1 matched sample. The kernel matched sample produces a similar figure and is not reported here, but is available from the authors upon request. The predicted net farm income after program implementation is more informative than the actual income numbers because it is conditional on the control covariates and allows one to observe the pure program effect. As can be seen in figure 2, the density of the predicted net farm income for the MAUNLAD program recipients is to the right of the non-MAUNLAD farmers. Thus, the probability mass to the left of the relevant poverty line (the vertical line) is smaller for the MAUNLAD program recipients as compared to the non-MAUNLAD producers. This

[9] The poverty lines used here are based on the estimates from the Philippine National Statistical Coordination Board (2005).

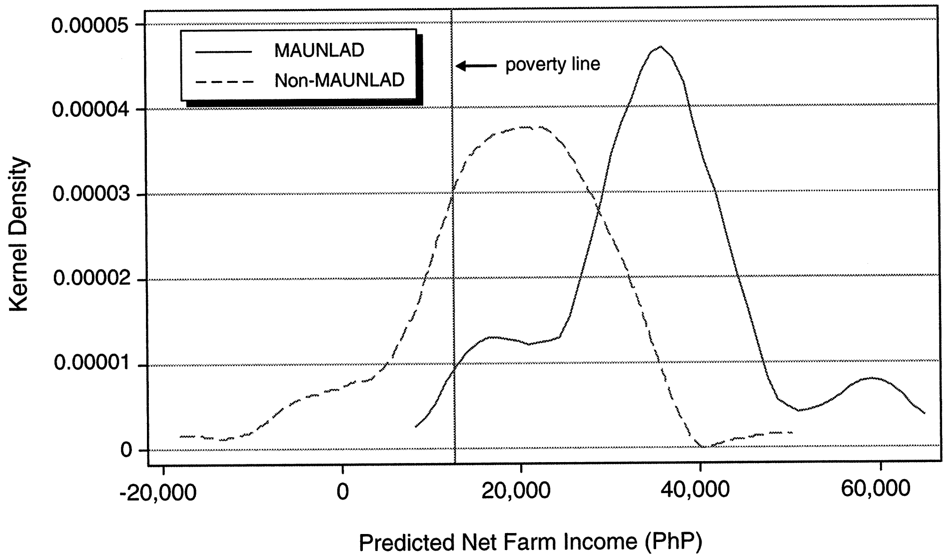

Figure 2. Kernel density of predicted net farm income after implementation of the MAUNLAD program using fixed-effects parameters and the 1-to-1 matched sample

suggests that the probability of being below the poverty line declines when a coconut farmer participates in the MAUNLAD program (holding other factors affecting income constant).

Conclusions and Policy Implications

This study estimates the impact of the Philippines' MAUNLAD agricultural development program using panel data and matching techniques to control for problems associated with unobserved heterogeneity and endogenous selection. Overall, our results suggest that the MAUNLAD program has a statistically significant positive mean impact on the total net farm income of the program participants. This result seems to be robust to the matching technique used, as well as to dropping outliers in the sample. In light of the positive program effect on net farm income, we also show that the probability of being below the poverty line is reduced when a coconut farmer participates in the MAUNLAD program (controlling for other observable factors that affect income).

The strong positive impact of the program suggests that the different components initially emphasized by the MAUNLAD administrators may have played a major role in the realization of this result. The initial emphasis on improved training, promotion of intercropping and livestock integration, improved access to credit, and technical assistance contributed to the success of the program. Informal qualitative opinions solicited from MAUNLAD recipients in the Northern site area (i.e., in Batangas) in a recent post-implementation visit indicate that promotion of intercropping and livestock integration, as well as the training provided with regard to these two topics, were considered the most important components contributing to the success of the program. For example, a number of MAUNLAD farmers in Batangas mentioned they had benefited from the program's recommendations with respect to choosing higher-value annual crops as their intercrops. In contrast, the technical assistance and training associated with coconut production and marketing were the components viewed by the Southern MAUNLAD recipients (i.e., in Biliran, Davao) as most important. A study to help quantify which component has the largest impact would be an interesting future endeavor.

One limitation of this study is that the "after-implementation" data were collected after the initial year of implementation. Because there may be some lags in the impacts of the different program components, it may take several years for the effects to be realized and observed. Hence, further monitoring and assessment are needed over the next few years. Follow-up surveys and further data collection from the program participants and nonparticipants would be important to more comprehensively assess the medium- to longer-term impacts of the effort. Continuous monitoring and evaluation are essential to sustain the positive impact of the program.

Even though the MAUNLAD program was shown to have strong positive impacts in terms of net farm income, it is important to note that the majority of participants still did not have farm incomes comparable to the national average (PCA-ARDB, 1998). As a consequence, the Philippine Coconut Authority (PCA) may wish to consider incorporating other program elements which would further help these impoverished coconut producers. For example, the PCA might consider promotion of more intensive utilization of coconut by-products as a new aspect of the program to help boost incomes. Handicraft producers have strong demand for coconut by-products such as midribs, twigs, and leaves, but most poor coconut producers do not exploit these niche markets in selling their products. The MAUNLAD program can help producers take advantage of these potential markets by providing guidance and information, and assisting them in making contact with these handicraft manufacturers.

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Table A1. Comparison of the Means of Pre-intervention Farmer Characteristics: MAUNLAD vs. *All* Non-MAUNLAD Farmers (unmatched vs. matched samples)

	Unmatched Sample			Matched Sample (1-to-1 Nearest Neighbor Matching)			Matched Sample (Kernel Matching)		
Observable Characteristics	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 211)	p-Value	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 48)	p-Value	MAUNLAD Recipients Mean (n = 46)	Non-MAUNLAD Farmers Mean (n = 46)	p-Value
TFI (PhP)	22,973	27,274	0.53	22,973	20,555	0.77	23,440	31,200	0.50
TRAINING	0.06	0.02	0.30	0.06	0.02	0.31	0.02	0.02	1.00
LVSTOCK	0.31	0.37	0.45	0.31	0.33	0.82	0.30	0.36	0.51
IC_AREA (ha)	0.77	0.81	0.79	0.77	0.77	0.98	0.78	0.71	0.74
CREDIT (PhP)	10.41	6,398	< 0.01	10.41	25	0.53	10.87	0	0.32
EDUC (years)	8.10	8.65	0.36	8.10	8.83	0.32	8.06	8.56	0.50
HH_SIZE (no.)	5.31	4.44	< 0.01	5.31	5.10	0.62	5.15	5.21	0.88
NFI (PhP)	29,099	61,899	< 0.01	29,099	54,034	0.10	29,462	55,153	0.09
C_AREA (ha)	1.93	1.65	0.24	1.93	1.55	0.26	1.96	1.86	0.78
LABOR (mandays)	76.57	119.16	0.03	76.57	66.37	0.63	78.50	72.90	0.80
MAT_EXP (PhP)	3,977	4,100	0.95	3,977	5,084	0.76	4,135	7,818	0.42
COOP	0.54	0.43	0.19	0.54	0.52	0.84	0.52	0.50	0.83
RAIN (mm)	2,457	2,395	< 0.01	2,457	2,467	0.52	2,454	2,464	0.52
TF_AREA (ha)	2.48	2.35	0.61	2.48	2.43	0.89	2.51	2.61	0.79

Table A2. Comparison of the Means of Pre-intervention Farmer Characteristics: MAUNLAD vs. Non-MAUNLAD Farmers in the Selected MAUNLAD Town (unmatched vs. matched samples)

	Unmatched Sample			Matched Sample (1-to-1 Nearest Neighbor Matching)			Matched Sample (Kernel Matching)		
Observable Characteristics	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 107)	p-Value	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 21)	p-Value	MAUNLAD Recipients Mean (n = 46)	Non-MAUNLAD Farmers Mean (n = 24)	p-Value
TFI (PhP)	22,973	34,108	0.15	22,973	16,612	0.38	23,440	35,346	0.48
TRAINING	0.06	0.02	0.25	0.06	0	0.08	0.02	0	0.32
LVSTOCK	0.31	0.38	0.39	0.31	0.19	0.28	0.30	0.29	0.91
IC_AREA (ha)	0.77	0.78	0.96	0.77	0.50	0.16	0.78	0.65	0.52
CREDIT (PhP)	10.41	10,862	< 0.01	10.41	0	0.32	10.87	0	0.32
EDUC (years)	8.10	8.44	0.60	8.10	8.47	0.70	8.06	8.75	0.46
HH_SIZE (no.)	5.31	4.46	0.02	5.31	5.00	0.63	5.15	5.17	0.98
NFI (PhP)	29,099	68,359	< 0.01	29,099	64,373	0.17	29,462	67,013	0.10
C_AREA (ha)	1.93	1.81	0.62	1.93	1.74	0.63	1.96	2.13	0.71
LABOR (mandays)	76.57	138.68	0.01	76.57	67.58	0.76	78.50	68.46	0.71
MAT_EXP (PhP)	3,977	4,320	0.88	3,977	957.62	0.13	4,135	6,137	0.72
COOP	0.54	0.48	0.52	0.54	0.67	0.33	0.52	0.58	0.63
RAIN (mm)	2,457	2,385	< 0.01	2,457	2,467	0.63	2,454	2,453	0.98
TF_AREA (ha)	2.48	2.40	0.78	2.48	2.49	0.97	2.51	2.70	0.66

Table A3. Comparison of the Means of Pre-intervention Farmer Characteristics: MAUNLAD vs. Non-MAUNLAD Farmers in the Control Town (unmatched vs. matched samples)

	Unmatched Sample			Matched Sample (1-to-1 Nearest Neighbor Matching)			Matched Sample (Kernel Matching)		
Observable Characteristics	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 104)	p-Value	MAUNLAD Recipients Mean (n = 48)	Non-MAUNLAD Farmers Mean (n = 27)	p-Value	MAUNLAD Recipients Mean (n = 46)	Non-MAUNLAD Farmers Mean (n = 22)	p-Value
TFI (PhP)	22,973	20,242	0.69	22,973	23,623	0.95	23,440	26,677	0.80
TRAINING	0.06	0.03	0.39	0.06	0.04	0.62	0.02	0.05	0.64
LVSTOCK	0.31	0.36	0.60	0.31	0.44	0.27	0.30	0.45	0.25
IC_AREA (ha)	0.77	0.85	0.67	0.77	0.98	0.48	0.78	0.77	0.98
CREDIT (PhP)	10.41	1,805	< 0.01	10.41	44.44	0.39	10.87	0	0.32
EDUC (years)	8.10	8.88	0.23	8.10	9.11	0.23	8.06	8.36	0.72
HH_SIZE (no.)	5.31	4.42	0.01	5.31	5.18	0.77	5.15	5.27	0.79
NFI (PhP)	29,099	55,253	0.01	29,099	45,992	0.32	29,462	42,214	0.48
C_AREA (ha)	1.93	1.50	0.09	1.93	1.42	0.23	1.96	1.57	0.43
LABOR (mandays)	76.57	99.07	0.25	76.57	65.43	0.65	78.50	77.76	0.98
MAT_EXP (PhP)	3,977	3,874	0.97	3,977	8,294	0.45	4,135	9,652	0.43
COOP	0.54	0.38	0.07	0.54	0.41	0.27	0.52	0.41	0.39
RAIN (mm)	2,457	2,405	< 0.01	2,457	2,467	0.58	2,454	2,477	0.25
TF_AREA (ha)	2.48	2.31	0.52	2.48	2.38	0.83	2.51	2.52	0.99