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How can the environmental efficiency of Indonesian cocoa farms be increased?

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Abstract:

We look at the trade-off between smallholder cocoa intensification and the ecosystem in Indonesia and investigate the determinants of environmental efficiency in cocoa production. In our analysis, we apply a distance output function that includes cocoa production and the abundance of native rainforest plants as outputs. Our data set, based on a household and environment survey conducted in 2015, allows us to analyze 208 cocoa producers with both measured and self-reported data. We find that the intensification of cocoa farms results in higher ecosystem degradation. Additionally, the estimations show substantial mean inefficiencies (50 percent). On average, the efficiency scores point to a possible production expansion of 367 kg of cocoa per farm and year, to a possible increase of 43680 rainforest plants per farm, or to a possible acreage reduction of 0.52 hectares per farm. Finally, our results show that agricultural extension services have a substantial role in increasing efficiency.

Keywords: cocoa production, Indonesia, environmental efficiency.

JEL codes: O13, Q01, Q12.

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1. Introduction

1.1 Background

The global demand for cocoa grew steeply over the last 15 years. This increase was primarily due to the population and economic growth of the Asian and African countries (ICCO, 2014; Squicciarini and Swinnen, 2016). Growing demand led to increased cocoa prices which, together with the incentives by government subsidies for the sector, triggered farmers to increase production by raising cultivated land and intensification (Teal et al., 2006).

As a consequence of the acreage expansion, the more fertile rainforest soils, and the lack of other available land, cocoa plantations are increasingly intruding into the Indonesian rainforest, which is a world biodiversity hotspot hosting a large number of endemic species (REDD, 2012).[1] Findings from Frimpong et al. (2007) show a similar phenomenon in Africa. The production expansion into rainforest areas threatens biodiversity conservation and the functionality of ecological systems, and it contributes to climate change (Asare, 2005).

The Indonesian Government announced the Gernas Pro Kakao revitalization program (KKPOD, 2013) for the cocoa industry in 2009. It was established to increase the adoption of pesticides and fertilizers to restore soil nutrients and the use of enhanced cocoa seedlings to boost productivity. However, the support of intensification and the ensuing increase in cocoa production can also cause environmental deterioration and raise concerns about biodiversity conservation (Asare, 2005).

Welford (1995) consolidates the widespread definition of sustainable development into three components. First, the environment is not observed separately from the economic process but is included in it. Second, the prospective recognition of resources and third, the equal distribution of goods between all members of society.

Agriculture is a crucial source of income for many low-income households in countries such as Indonesia. However, the benefits of income generation must be weighed against possible environmental effects such as nutrient losses, pollution, biodiversity losses, and climate change effects. The concept of environmental efficiency was developed in the economics literature to describe how the performance of environmental elements meet human

[1] Indonesia has only 1.2 percent of the world's land area. However, its forests host 11 percent of all plant species, 12 percent of all mammal species, 17 percent of all bird species, 16 percent of all reptile and amphibian species, 33 percent of all insect species, and 24 percent of all fungi species. In this country, 772 species are threatened or endangered, among them 147 mammal species. Moreover, 20 of Indonesia's 40 primate species have lost more than 50 percent of their original habitat in the last ten years, among them orangutans (FAO, 2010).

demand (Huppes and Ishikawa, 2005). The World Business Council for Sustainable Development (WBCSD, 1992) probably first provided a formal definition of environmental efficiency. They describe environmental efficiency as a ratio of reduced environmental impact and increased production value.

The goal of this paper is to study the environmental efficiency of cocoa production in Sulawesi, Indonesia. This region is an important example of environmental degradation due to economic development in terms of agricultural expansion and intensification. On this island, 80 percent of the rainforests were gone by 2010 causing, sometimes, irreversible losses of biodiversity (FAO, 2010).

1.2 Contribution

Our research investigates the scope for increasing the environmental efficiency of Indonesian cocoa production as a means of fostering sustainability. We estimate based on household, agricultural and environmental surveys and stochastic frontier analysis (Coelli et al., 2005), the environmental efficiency of production. With the results, we aim to determine the magnitude of the attainable efficiency increases, and the methods that can be used to attain them.

A number of studies (Ruf and Schroth, 2004; Schroth et al., 2004; Scherer-Lorenzen et al., 2005a) address various issues related to the environmental effects of cocoa farming. However, these papers do not deal with efficiency. Efficiency estimations are available for the large producing countries such as Ghana: Besseah and Kim (2014), Nigeria: Awotide et al. (2015), and Indonesia: Effendi et al. (2013). However, none of them consider the environmental effect of production. In order to do this, we include an environmentally relevant variable, the abundance of native rainforest plants, in the analysis. We use this, together with the cocoa production quantity, as multiple outputs in an output distance function (Fare et al., 2005).

Furthermore, previous studies analyze the effect of shading trees and intercropping only on efficiency and this leads to inconclusive results (Besseah and Kim, 2014; Nkamleu et al., 2010; Ofori-Bah and Asafu-Adjaye, 2011). We include these variables in the production frontier because we assume that they have a direct effect on production. Additionally, unlike previous studies in Indonesia, we include the Gernas Pro Kakao government program in our analysis.

Moreover, based on Maytak (2014), we collect both measured and self-reported data to improve the reliability of estimation. He synthesizes results from cocoa studies using household data and shows that self-reported data can exhibit significant bias. For example, he reports an average of 10 percent underestimation of farm size when self-reported, with substantial deviations from farm sizes 10 hectares and above.

Our research sheds more light on the environmental effects of cocoa production and on the dissonances between economic and environmental objectives. We focus on yield expansion because, with appropriate technologies, it has a smaller negative effect than acreage expansion. Our results help to inform policies and practices to sustainably improve yields and income, thus reducing deforestation. The results indicate which investments produce the highest marginal benefits: for example, improving education or access to financing or to extension services (Ingram et al., 2014).

2. Methodology

2.1 Multi-output frontier model

In the economic literature, there are three main frameworks to measure environmental efficiency. First, one can compare the environmental performances of production units (Yaisawarng and Klein, 1994). Second, one can use environmental variables as inputs in the production function (Reinhard et al., 2002). In the latest methodology, environmental effects are treated as outputs of production (Fare et al., 2005). Following Picazo-Tadeo et al. (2014), we choose this third framework to account for environmental outputs.

Efficiency is the capability to maximize outputs given a level of inputs used in the production. Debreu (1951) introduced the first concept of creating a production frontier to measure efficiency. This led to two main empirical methods for frontier estimation: the deterministic Data Envelopment Analysis (DEA) and the parametric Stochastic Frontier Analysis (SFA). We assess efficiency using the parametric method since it can differentiate between technical inefficiency and the effects of random shocks (Coelli et al., 2005). The most established SFA model is based on the output distance function. It is used by a number of researchers including Brümmer et al. (2006).

According to Coelli et al. (2005), the output distance function treats inputs as fixed and extends output vectors as long as the outputs are still technically feasible:

$$D_o(\boldsymbol{x},\boldsymbol{y}) = inf\left\{\theta > 0: \frac{y}{\theta} \in P(\boldsymbol{x})\right\} \tag{1}$$

where $P(\boldsymbol{x})$ represents the set of feasible output vectors ($\boldsymbol{y}$) which can be produced using the input vectors ($\boldsymbol{x}$). $D_o(\boldsymbol{x},\boldsymbol{y})$ describes the technology completely and gives the reciprocal of the maximum proportional expansion of the output vector with given inputs. It is linearly homogeneous, non-decreasing, and convex in outputs and non-increasing and quasi-convex in inputs. For two outputs, Figure 1 depicts the distance function in output space (Brümmer et al., 2006). The output set $P(\boldsymbol{x})$ is bounded by the production-possibility frontier (PPF), which represents the technically efficient points for all output combinations, given the input combination $\boldsymbol{x}$. To determine the value of the distance function, all observed points of production are scaled radially toward the output set boundary. The distance function shows the relation of a given output vector ($\overline{OA}$ in Figure 1) to the maximal feasible output with unchanged output mix ($\overline{OB}$ in Figure 1). The output orientated measure of technical efficiency equals the reciprocal of the output distance function:

$$TE = 1/D_o(\boldsymbol{x},\boldsymbol{y}). \tag{2}$$

It is difficult to estimate the output distance function directly with ordinary least squares (OLS) or maximum likelihood (ML) methods because its value is unobserved. However, we can transform the function into an estimatable equation by exploiting its linear homogeneity property in outputs. A possible way to impose this condition is by normalizing the output distance function by an output (Coelli et al., 2005). We choose y_1, which leads to the following expression:

$$D_o\left(\boldsymbol{x_i}, \frac{y_i}{y_{1i}}\right) = \frac{1}{y_{1i}} D_o(\boldsymbol{x_i}, \boldsymbol{y_i}). \tag{3}$$

Subsequently, taking the log of both sides and rearranging yields

$$\ln y_{1i} = -\ln D_o\left(\boldsymbol{x_i}, \frac{y_i}{y_{1i}}\right) + \ln D_o(\boldsymbol{x_i}, \boldsymbol{y_i}) \tag{4}$$

In this case, the technical efficiency of farm i can be written as

$$TE_i = exp\,(-u_i) \tag{5}$$

where u_i is a non-negative unobservable term assumed to be independently and identically distributed as $N(\mu_i, \sigma_u^2)$. Finally, substituting equations (2) and (5) into (4), and then adding a random error term v_i that is independently and identically distributed as $N(\mu_i, \sigma_u^2)$ and independent of u_i gives

$$\ln y_{1i} = -\ln D_o\left(\boldsymbol{x_i}, \frac{y_i}{y_{1i}}\right) + v_i - u_i \tag{6}$$

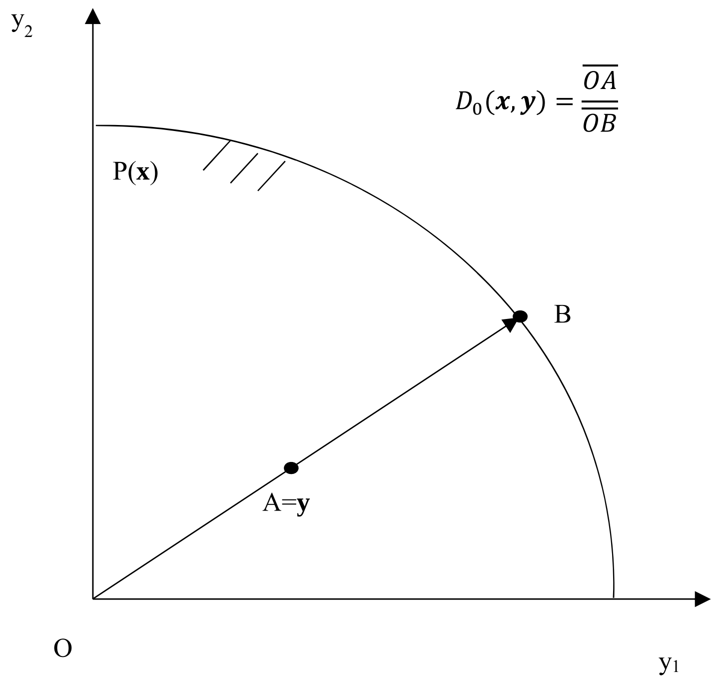
The parameters of the distance function in equation (6) must theoretically satisfy the regularity conditions: monotonicity and curvature (Coelli et al., 2005). Because the Cobb-Douglas production function has the wrong curvature in the y_i/y_{1i} space of a distance function framework, we use a translog functional form. In this function, the inclusion of squared and interaction terms provides a high level of flexibility, an easy calculation, and the possibility to impose homogeneity (Brümmer et al., 2006).

The extension of our model in equation (6) enables us to measure how household characteristics influence efficiency. We choose a specification proposed by Coelli et al. (2005), which models the mean of the technical inefficiency (μ_i) as a function of several variables:

$$\mu_i = \varphi Z_i + e_i \tag{7}$$

where Z_i is a vector of farm-specific factors that are assumed to affect efficiency, φ is a vector with parameters to be estimated, and e_i is an independent and identically distributed random error term. If the estimated parameter is positive, then the corresponding variable has a negative influence on technical efficiency.

Figure 1: Output distance function for two outputs



Source: Brümmer et al. (2006).

2.2 Estimation issues

We look at three issues of the statistical inference: the estimation technique of the frontier model, the estimation technique of the inefficiency model, and endogeneity.

First, standard techniques such as OLS are inappropriate for estimating the unobservable frontier function from observable input and output data because they focus on describing average relationships. Therefore, we base the parameters on ML. Before carrying out the estimation, each variable is normalized by its sample mean. Given this transformation, the first-order coefficients can be viewed as partial production elasticities at the sample mean (Coelli et al., 2005).

Regarding the second inference issue, Greene (2008) points out that researchers often incorporate inefficiency effects using two-step estimation techniques. In the first step, the production function is specified and the technical inefficiency is predicted. The second step regresses the assumed characteristics on the predicted inefficiency values via OLS. This approach leads to severely biased results. The issue is addressed by using a simultaneous estimation that includes the efficiency effects in the production frontier estimation.

Furthermore, the direct inference of a stochastic frontier may be susceptible to simultaneity bias that occurs if each farmer selects the output and input levels to maximize profit for given prices. But no simultaneity bias ensues if farmers maximize expected rather than actual profit (Coelli et al., 2005). We make this reasonable assumption meaning that technical efficiency is unknown to producers before they make their input decisions. Thus, the quantities of variable inputs are largely predetermined and uncorrelated with technical efficiency.

Finally, according to Brümmer et al. (2006), several studies also question the transformation of the distance function by applying the ratio method. For example, Kumbhakar and Lovell (2000) argue that the Euclidean norm of output model, which avoids the choice of a specific output, might be less susceptible to the endogeneity bias than the ratio model. However, Sickles et al. (2002) conclude that in the stochastic production frontier context, the ratio of two output variables is not endogenous, even if the output levels are. Another advantage of the ratio transformation is that in this model, the degree of multicollinearity is considerably smaller than in the norm model.

3. Empirical specification

3.1 Production frontier model

The translog output distance function for the observation i with two outputs, three inputs, and five dummy variables is specified as:

$$lny_{1i} = -\alpha_1 - \alpha_2 ln\frac{y_{2i}}{y_{1i}} - \sum_{k=1}^{3}\beta_k lnx_{ki} - \frac{1}{2}\alpha_{11} ln\frac{y_{2i}}{y_{1i}} ln\frac{y_{2i}}{y_{1i}} - \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk} lnx_{ji} lnx_{ki} - \sum_{k=1}^{3}\gamma_{1k} ln\frac{y_{2i}}{y_{1i}} lnx_{ki} - \sum_{j=1}^{5}\delta_j D_{ji} + v_i - u_i \quad (8)$$

where the unit of observation is the farm of household i, y_{1i} is the amount of cocoa beans harvested in kilograms, y_{2i} is the environmental output, x_k is a vector of observations on inputs, D_j is a vector of observations on dummy variables characterizing the production process, the α's, β's, γ's, and δ's are unknown parameters to be estimated, v is a random error term, and finally u is a non-negative unobservable variable representing inefficiency.

Based on Gockowski and Sonwa (2011), we use plant abundance as a measure of the environmental output y_2. We did not include tree biomass and other crop outputs in the production function because of the small number of forest and other crop trees on the sample cocoa farms.

We draw on Nkamleu et al. (2010) and Ofori-Bah and Asafu-Adjaye (2011) to identify the production factors that we consider in our analysis (Table 1). These include land (x_1), costs (x_2), tree age (x_3), and dummies representing the cocoa farmers' management capabilities (Wollni and Brümmer, 2012). In our model, land indicates the total cultivated cocoa area measured in ares, while costs are calculated in Rupiah and involve all labor, fertilizer, and pesticide costs used on the cocoa farm.[2] We aggregate the latter inputs to avoid multicollinearity (Brümmer et al., 2006) and assume that the value of material inputs and labor costs reflects the quality of inputs better than quantity (Wollni and Brümmer, 2012). The age of cocoa trees (x_4) is also added to the classical production factors. It influences the cocoa output the following way. Cocoa trees begin to produce pods only from about three years after planting, reach full bearing capacity around the age of 10 years, and their output starts to diminish gradually thereafter (Dand, 2010). Hence, the sign and magnitude of the effect of tree age varies depending on the average tree age in the sample.

[2] 1 hectare equals 100 ares. In December 2015, 1 euro cost around 15000 Rupiahs.

Following Wollni and Brümmer (2012), we enhance the basic production frontier with five dummy variables to describe the cocoa cultivation process more accurately. The first dummy variable equals one if only family labor (no material inputs or hired labor) was used for maintenance and harvesting tasks. According to Binswanger and Rosenzweig (1986), if family members cannot get off-farm jobs in imperfect input and labor markets, their time may be allocated to work on the cocoa farms up to the extent where the marginal utility of production is equal to the marginal utility of leisure. Therefore, using exclusively family workers may negatively affect production if cocoa plantations are used to absorb surplus family labor. The second dummy variable equals one if the smallholder participated in the Gernas Pro Kakao government program. The objective of this program is to rehabilitate cocoa farms and expand intensification by providing easier access to inputs (KKPOD, 2013). The third dummy variable for yield loss is used to reflect the effect of pests and adverse weather on cocoa harvest quantity.

Some cocoa is grown in an agroforestry or an intercropping system (Ofori-Bah and Asafu-Adjaye, 2011). Ruf and Zadi (1998) and Asare (2005) suppose that cocoa yields can be maintained in the long run only with the use of forest tree species in cocoa cultivation. Cocoa agroforests also support conservation policies because they connect rainforest areas and provide habitat for native plants and animals. However, the influence of shading trees on cocoa yields is highly debated. Although some papers report the advantages of these trees because they decrease plant stress, others provide evidence that shade can limit cocoa yields (Frimpong et al., 2007). Following Bentley et al. (2004), we add a fourth dummy variable to our model that captures the influence of the higher shade (larger than 35 percent) production system and expect the sign to be negative.

To assess the effect of crop diversification on cocoa production (Ofori-Bah and Asafu-Adjaye, 2011), a fifth dummy variable for intercropping is also added to the model. Farmers can grow a variety of fruit-bearing trees to help cope with the volatile cocoa prices by supplementing their income. In Indonesia, banana, durian, and coconut are mainly intercropped with cocoa at its fruit-bearing age (Ministry of Agriculture, 2015). But crop diversification has also another advantage. An increasing number of studies demonstrate that intercropping improves erosion control (soil and water retention), nutrient cycling, carbon dioxide capture, biodiversity, and the relationship of fauna and flora (Scherer-Lorenzen et al., 2005b; Gockowski and Sonwa, 2011). Therefore, interplanting is often supported to take advantage of the mutualism between different plants and to compensate for the low level of intermediate inputs (Pretzsch, 2005). We anticipate that intercropping has a positive effect on cocoa yields.

Table 1: Description of the cocoa farm variables.

Variable	Description
Output	
Cocoa	Cocoa quantity harvested on the farm (kilograms)
Plants	Number of native rainforest plants in a random 5*5m area on the cocoa farm
Input	
Tree age_M	Average cocoa tree age (years), measured
Tree age_S	Average cocoa tree age (years), self-reported
Land_M	Total area planted with cocoa, measured (ares)
Land_S	Total area planted with cocoa, self-reported (ares)
Costs	Fertilizer, pesticide, transport, processing, and labor costs for the farm (1000 Rupiah)
Technology	
No expense	Dummy, 1 = household used only family labor (no material inputs or hired labor)
Gernas	Dummy, 1 = household joined the Gernas Pro Kakao program in the last 3 years
Intercrop_M	Dummy, 1 = there was intercropping on the cocoa farm, measured
Intercrop_S	Dummy, 1 = there was intercropping on the cocoa farm, self-reported
Shade_M	Dummy, 1 = shade level of the cocoa farm is larger than 35 percent, measured
Shade_S	Dummy, 1 = shade level of the cocoa farm is larger than 35 percent, self-reported
Crop loss	Dummy, 1 = yield loss because of adverse weather or pests
Inefficiency	
Male	Dummy, 1 = household head is male
High school	Dummy, 1 = household head completed the junior high school
Extension	Dummy, 1 = household head had extension contacts
Credit	Dummy, 1 = household head obtained credit in the last 3 years

Notes: All variables refer to the last 12 months with the mentioned exceptions.

3.2 Inefficiency model

We specify six elements in the vector $\boldsymbol{Z}$ in equation (7) that express the management skills of cocoa smallholders and their access to productive resources and knowledge (Wollni and Brümmer, 2012). First, we anticipate that it is more difficult for households with female heads to access markets (Wollni and Brümmer, 2012). They are also usually widows, which can limit labor availability to accomplish agricultural work timely (Onumah et al., 2013b). As a result, we expect female-headed households to display lower efficiency levels.

Second, the education dummy equals one if the head of the household completed junior high school. We expect that it affects positively the management skills of the cocoa farmers and hence efficiency (Ingram et al., 2014). However, a number of papers show that smallholders with higher educational attainment reveal lower technical efficiency levels (Teal et al., 2006). An explanation of these findings is that smallholders with higher educational levels have more likely additional sources of income and they concentrate more on these off-farm activities than on the farm management.

The next two variables indicate the external support for cocoa farming households (Nkamleu et al., 2010; and Ofori-Bah and Asafu-Adjaye, 2011). Contacts with extension agents are commonly considered to influence efficiencies positively since the information circulated in extension services should enhance farming methods (Dinar et al., 2007). However, some factors such as other information sources, the ability and willingness of smallholders to employ the distributed information, and the quality of agricultural extension services can confound the results of extension contacts (Feder et al., 2004).

Furthermore, the credit dummy variable indicates whether the cocoa farmer has access to credit. If smallholders can buy intermediate inputs with credit when required and not just when they have sufficient cash, then input use can become more optimal. Consequently, the economic literature underlines the failure of credit markets as the cause of non-profit maximizing behaviors and poverty traps (Dercon, 2003). Additionally, reducing capital constraints decreases the opportunity cost of intermediate inputs relative to family labor and allows the application of labor-saving technologies such as enhanced cocoa hybrid-fertilizer methods (Nkamleu et al., 2010). Therefore, many economists view the spread of feasible agricultural credit services crucial for raising the productivity of labor and land (Zeller et al., 1997).

Based on Rao et al. (2012), we also include production frontier variables in the inefficiency model. Following Wollni and Brümmer (2012) and Waarts et al. (2015), the size of the farm reflects households' endowments. It influences the technical efficiency ambiguously. If farmers with larger plantations specialize less in cocoa cultivation, then the size of the farm may negatively affect efficiency. However, farm size as a proxy for total wealth is anticipated to positively influence technical efficiency if financial markets are constrained (Binswanger and Rosenzweig, 1986).

The Gernas variable is also part of the inefficiency specification because we expect that this government program did not just influence the output directly but also indirectly through the efficiency. In particular, we hypothesize that, although Gernas increases output, it reduces efficiency temporarily due to a learning curve effect: it shifts out the production frontier but producers are not able to keep pace in the short run (Brümmer et al., 2006).

4. Data description

4.1 Data sources

We acquire the data using the survey infrastructure of the earlier STORMA (Stability of Rainforest Margins in Indonesia) project in Göttingen. This project conducted four rounds of household and agricultural surveys in Indonesia between 2001 and 2013. The survey data were collected from 722 randomly selected cocoa farmer households in 15 random villages near the Lore Lindu National Park in Central Sulawesi province. This province is the second largest cocoa producer in Indonesia with 17 percent of the Indonesian production in 2014 (Ministry of Agriculture, 2015). The park provides habitat for some of the most unique animal and plant species in the world. However, the increase of land used for farming is threatening its integrity (Zeller et al., 2002).

For our survey, we randomly selected one third (240) of the STORMA households in 2015. First, these households were interviewed using standardized structured questionnaires. The researchers edited the questionnaire in English first, then translated it into Indonesian and tested it with a pilot survey. The interviews lasted, on average, about 2 hours. Because some farmers cultivated several cocoa plots simultaneously, output and input details were collected at plot level to increase data accuracy (Rao et al., 2012).

Second, we extended this data by verifying the self-reported values of variables and by measuring environmental outputs such as native plant abundance on the farm of every sampled household. Based on Maytak (2014), we expect that estimations with measured and self-reported data lead to significantly different results. In particular, we hypothesize that self-reported data overestimates efficiencies because farmers tend to paint a too rosy picture of their operations.

The data collection protocol for our survey was developed with the help of the EFFORTS (Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems) project at Göttingen.[3] We tested this protocol on 12 cocoa farms to improve it. To implement it, we hired six BA graduates in botany from the University of Tadulako in Palu, Central Sulawesi, who also carried out the household interviews. A representative 5 meter by 5 meter area in the middle of the each cocoa farm was selected for plant counting and plant identification in the understory vegetation (Gockowski and Sonwa,

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[3] Funded by the German Research Foundation (DFG).

2011). Furthermore, cameras with GPS reception were used to photograph all the unknown plants for later identification and to verify the farm size and the other farm characteristics.

4.2 Descriptive statistics

Table 2 shows the summary statistics of the independent and dependent variables in the production frontier and inefficiency equations. On average, we find 106 native rainforest plants on the 5x5 meter sampling areas. However, the standard deviation and the extreme values reveal huge differences between the farms. Compared with the last survey done in our sample area in 2012, the average output of the cocoa farms almost halved in 2015, while the average farm size remained almost constant at around one hectare, which is about one third of the African average (ICCO, 2016). This resulted in an almost 50 percent decrease in the average cocoa yield, which was in 2015 around 350 kg/hectare. We can list two reasons for this. First, cocoa trees are now considerably older than the most productive age: in 2015, they were on average 15 years old. This is still just one half of the African average because of the later start of cocoa cultivation in Indonesia. Second, a record drought hit Sulawesi in 2015 because of the latest El Niño cycle. Due to the extremely dry weather, 90 percent of the households reported significant yield losses.

Labor, fertilizer, and pesticide use more than doubled in the last three years. The continued expansion of the Gernas Pro Kakao government program could have contributed to this phenomenon by providing easier access to intermediate inputs (KKPOD, 2013). According to our survey data, the level of labor and intermediate input use is now approaching the African average (Maytak, 2014). Furthermore, we find that cocoa in our sample area is cultivated mostly in a full-sun monoculture system, in contrast to Africa (Gockowski and Sonwa, 2011; Nkamleu et al., 2010).

The statistics of the inefficiency variables show that the share of female household heads stood at 6 percent in 2015, which is consistent with past studies that show cocoa cultivation as a male-dominated livelihood (Nkamleu et al., 2010; Maytak, 2014). Moreover, the educational attainment of the average household head increased considerably over the years: in 2015, more than 50 percent of the household heads completed junior school. Furthermore, we could observe an increase of extension services in the last three years: 40 percent of household heads had extension contacts in 2015. However, credit access fell back significantly just to 8 percent in 2015.

Finally, let us compare the measured and self-reported variables. Two dummy variables have both values: intercropping and shade cover. As we can see from Table A1, the self-reported dummy variables differ in about 5-10 percent of observations from the measured ones and there are no clear directions in the inaccuracies. Figure A1 shows us the differences in the two continuous variables: tree age and farm size. We can find alternative values in 30 and 80 percent of the observations. Again, the inaccuracies seem to be random. T-tests confirm that there are no significant differences in the means of the four self-reported and measured variables.

Table 2: Summary statistics of the cocoa farm variables.

Variable	Observations	Mean	Standard	Minimum	Maximum
Output					
Cocoa	208	372	542	15	4500
Plants	208	106	65	10	315
Input					
Tree age_M	208	14.9	5.8	3	40
Tree age_S	208	15.0	5.6	3	40
Land_M	208	104	73	20	500
Land_S	208	106	74	17	540
Costs	208	1557	2027	30	11735
Technology					
No expense	208	0.02	0.14	0	1
Gernas	208	0.26	0.44	0	1
Intercrop_M	208	0.13	0.34	0	1
Intercrop_S	208	0.14	0.35	0	1
Shade_M	208	0.15	0.36	0	1
Shade_S	208	0.16	0.37	0	1
Crop loss	208	0.90	0.30	0	1
Inefficiency				0	1
Male	208	0.94	0.24	0	1
High school	208	0.51	0.50	0	1
Extension	208	0.40	0.49	0	1
Credit	208	0.08	0.27	0	1

5. Results and discussion

5.1 Production frontier

Table 3 shows the parameter estimates of the frontier models. According to equation (8), a positive rainforest plants distance elasticity implies a negative effect on the cocoa production.

Similarly, a negative input distance elasticity is interpreted as a positive contribution of the input to the cocoa production.

The coefficients of the native plants variable are significant and have the expected positive signs. Their values, 0.651 and 0.698, mean that a one percent increase in the number of rainforest plants on the cocoa farm reduces the cocoa output by almost 0.7 percent. Each significant first-order input distance elasticity possesses the expected sign and, therefore, satisfies the monotonicity property at the sample mean. In the measured variables model, the partial production elasticities of land and costs are 0.699 and 0.194. The values from the model using the self-reported variables are similar. We use t-tests to evaluate whether the scale elasticities of 0.893 and 0.906 at the sample mean significantly differ from one. The null hypothesis of constant returns to scale is rejected at the 5 percent level, according to the test results. This implies that cocoa production exhibits a diminishing returns to scale. Normally, undertakings with this characteristics are viewed as too big. However, the average cocoa farm size in our sample is small: just around one hectare. A plausible cause of the diminishing return to scale can be some impediments to growth (Brümmer et al., 2006).

The positive square terms of plants and tree age fulfil the curvature conditions of the production function at the sample mean. The values for the tree age variable point to the maturing and aging process of the cocoa trees, although the coefficient in the self-reported variables model is not significant. Moving to the cross-term coefficients, we find evidence of input complementary effect between land and costs. In the case of the measured variables model, two additional interaction terms are significant. They show complimentary effect between plants and costs, and substitution effect between plants and tree age.

Additionally, various dummy variables are incorporated into the models to describe cocoa farming more accurately. The coefficient of the Gernas Pro Kakao government program is negative and significant at the 1 percent level in both models. This means that, as anticipated, farms participating in this program have higher cocoa output levels. However, it seems that the self-reported variables substantially overestimate the effect of Gernas Pro Kakao. The crop loss variable is also significant in both models and possesses the expected sign. This points to the exceptionally dry El Niño weather. However, the self-reported variables largely underestimated its effect. Finally, high shade cover seems to decrease production, but its coefficient is only significant in the self-reported model.

Table 3: Parameter estimates of the cocoa production frontier models.

Variable	TE measured variables	TE self-reported variables
Input		
ln Plants	0.651 (0.058)***	0.698 (0.065)***
ln Tree age_M/S	0.221 (0.165)	0.042 (0.123)
ln Land_ M/S	-0.699 (0.355)**	-0.697 (0.165)***
ln Costs	-0.194 (0.080)**	-0.209 (0.071)***
0.5 (ln Plants)^2	0.113 (0.039)***	0.143 (0.047)***
0.5 (ln Tree age_ M/S)^2	0.609 (0.283)**	0.242 (0.197)
0.5 (ln Land_ M/S)^2	0.026 (0.362)	-0.118 (0.165)
0.5 (ln Costs)^2	-0.048 (0.064)	-0.062 (0.051)
ln Plants * ln Tree age_ M/S	0.082 (0.039)**	0.028 (0.054)
ln Plants * ln Land_ M/S	0.024 (0.081)	-0.090 (0.059)
ln Plants * ln Costs	-0.078 (0.022)***	-0.044 (0.039)
ln Tree age_ M/S * ln Land_ M/S	0.019 (0.180)	-0.059 (0.115)
ln Tree age_ M/S * ln Costs	0.072 (0.075)	0.038 (0.081)
ln Land_ M/S * ln Costs	-0.195 (0.051)***	-0.232 (0.065)***
Technology		
No expense	0.380 (0.240)	0.170 (0.336)
Gernas	-0.357 (0.031)***	-0.516 (0.121)***
Intercrop_ M/S	0.153 (0.117)	0.103 (0.094)
Shade_ M/S	0.121 (0.080)	0.212 (0.072)***
Crop loss	0.459 (0.195)**	0.282 (0.133)**
Constant	-0.389 (0.098)***	-0.007 (0.152)
Variance		
σ_u	0.487 (0.052)***	0.501 (0.071)***
σ_v	0.000 (0.000)***	0.154 (0.049)***
RTS	0.893	0.906

Notes: Robust standard errors are in the parentheses. *: p<0.10, **: p<0.05, ***: p<0.01.

5.2 Efficiency levels

Generalized likelihood ratio tests are employed to evaluate whether average response functions would fit the models or inefficiency effects are present in the models. We reject the null hypothesis for both specifications at the 1 percent level, which means that the stochastic frontier model represents the data better than the OLS model.

Table 4 documents the average degree of technical efficiency, while Figure A2 presents the distributions of efficiencies for the sample farms. Based on the measured variables, we estimate that the average technical efficiency of cocoa farms is around 50 percent. Low values such as this tend to indicate a less specialized and less competitive market (Coelli et al., 2005).

According to our field observations, this coincides with smallholder cocoa markets in Sulawesi, where the only controllable characteristic is the quality of the raw product and many producers do not pay too much attention to this. Compared with this value, the self-reported variables model overestimates the efficiency by 7 percentage points. The histogram of the differences is depicted in Figure A3. Using a t-test, we find that the difference in means is statistically significant.

In both cases, the range of efficiency estimates is very wide and many scores are inside the bottom quarter of the distribution range. This means that most cocoa farmers have an ample scope to expand cocoa output or increase the number of native rainforest plants without increasing input use. The efficiency scores point, on average, to a possible expansion of production by 367 kg of cocoa per farm and year or to a possible increase of 43680 rainforest plants per farm.

By plotting the individual efficiencies against the numbers of rainforest plants on the corresponding farms, we can detect a logistic increase of efficiencies with the increasing number of native plants (Figure 2). This means that native plants can positively affect the output level via efficiency. Furthermore, the efficiency distributions show, at the mean, a higher degree of efficiency for producers with smaller farms. Other factors such as allocation of labor, fertilizer, and pesticide are also lower on farms with higher efficiencies, suggesting a more efficient use of the available labor force and materials.

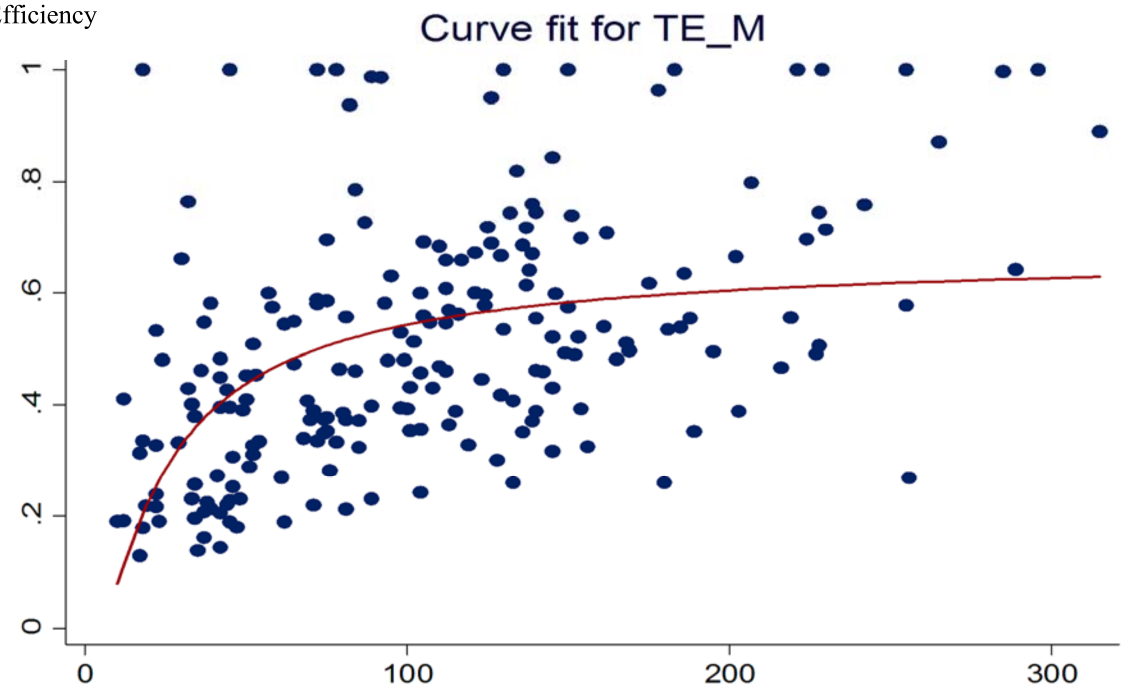
Table 4: Descriptive statistics of the cocoa farm efficiency estimates (percentages).

Model	Observations	Mean	Standard deviation	Minimum	Maximum
TE measured variables	208	50	22	13	100
TE self-reported	208	57	21	12	93
TE difference	208	7	9	-24	32

Figure 2: Scatter plot of the cocoa farm efficiencies and the number of native rainforest plants.

a) technical efficiency estimated using measured explanatory variables

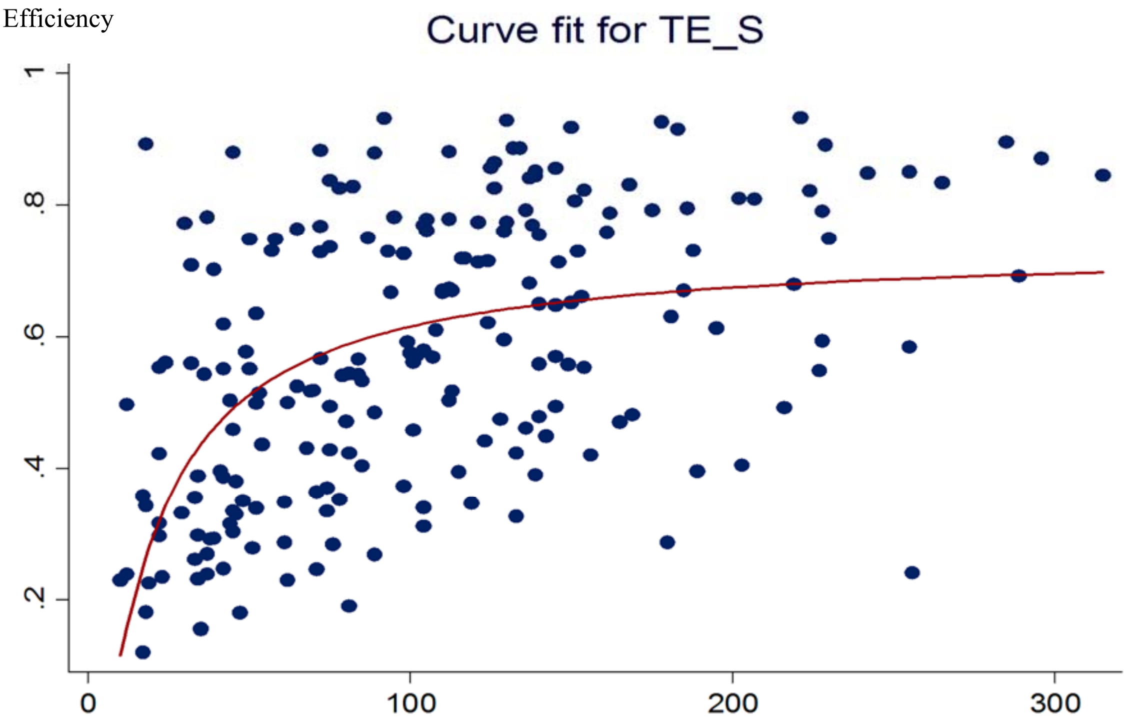
Efficiency



Number of native plants

b) technical efficiency estimated using self-reported explanatory variables

Efficiency



Number of native plants

5.3 Inefficiency effects

Table 5 presents the results of the inefficiency model estimations: both the estimated coefficients and the corresponding marginal effects at the means. For dummy variables, the marginal effects are calculated for a discrete change from zero to one. A negative sign indicates that the variable in question has a negative influence on inefficiency, which means a positive influence on efficiency. We check the joint significance of the possible inefficiency effects with likelihood ratio tests. Based on the results, we reject at the 1 percent level for all three models that all inefficiency variables are insignificant.

In both models, the Gernas Pro Kakao government program has a significant influence on farm-specific productive efficiencies. Efficiency decreases by 34 percent, on average, with participation in this program in the measured variables model. This is plausible because Gernas farmers have to apply new production methods due to new hybrid cocoa varieties and chemicals. The model using the self-reported data substantially overestimates the effect of the Gernas Pro Kakao program. Agricultural extension is the other variable that is significant in both cases. In the measured variables model, it increases efficiency by 21 percent. Again, the coefficient is largely overestimated with the self-reported variables.

Finally, we find that credit access does not have a significant effect on efficiency. This result does not match with African studies which show positive linkages (Nkamleu et al., 2010; Awotide et al., 2015). For example, many economists view the spread of feasible agricultural credit services crucial for raising technical efficiency (Zeller et al, 1997).

Table 5: Estimates and average marginal effects of the cocoa farm inefficiency models.

Variable	TE measured variables		TE self-reported variables	
	Coefficients	Marginal effects	Coefficients	Marginal effects
ln Land_M/S	0.321 (0.317)	0.236	0.309 (0.216)	0.184
Gernas	0.337 (0.99)***	0.248***	0.660 (0.233)***	0.394***
Male	0.408 (0.226)*	0.300*	0.547 (0.341)	0.326
High school	0.148 (0.105)	0.109	0.186 (0.116)	0.111
Extension	-0.211 (0.104)**	-0.155**	-0.318 (0.155)**	-0.190**
Credit	-0.254 (0.204)	-0.187	-0.242 (0.216)	-0.144
Constant	0.306 (0.337)		-0.134 (0.433)	

Notes: Robust standard errors are in the parentheses. *: p<0.10, **: p<0.05, ***: p<0.01.

5.4 Shadow prices

To understand the trade-off between the cocoa output and the native rainforest plants, the monetary quantification of this connection is desirable. Because markets for these herbaceous plants in our specification do not exist, we estimate the shadow price based on our output distance function and the corresponding revenue function. In combination with the cocoa bean price, we can calculate the absolute price for the native plants. According to FAO Statistics, the aggregated Indonesian cocoa price was 1.74 US dollars/kg in 2015. We compute the shadow price with the following equation (Fare et al., 2005):

$$q = -p * \frac{\partial D_o(x,y_1,y_2)/\partial y_2}{\partial D_o(x,y_1,y_2)/\partial y_1} * \frac{\mu_{y1}}{\mu_{y2}} \tag{9}$$

Because of the normalization of our variables, we have to multiply the derivatives in the equation by the ratio of output averages to obtain real values. The shadow price of a rainforest plant describes the monetary value of production that must be forgone to increase the number of native plants by one moving along the efficient points on the production frontier. According to the measured variables model (Table 6), the average price for one plant is 3.7 US cents. The t-test did not find a significant difference (Figure A4) between the results of two estimates. Due to violations of monotonicity, two observations of the shadow price estimations are dropped to prevent scaling in the reverse direction on the production frontier (Fare et al., 2005).

The connection between the abundance of native plants and the shadow price gives an additional insight on the shape of the trade-off function. It appears that farms with lower abundance of rainforest plants are linked to higher shadow prices than farms with a high abundance. Plotting the individual shadow prices against the characteristics of producers also reveals that bigger farm sizes and costs are connected to lower prices.

Table 6: The calculated shadow prices of the native rainforest plants in US cents.

Model	Observations	Mean	Standard deviation	Minimum	Maximum
SP measured variables	206	3.71	4.93	0.47	48.47
SP self-reported	206	3.57	2.79	0.60	20.48
SP difference	206	-0.14	3.06	-27.98	3.94

6. Conclusion

The surge in cocoa demand and price prompts us to search for sustainable ways to improve cocoa yields. We look at the trade-off between smallholder cocoa intensification and the ecosystem in Central Sulawesi and investigate the determinants of environmental efficiency in cocoa production. We apply a distance output function that includes cocoa production and the abundance of native rainforest plants as outputs. Our data set, based on a household and environmental survey conducted in 2015, allows us to analyze 208 cocoa producers with both measured and self-reported data.

We find that there is a trade-off between cocoa yields and abundance of native rainforest plants. According to this connection, the intensification of cocoa farms results in higher ecosystem degradation. By computing the shadow prices of these rainforest plants, we estimate the monetary value of reductions in their abundance. Additionally, each significant first-order input distance elasticity possesses the expected sign and the results indicate that most cocoa farmers operate under diminishing returns to scale. Given the small average farm size, the latter could reflect the impediments to growth. As expected, the Gernas Pro Kakao government program helps the participating farmers to increase their output.

The estimations show substantial inefficiencies for the majority of cocoa farmers. The low average efficiency value of 50 percent indicates a less specialized and less competitive market with low pressure for cocoa producers. Increasing efficiency could lead to a win-win-win situation: more production coming from less hectares, with more native plants co-existing with cocoa on the remaining hectares. On average, the efficiency scores point to a possible production expansion of 367 kg of cocoa per farm and year, to a possible increase of 43680 rainforest plants per farm, or to a possible acreage reduction of 0.52 hectares per farm.

Looking at the inefficiency effects, we can see that the participation in the Gernas Pro Kakao program decreases efficiency. This is plausible because Gernas farmers have to learn new production methods due to new cocoa varieties and chemicals and they are not able to catch up to the outward-shifting production frontier in the short run. Furthermore, we find that agricultural extension services have a substantial role in increasing efficiency, confirming evidence from West Africa. We can also observe that the model using self-reported variables overestimates the inefficiency effects, as well as the distance elasticities and efficiencies.

Finally, we find that credit access does not have a significant effect on efficiency. This result is inconsistent with African studies which show positive linkages. Feasible agricultural credit services are viewed by numerous economists as a crucial prerequisite for improving efficiency, a critical part of encouraging development. We recommend linking credit to extension services as part of this effort.

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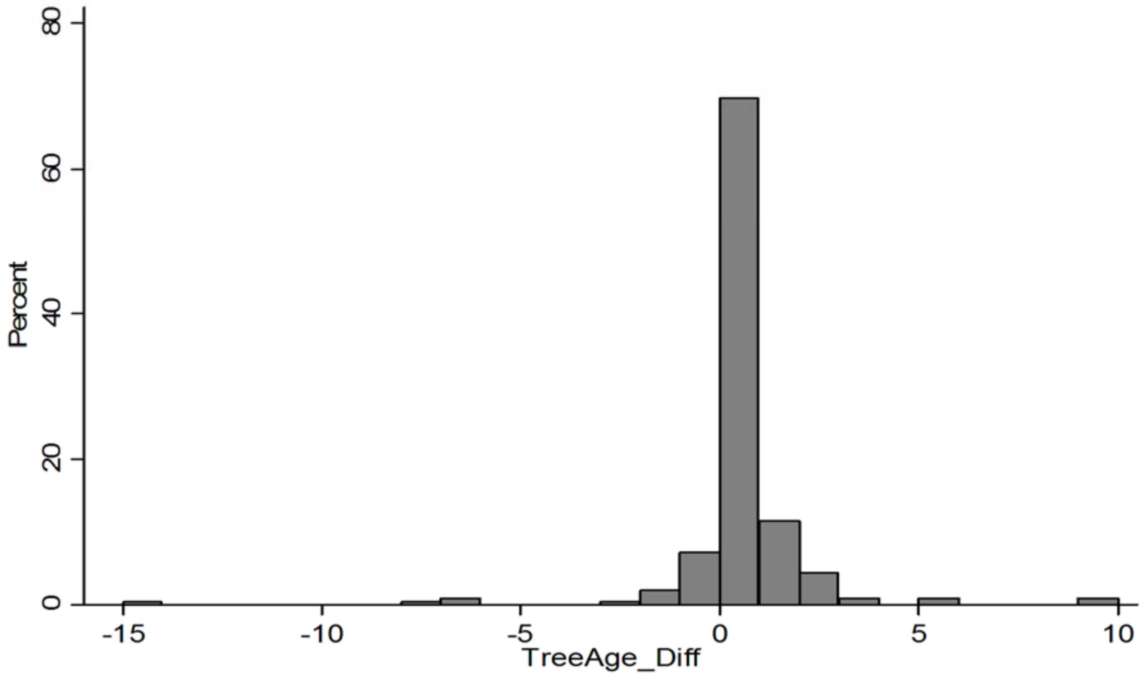
Appendix

Figure A1: Histograms of the differences between the self-reported and measured cocoa farm variables.

a) Cocoa tree age



b) Total cocoa farm size

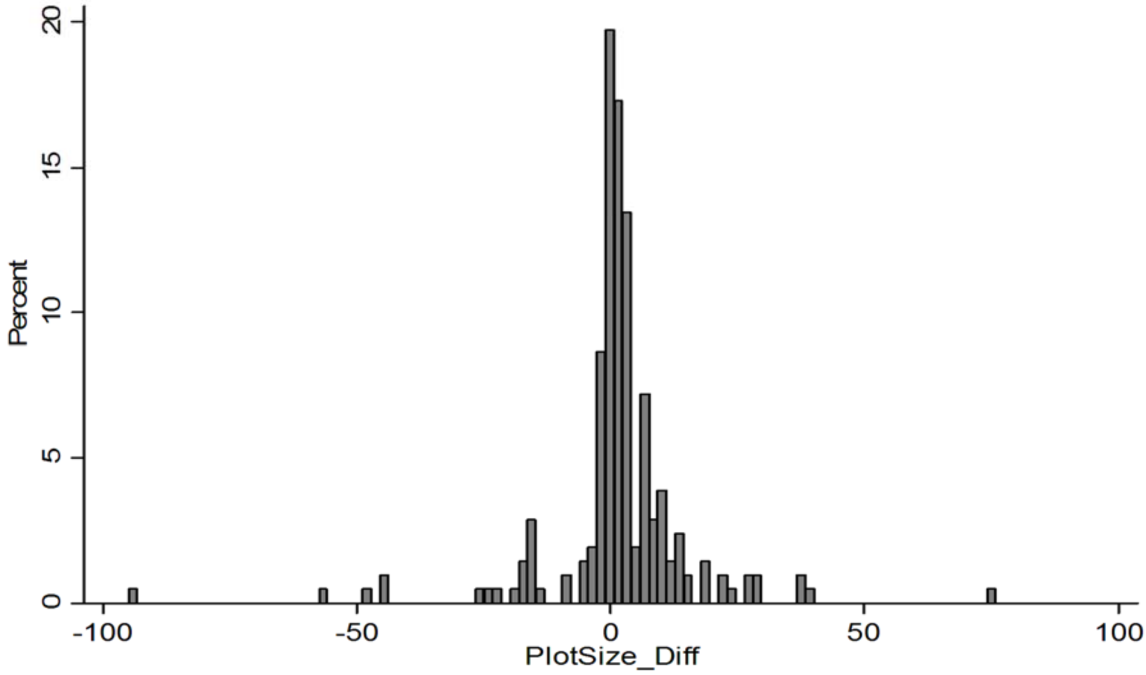
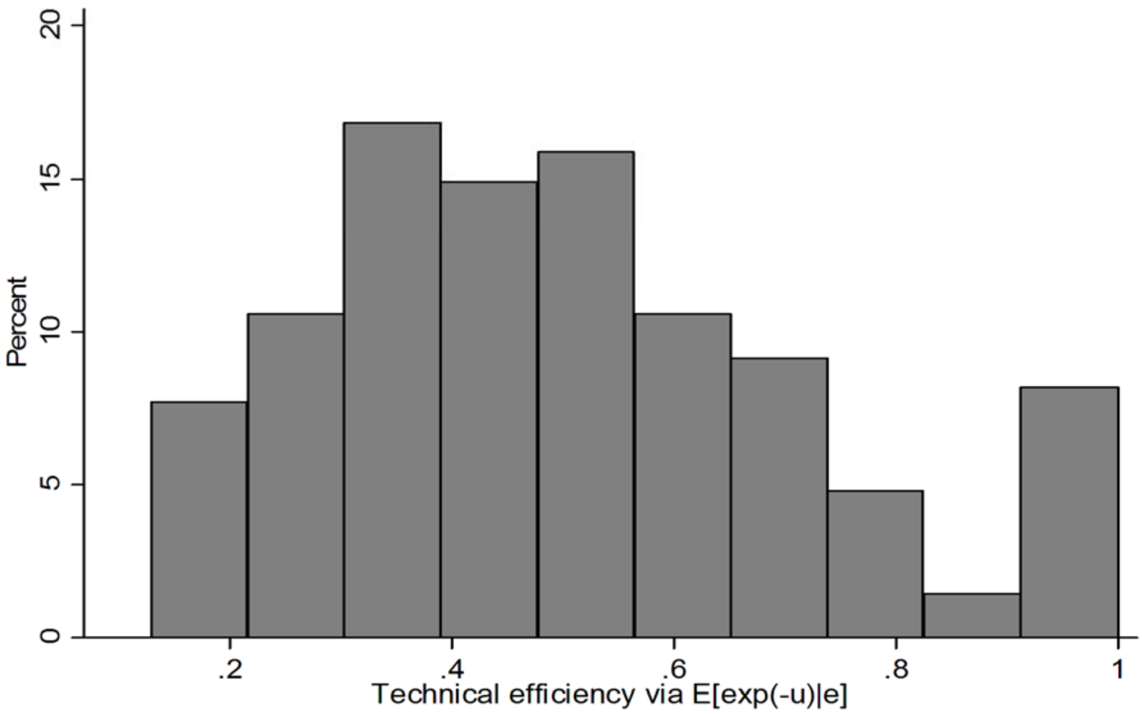


Figure A2: Distribution of cocoa farm efficiencies in the models.

a) technical efficiency estimated using measured explanatory variables



b) technical efficiency using self-reported explanatory variables

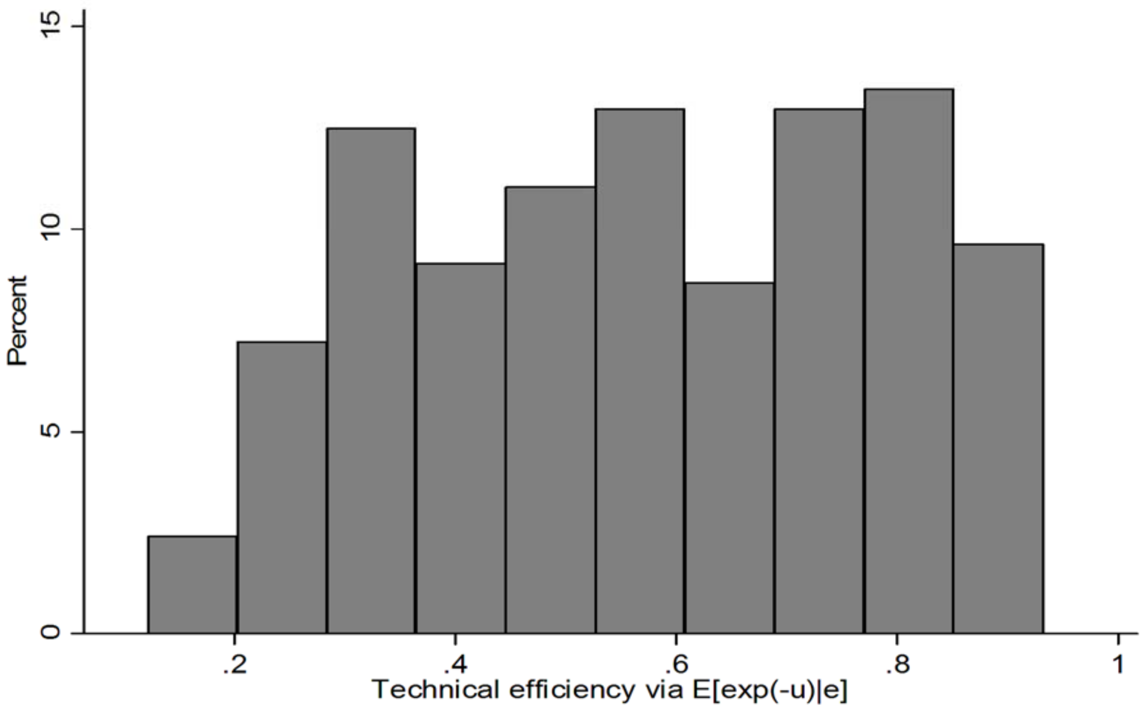


Figure A3: Histogram of the differences between the cocoa farm efficiencies (self-reported – measured variables method).

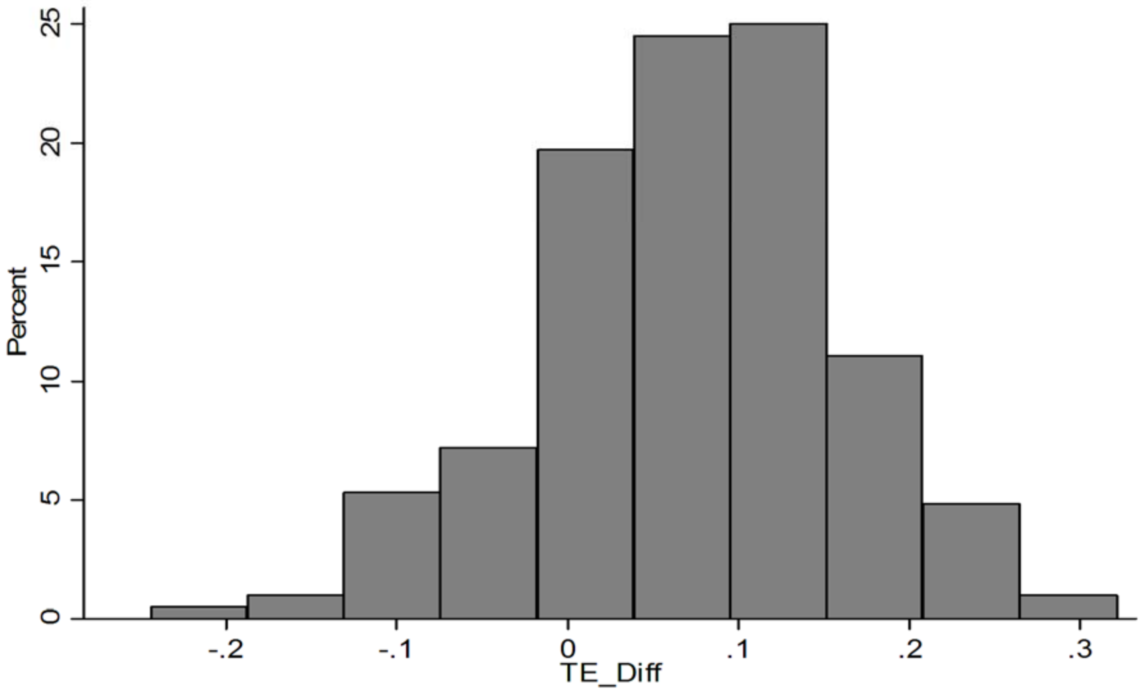


Figure A4: Histogram of the differences between the shadow prices of native rainforest plants in US cents (self-reported – measured variables method).

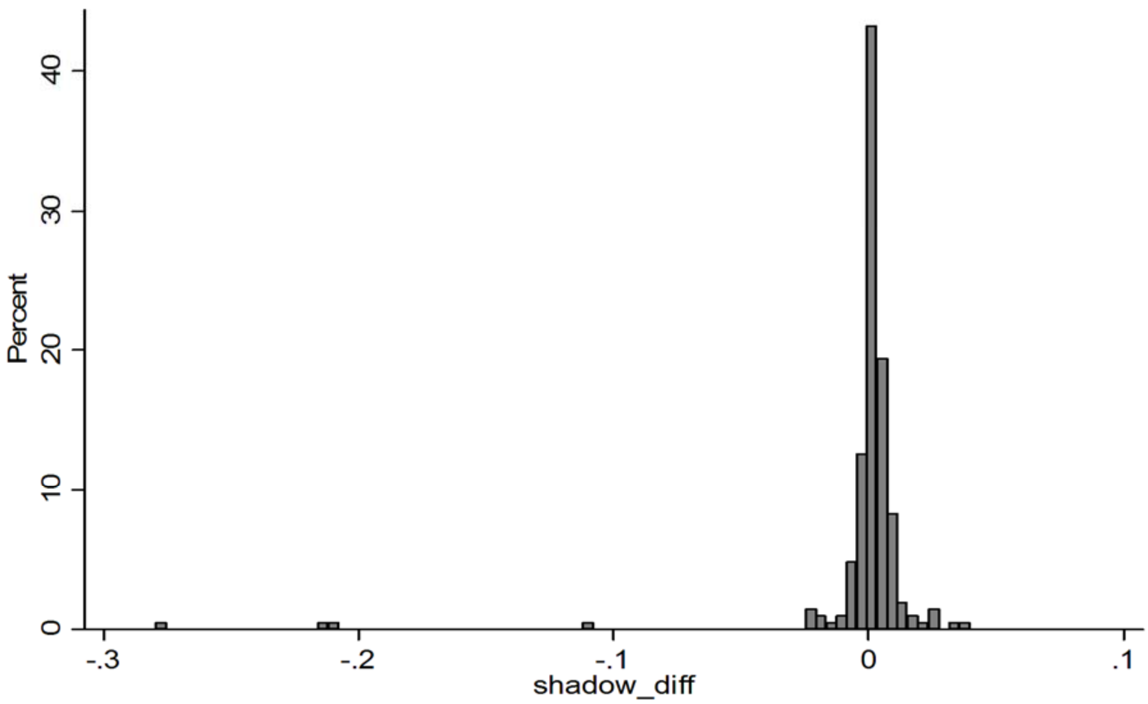


Table A1: Comparison of the self-reported and measured values of the cocoa farm dummy variables.

Variables	Observations	Same	$1 \rightarrow 0$	$0 \rightarrow 1$
Intercrop_M vs. Intercrop_S	208	199	3	6
Shade_M vs. Shade_S	208	189	8	11