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How can the productivity of Indonesian cocoa farms be increased?

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Abstract:

This study investigates the Indonesian cocoa production to reveal the possibilities for poverty alleviation while considering the threats to environmental sustainability. We estimate, based on a large household panel data set and stochastic frontier analysis, the technical efficiency of cocoa production and decompose productivity growth. According to our results, the productivity of Indonesian cocoa farming increased by 75 percent between 2001 and 2013. Technical efficiency growth and the increased chemicals use supported by government subsidies were responsible for the majority of this gain. Furthermore, we find large distortions in the input allocations. Hence, policies that encourage the adjustment of the cocoa farms' input use would be highly beneficial. Moreover, because of the weather-induced volatility in cocoa production, policy makers should also promote investment in agricultural research and transfer of drought-resistant cocoa varieties to farmers. Additionally, the average efficiency of cocoa farmers is estimated to be around 50 percent. We find that farmers' educational attainment and their experience in cocoa farming are significant factors that can increase the efficiency levels.

Keywords: cocoa, Indonesia, productivity change decomposition, technical efficiency.

JEL codes: D24, O13, Q01, Q12.

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1. Introduction

1.1 Background

Cocoa, one of the main ingredients of chocolate is primarily cultivated by smallholders in developing countries. Most of these producers live below the poverty line and have never tasted chocolate (Hütz-Adams and Fountain, 2012). After the Ivory Coast and Ghana, Indonesia is the third largest cocoa producer in the world with 10 percent of the global production (ICCO, 2016). Nearly 1.5 million Indonesian households depend on cocoa farming (ICCO, 2012). On the island of Sulawesi, which accounts for two thirds of Indonesia's cocoa production (Ministry of Agriculture, 2015)**,** 60 percent of cocoa farmers were living below the World Bank poverty threshold of 1.90 US dollar per day in 2009 (van Edig et al., 2010).

Cocoa is consumed mainly by the developed countries such as the US and Germany (21 and 13 percent of the total net imports in 2012). The average chocolate consumption per capita in both countries is over 10 kilograms (ICCO, 2012). The global demand for cocoa grew steeply over the last 15 years. This growth was primarily due to the Asian and African countries (Squicciarini and Swinnen, 2016). The prospect for cocoa demand growth is still high in China and India because the average chocolate consumption there is under 1 kilograms per capita (ICCO, 2012). However, cocoa growing countries can barely meet this expanding demand due to lack of appropriate production procedures and resources (ICCO, 2016). This generated an imbalance between the cocoa supply and demand in the global market and, because of their low price elasticity (Tothmihaly, 2017), an increase and high volatility in world cocoa prices (Onumah et al., 2013b).

Cocoa demand can be met and the income of cocoa farmers can be improved by increasing the cocoa growing area, by increasing input use, or by increasing technical efficiency (Onumah et al., 2013b). Both in Indonesia and Africa, most expansion in the cocoa cultivation was achieved by the first route (Nkamleu et al., 2010). The increased cocoa prices, together with the incentives by government subsidies for the sector, triggered farmers to increase cocoa production by raising cultivated land. This led to the conversion of virgin tropical forests to cocoa plantations (Teal et al., 2006).

This procedure usually includes tree felling, slash-and-burning, followed by the planting of cocoa and other crop trees (for example, banana) together. The latter trees provide shade for the young cocoa plants for two years. After three years, the cocoa trees start to produce and until about 10 years after planting, production rises yearly (Dand, 2010). Then, the cocoa yield starts to decrease gradually because of the higher frequency of cocoa diseases, erosion, and the decrease of soil nutrients (Smaling and Dixon, 2006). Some 20 years after planting, cocoa farmers have to either invest in uprooting, soil improvement, replanting, and disease reduction or shift to a new area. In places with low population density, it is easier to move the cocoa production than to use the old growing area (Asase et al., 2009). Also, replanting is usually more costly for smallholders with regard of intermediate inputs, labor, crops risks, and capital demand.

As a consequence of acreage expansion, 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] In Sulawesi, 80 percent of the rainforests were gone by 2010 causing, sometimes, irreversible losses of biodiversity (FAO, 2010). Findings from Frimpong et al. (2007) show a similar phenomenon in Africa.

Cocoa production can also be enhanced by increasing the cocoa yield with input intensification. Cocoa yields in Indonesia average just above 400 kilograms/hectare. This number is much lower than the potential 1500 kilograms/hectare based on the best performances of Indonesian cocoa farmers (ICCO, 2012). Various pests (mainly the vascular streak dieback and the cocoa pod borer) and the fact that most of the cocoa plants are more than 15 years old have contributed to the decline in cocoa yields (Ministry of Agriculture**,** 2015). In the face of this situation, the Indonesian Government announced the 3-year, 350-million US dollar 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 cause environmental deterioration and raise concerns about biodiversity conservation (Asare, 2005).

The third method to increase cocoa production is to improve technical efficiency. For environmental sustainability, this is the most desirable option. According to the Ministry of Agriculture (2015), the main causes of the low productive efficiency in Indonesia are aging farmers, aging farms, lack of knowledge, poor farming techniques, and capital problems (high bank interests). To tackle these issues, the government introduced a number of measures such

[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).

as the formation of agricultural extension services and later the expansion of credit access (Ministry of Agriculture, 2015).

Negating the adverse environmental outcomes of the low productivity systems requires large investments from both the private and public sectors. The first important question for decision makers is to what extent and how cocoa cultivation can be made more technically efficient. The second question is how the proposed measures affect the environment.

1.2 Contribution

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

We extend the previous research on the technical efficiency of cocoa farming. Technical efficiency estimations are available for the large producing countries such as Ghana: Aneani et al. (2011), Besseah and Kim (2014), Danso-Abbeam et al. (2012), Kyei et al. (2011), Nkamleu et al. (2010), Ofori-Bah and Asafu-Adjaye (2011), Onumah et al. (2013a), Onumah et al. (2013b) and Nigeria: Adedeji et al. (2011), Agom et al.(2012), Amos (2007), Awotide et al. (2015), Nkamleu et al. (2010), Ogundari and Odefadehan (2007), Ogunniyi et al. (2012), Oladapo et al. (2012), Oyekale (2012). However, they all use cross-sectional data. With the information gain of our panel data, which contains 4 time periods over 13 years, we decompose the total factor productivity change and characterize inefficiencies more realistically. We can track changes in time and control for omitted and mismeasured variables to produce more reliable estimates (Hsiao, 2007). Furthermore, previous cocoa 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 cocoa production.

In Indonesia, Effendi et al. (2013) assess the technical efficiency of cocoa smallholders. However, additionally to the previous issues, they do not include the Gernas Pro Kakao government program in their model and work with just a small sample size of 98. Table A1 summarizes the estimated average technical efficiencies and the sample sizes in previous cocoa studies. With 1290 observations, our sample size is larger than in any previous study on the technical efficiency of cocoa production.

Our results can be used to inform policies and practices to sustainably improve yields and income, thus reducing deforestation. The estimates could tell us which investments produce the highest marginal benefits: for example, improving education, access to financing or to extension services, or fostering the formation of farmer groups (Ingram et al., 2014).

2. Methodology

2.1 Stochastic frontier analysis

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 has 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). It is used by various researchers including Brümmer et al. (2006).

Based on Coelli et al. (2005), we can write the basic frontier model the following way:

$$\ln y_i = \ln f(\boldsymbol{x_i};\beta_i) + v_i - u_i \qquad (1)$$

where y_i represents the output, $f(\boldsymbol{x_i};\beta_i)$ denotes the production function at complete efficiency with $\boldsymbol{x_i}$ as input vectors and β_i as the parameters to be estimated, v_i is a random error term independently and identically distributed as $N(0,\sigma_v^2)$, and u_i is a non-negative unobservable term assumed to be independently and identically distributed as $N(0,\sigma_u^2)$ and independent of v_i. The last component measures the shortfall of the output from its maximum attainable level and, therefore, captures the effect of technical inefficiency. In this case, the technical efficiency of farm *i* can be written as

$$TE_i \;=\; exp\,(-u_i). \qquad (2)$$

The parameters of the production function in equation (1) must theoretically satisfy the regularity conditions: monotonicity and curvature (Coelli et al., 2005). We specify a translog production function. In this function, the inclusion of squared and interaction terms provides a high level of flexibility.

The extension of our model in equation (1) 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:

$$\mu_i = \varphi Z_i + e_i \tag{3}$$

where Z_i is a vector with farm-specific factors that are assumed to affect efficiency, φ is a vector with the 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.

2.2 Estimation issues

We have to look at four issues of the statistical inference: the estimation technique of the frontier model, the estimation technique of the inefficiency model, the estimation with panel data, 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.

With the availability of a large panel dataset, we can characterize inefficiencies more realistically. However, panel data also causes some issues in the estimation. The common feature of pooled SFA models is that the intercept is the same across productive units, thus generating a misspecification bias in presence of unobserved time-invariant variables. As a consequence, the inefficiency term may capture the influences of these variables, generating biased results. Greene (2008) approaches this problem with unit-specific intercepts. In contrast to the pooled model, his true fixed-effect (TFE) and true random-effect (TRE) panel specifications allow to differentiate between time-varying inefficiency and unit-specific unobservable time-invariant heterogeneity. The TFE model assumes the non-randomness while the TRE model the randomness of the unobserved unit-specific heterogeneity.

The ML estimation of the TFE specification needs the solution of the so-called incidental parameters problem. This inferential issue arises when the length of the panel is relatively small compared with the number of units, causing the inconsistent estimation of the parameters. As shown in Belotti and Ilardi (2012), the dummy variable approach for estimation appears to be suitable only when the panel length is large enough (T >10). Our sample is highly unbalanced and contains just 5 time periods. The common method to solve this problem is based on the elimination of the individual effects through within transformation, i.e., working with the deviations from the means. The consistent estimation of the TFE variant is proposed by Belotti and Ilardi (2012). However, the disadvantage of these methods is that they do not permit the use of time-invariant factors such as gender and education, which we assume are significant determinants of inefficiency. In our estimations, we use both the TRE and TFE specifications and choose between the two according to the Mundlak (1978) approach.

As pointed out by Greene (2008), neither the pooled nor the "true" formulation is completely satisfactory. Although the "true" model may appear to be the most flexible choice, it can be argued that a portion of the time-invariant unobserved heterogeneity does belong to inefficiency or that these two components should not be disentangled at all. Therefore, we estimate both extremes: the Coelli et al. (2005) model in which all time-invariant unobserved heterogeneity is considered as inefficiency and the TRE/TFE specification in which all time-invariant unobserved heterogeneity is ruled out from the inefficiency component.

Finally, 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.

2.3 Total factor productivity change

We base our calculations of total factor productivity (TFP) change on Brümmer et al. (2006). The TFP change is decomposed into technical efficiency change (TEC), scale efficiency change (SEC), allocative efficiency change (AEC), and technical change (TC) to control for productivity adjustments connected to these factors:

$$TFPC_1 = TEC + SEC + AEC + TC \quad (4)$$

According to Zhu and Lansink (2010), we can disaggregate technical efficiency change further:

$$TEC = TEC_{EV} + TEC_{TC} + TEC_{UF} \quad (5)$$

where $TEC_{EV,}$ TEC_{TC}, and TEC_{UF} are effects of the change in various inefficiency model variables, technical change of the inefficiency component, and unspecified factors.

Because we have dummy variables that further describe the production technology, we also calculate an augmented TFP change that includes two additional components connected to technology:

$$TFPC_2 = TFPC_1 + T_{IU} + T_{GK} \quad (6)$$

where T_{IU} and T_{GK} are contributions from input use change and the Gernas Pro Kakao program. Thus, we arrive at the following detailed decomposition:

$$TFPC_2 = TEC_{EV} + TEC_{TC} + TEC_{UF} + TC + T_{GK} + T_{WP} + SEC + AEC \quad (7)$$

3. Empirical specification

3.1 Production frontier model

The translog production function for the cocoa farm *i* with four inputs, and seven dummy variables is specified as:

$$lny_{it} = \alpha_0 + \sum_{k=1}^{4}\beta_k lnx_{kit} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4}\beta_{jk} lnx_{jit} lnx_{kit} + \sum_{j=1}^{7}\delta_j D_{jit} + \sum_{j=1}^{3}\theta_j T_{jt} + v_{it} - u_{it} \quad (8)$$

where y_i is the amount of cocoa beans harvested in kilograms, x_k is a vector of observations on inputs, D_j is a vector of observations on dummy variables characterizing the production process, T_j represents time dummies controlling for unobservable influences that vary between the years, such as technical change, the α's, β's, δ's, and θ's are unknown parameters to be estimated, v is a random error term, and finally u is a non-negative unobservable variable describing inefficiency. We do 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 cocoa farms in our sample area.

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). The variables used in these and other previous cocoa technical efficiency studies are summarized in Table A2. According to the classical model, with a given technology, output is determined by land (x_1), labor (x_2), and intermediate inputs (x_3). In our model, land indicates the total cultivated cocoa area measured in ares, while labor is calculated in Rupiah and involves all harvest and maintenance tasks on the cocoa farm.[2] We assume that the latter is a good approximation for quality-adjusted labor input. Furthermore, intermediate inputs are measured as the cost of fertilizers, pesticides, transport, and processing in Rupiah. We aggregate these inputs to avoid multicollinearity (Brümmer et al., 2006) and presume that the value of material inputs reflects the quality of inputs better than quantity because of the different concentrations of active components and nutrients (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). In some previous studies, the sign of this variable is positive and in other studies, negative depending on the average tree age in the sample (Table A2).

We enhance the basic production frontier with seven dummy variables to describe the cocoa cultivation process more accurately (Wollni and Brümmer, 2012). Because zero values of input variables can cause biased inference, a dummy variable is added that equals one if intermediate inputs equal zero (D_1). The second dummy variable is equal to 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 equals one if hybrid cocoa variety is cultivated by the farmer. We anticipate that hybrids produce higher yields than the local varieties (Dand, 2010). Moreover, the pruning of cocoa trees (D_4) is expected to improve output levels because it gives room for sufficient sunlight that stimulates the growth of flowers. Additionally, it keeps the farm environment clean, preventing the development and

[2] 1 hectare equals 100 ares. During the last 15 years, 1 euro fluctuated between 10000 and 17000 Indonesian Rupiahs.

spread of pests (Danso-Abbeam et al., 2012; Effendi et al., 2013; Amos, 2007). Furthermore, a dummy for yield loss is used to reflect the effect of pests and adverse weather on the cocoa harvest quantity.

Table 1: Description of the cocoa farm variables.

Variable	Description
Output	
Cocoa	Cocoa quantity harvested on the farm (kilograms)
Input	
Tree age	Average cocoa tree age (years)
Land	Total area planted with cocoa (ares)
Labor	Maintenance and harvest labor costs for the cocoa farm (constant 2001 Rupiah)
Intermediate inputs	Fertilizer, pesticide, transport, and processing costs for the farm (constant 2001 Rupiah)
Technology	
No input	Dummy, 1 = household did not use intermediate inputs for the cocoa farm
Gernas	Dummy, 1 = household joined the Gernas Pro Kakao program in the last 3 years
Hybrid	Dummy, 1 = hybrid cocoa variety was cultivated by the farmer
Pruning	Dummy, 1 = cocoa trees were pruned
Intercrop	Dummy, 1 = there was intercropping on the cocoa farm
Shade 60	Dummy, 1 = shade level of the cocoa farm is larger than 60 percent
Crop loss	Dummy, 1 = cocoa yield loss because of adverse weather or pests
Inefficiency	
Male	Dummy, 1 = household head is male
Age	Age of the household head (years)
High school	Dummy, 1 = household head completed the senior high school
Extension	Dummy, 1 = household head had agricultural extension contacts
Credit	Dummy, 1 = household head obtained credit in the last 3 years
Association	Dummy, 1 = household head was member in a cocoa cooperative in the last 3 years
Time	
Year 2004	Dummy, 1 = observation is in 2004
Year 2006	Dummy, 1 = observation is in 2006
Year 2013	Dummy, 1 = observation is in 2013

Notes: All variables refer to the last 12 months with the mentioned exceptions. Labor and intermediate input costs are adjusted for inflation with the Indonesian Consumer Price Index (2001=1.00).

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). The current consensus on this issue implies that shade starts to reduce cocoa yields beyond a level of around 30 percent. Following Bentley et al. (2004), we add a sixth dummy variable to our model that captures the influence of the high shade (larger than 60 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 seventh 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 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., 2005; 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.

3.2 Inefficiency model

In addition to the production frontier model above, we specify the following inefficiency equation for cocoa farm *i*:

$$\mu_{it} = \varphi_0 + \sum_{j=1}^{6} \varphi_j Z_{jit} + \sum_{j=1}^{3} \omega_j T_{jt} + e_{it} \qquad (9)$$

where μ is the mean of the inefficiency estimates u that follow a truncated normal distribution (Coelli et al., 2005), Z_j is a vector of observations on six factors that are expected to affect the efficiency level, T_j again denotes the three time dummies that account for variations in mean efficiency between the years, the φ's and ω's are the unknown parameters to be estimated, and e is the random error term. We include explanatory variables in the inefficiency model that express the management skills of cocoa smallholders and their access to productive resources and knowledge (Wollni and Brümmer, 2012).

The first two explanatory variables reflect the household structure (Wollni and Brümmer, 2012). First, we expect that it is more difficult for households with female heads to access markets. 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 (Table A2).

Furthermore, farmer age is thought to increase technical inefficiency partly because older smallholders take up less likely the latest technologies (Coelli et al., 2005). They are also less energetic than their younger counterparts. However, Onumah et al. (2013b) suggest that older farmers might develop a higher technical efficiency level than younger farmers because of their longer farming experience.

The next variable refers to the inner capabilities of the household head (Ofori-Bah and Asafu-Adjaye, 2011). The education dummy equals one if the head of the household completed 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 last three 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; Table A2).

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). Thus, many economists view the spread of feasible agricultural credit services crucial for raising the productivity of labor and land (Zeller et al., 1997).

Finally, we include a dummy variable for membership in a cocoa association. We expect that associations assist smallholders in reducing transaction costs and, therefore improve their access to various resources and increase their technical efficiency (Binam et al., 2004; Hafid et al., 2013).

4. Data description

4.1 Data sources

We acquire the data using the STORMA (Stability of Rainforest Margins in Indonesia) project survey data from Göttingen.[3] This project conducted four rounds of household and agricultural surveys in Indonesia in 2001, 2004, 2006, and 2013. The survey data were collected from 722 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.

In each sample village, the head of the village and the leaders of the hamlets listed the names of every household head living in the village. Next, the sample households were randomly selected from these lists and 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. In the four rounds, those panel and split-off households were tracked who were still living in those 15 villages.

4.2 Descriptive statistics

Table 2 shows the summary statistics of the independent and dependent variables in the production frontier and inefficiency equations. The dataset is an unbalanced panel of 722 cocoa farms and contains 1290 observations. Therefore, on average, one farm appears in just 1.8 rounds.

Over the 12 years, the average output of the cocoa farms rose almost twofold, while the average farm size remained almost constant at around 0.75 hectares, which is about one third

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

of the African average (Nkamleu et al., 2010; ICCO, 2012). This resulted in an almost twofold increase in the average cocoa yield, which was in 2013 with around 600 kg/hectare above the world average of about 500 kg/hectare and well above the Indonesian average of about 400 kg/hectare (ICCO, 2016). We can list two reasons for this. First, cocoa trees reached their most productive age around 2011 and they were, on average, 12 years old in 2013. According to Nkamleu et al. (2010), this is just one half of the African average because of the later start of cocoa cultivation in Indonesia. Second, the use of labor and intermediate inputs (mostly, fertilizer and pesticide) increased more than threefold and the ratio of cocoa farms that used both increased from 15 percent to 42 percent. The Gernas Pro Kakao government program implemented in 2009 could have contributed to this phenomenon by providing easier access to intermediate inputs (KKPOD, 2013). However, the use of labor and intermediate inputs is still just one third and one half of the African average (Nkamleu et al., 2010; Maytak, 2014).

Over the years, we could also observe the spread of hybrid cocoa varieties: in 2013, they were planted on 10 percent of the cocoa farms. This is significantly larger than the world average of 5 percent (ICCO, 2012). Furthermore, the practice of tree pruning fluctuated around 95 percent in the last three survey rounds which is much higher than in Africa (Maytak, 2014). According to the data, 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 ratio of intercropping decreased to 8 percent in 2013, while the share of high shade farms stood at just 2 percent. Finally, in accordance with the world average, 43 percent of the cocoa farms experienced significant yield losses due to adverse weather and pests (Dand, 2010).

The statistics of the inefficiency variables point to a slow cultural change in our sample area, to more female household heads. The share of female household heads stood at 10 percent in 2013, which is consistent with past studies that show cocoa cultivation as a male-dominated livelihood (Nkamleu et al., 2010; Maytak, 2014). Moreover, the age and the educational attainment of the average household head increased considerably over the years. The average farmer age of 49 years in 2013 is consistent with data collected by Nkamleu et al. (2010) and Vigneri (2007). Furthermore, we do not observe an increase in extension services from the initial 25 percent but do see that credit access rose dramatically from almost zero to 23 percent. Finally, in 2013 about every third household was member of a cocoa farmer group. All the last three statistical values are close to the African averages (Nkamleu et al., 2010).

Table 2: Summary statistics of the cocoa farm variables.

Variable	2001		2004		2006		2013		Pooled	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Output										
Cocoa	315	464	379	618	300	328	607	729	427	589
Input										
Tree age			6.9	3.8	7.2	4.3	12.0	6.5		
Land	75	67	73	59	72	57	77	70	74	64
Labor	43838	139602	58497	257185	64283	195650	338792	822868	157764	535064
Int. inputs	152520	307663	122226	232994	77799	226500	319243	701444	185231	476924
Technology										
No input	0.85	0.36	0.86	0.35	0.79	0.41	0.58	0.49	0.74	0.44
Gernas	0	0	0	0	0	0	0.14	0.35	0.05	0.22
Hybrid			0.03	0.16	0.11	0.31	0.10	0.31		
Pruning			0.95	0.22	0.97	0.18	0.93	0.26		
Intercrop			0.16	0.36	0.11	0.32	0.08	0.27		
Shade 60							0.02	0.14		
Crop loss							0.43	0.50		
Inefficiency										
Male	0.99	0.12	0.97	0.18	0.93	0.25	0.90	0.30	0.94	0.24
Age	45	14	47	14	46	14	49	15	47	14
High school	0.12	0.33	0.15	0.36	0.19	0.40	0.17	0.38	0.17	0.37
Extension	0.31	0.46	0.25	0.44	0.22	0.41	0.25	0.43	0.25	0.43
Credit			0.01	0.09	0.09	0.28	0.23	0.42		
Association							0.36	0.48		
Time										
Year 2004	0	0	1	0	0	0	0	0	0.19	0.40
Year 2006	0	0	0	0	1	0	0	0	0.29	0.45
Year 2013	0	0	0	0	0	0	1	0	0.36	0.48
N		207		251		372		460		1290

5. Results and discussion

5.1 Production frontier

Table 3 displays the parameter estimates of the production frontiers. Because the Mundlak (1978) approach selects the random-effect specification over the fixed-effect model, we include only the random-effect results in this table. To check for the correct functional form of the models, we use likelihood ratio (LR) tests and the Akaike Information Criterion (AIC). They suggest that the Cobb-Douglas production function is preferred with our panel data and the translog function with the 2013 data. Thus, we report only these estimation results.

For the translog functional form, regularity properties must be checked after estimation since they are not automatically satisfied (Wollni and Brümmer, 2012). Therefore, we test for monotonically increasing marginal products and decreasing marginal returns regarding tree age, land, labor, and intermediate inputs in the 2013 model. The first-order coefficients are interpreted as partial output elasticities at the sample mean because we mean-correct each variable. We find both positive elasticities and diminishing marginal productivities at the sample mean. The monotonicity assumptions are violated in less than 1 percent of the observations for land, labor, and intermediate inputs but in 57 percent of the cases for tree age. We can explain the latter by the fact that, in 2013, the average age of cocoa trees was a little higher than their most productive age.

In the pooled panel model, the output elasticities of land, labor, and intermediate inputs are 0.622, 0.118, and 0.079. We employ a t-test to evaluate whether the elasticity of scale (0.819) at the sample mean significantly differs 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 smaller than one hectare. A plausible cause of the diminishing return to scale can be some impediments to growth (Brümmer et al., 2006).

Additionally, various dummy variables are incorporated into the models to describe cocoa farming more accurately. The variable “No input” is negative and significant at the 1 percent level. This means that, as anticipated, farms not using intermediate inputs have lower cocoa output levels. Furthermore, the variable “Gernas” indicates that smallholders who participated in the Gernas Pro Kakao government program achieve higher cocoa output levels. Finally, the negative signs of the 2004 and 2006 year dummies reflect lower cocoa production levels in these two years compared with the other years. This is the consequence of an exceptionally strong negative El Niño weather effect between 2004 and 2006.

The outcomes of the true random effect model are similar to pooled panel model. In the 2013 model, the square of the tree age variable is significant and negative. This points to the maturing and aging process of the cocoa trees. Furthermore, the output elasticities of land, labor, and intermediate inputs are 0.505, 0.257, and 0.088. According to the t-test results, the scale elasticity amounts to 0.850 and significantly differs from one. Therefore, we can also conclude here that cocoa farms exhibit a decreasing returns to scale. Finally, all dummy variables of the 2013 model confirm the expected signs, but two of them are not significant.

Our findings show the positive effect of intermediate input use, pruning, and the Gernas Pro Kakao program, but the negative effect of high shade on cocoa production.

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

Variable	Pooled panel model	TRE panel model	2013 model
Input			
ln Tree age			0.071 (0.086)
ln Land	0.622 (0.033)***	0.616 (0.034)***	0.505 (0.062)***
ln Labor	0.118 (0.028)***	0.123 (0.028)***	0.257 (0.051)***
ln Int. inputs	0.079 (0.026)***	0.081 (0.026)***	0.088 (0.045)**
0.5 (ln Tree age)^2			-0.584 (0.154)***
0.5 (ln Land)^2			0.006 (0.072)
0.5 (ln Labor)^2			0.002 (0.096)
0.5 (ln Int. inputs)^2			-0.010 (0.054)
ln Tree age * ln Land			0.285 (0.093)***
ln Tree age * ln Labor			-0.210 (0.095)**
ln Tree age * ln Int. inputs			-0.099 (0.070)
ln Land * ln Labor			-0.038 (0.094)
ln Land * ln Int. inputs			0.070 (0.052)
ln Labor * ln Int. inputs			0.022 (0.035)
Technology			
No input	-0.531 (0.058)***	-0.506 (0.059)***	-0.389 (0.114)***
Gernas	0.359 (0.145)**	0.308 (0.141)**	0.323 (0.122)***
Hybrid			0.170 (0.154)
Pruning			0.494 (0.171)***
Intercrop			0.058 (0.232)
Shade 60			-0.422 (0.208)**
Crop loss			-0.144 (0.087)*
Time			
Year 2004	-0.201 (0.117)*	-0.235 (0.116)**	
Year 2006	-0.410 (0.091)***	-0.405 (0.091)***	
Year 2013	0.130 (0.143)	0.182 (0.141)	
Constant	1.061 (0.087)***	1.004 (0.090)***	0.419 (0.195)**
Variance			
σ_u	2.258 (0.377)***	2.301 (0.411)***	1.633 (0.313)***
σ_v	0.535 (0.039)***	0.475 (0.048)***	0.493 (0.065)***
RTS	0.819	0.820	0.850

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 all three 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 annual rates of technical efficiency, while Figure A1 presents the efficiency distributions of the sample farms. Based on the panel models, the mean technical efficiency of cocoa farmers is estimated to be around 50 percent, but the range is very wide (1-90) and many scores are inside the bottom quarter of the range of the distribution. This means that most cocoa farmers have an ample scope to expand cocoa output without increasing input use. African cocoa farmers (Table A1) seem to have higher technical efficiencies which can be partly explained by the much longer cultivation of cocoa on the African continent. In terms of technical efficiency change over time, we find an overall increasing trend. This is not surprising, since cocoa production was introduced in Indonesia only in the 1990s and farmers had to learn to know-hows of cultivation.

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

Year	Pooled panel model				TRE panel model				2013 model			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2001	36	24	1	83	37	24	1	86				
2004	46	22	1	87	48	24	1	89				
2006	51	22	1	83	52	23	1	85				
2013	50	22	2	88	51	23	2	90	50	22	3	87
2001–2013	47	23	1	88	49	24	1	90				

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 the panel models, the cocoa farmers' age and the year dummies are the only significant factors that affect the productive efficiencies. As anticipated, efficiency increases with farmer age, which is also a proxy for experience in cocoa cultivation in our study. According to our model, every additional year provides a 0.7 percent increase in technical efficiency, on average. Furthermore, the significant year dummies identify an overall increasing trend in technical efficiency. The 2013 model finds an additional significant factor: educational attainment. As expected, a higher educational level enhances an individual's understanding of farming.

Finally, we find that credit access, extension services, and farmer associations do not significantly affect efficiency. These results are inconsistent with many African cocoa studies which show positive linkages (Table A2). For example, many economists view the spread of feasible agricultural credit services crucial for raising technical efficiency (Zeller et al, 1997). The limited effect of agricultural extension programs on efficiency can be due to the inherent deficiencies of public information systems, flawed service design ("top-down" manner), or bureaucratic inefficiency (Nkamleu et al., 2010). Furthermore, the ineffectiveness of farmer groups can be attributed to the missing social capital, that is, the lack of assistance to each other in the times of need (Ingram et al., 2014).

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

Variable	Pooled panel		TRE panel model		2013 model	
	Coefficients	Marg. eff.	Coefficients	Marg. eff.	Coefficients	Marg. eff.
Male	-0.173 (1.112)	-0.029	-0.164 (1.204)	-0.025	0.530 (0.911)	0.121
Age	-0.041 (0.018)**	-0.007**	-0.041 (0.020)**	-0.006**	-0.029 (0.016)*	-0.007*
High school	0.084 (0.595)	0.014	0.092 (0.652)	0.014	-1.272 (0.729)*	-0.291*
Extension	-0.108 (0.417)	-0.018	-0.100 (0.446)	-0.015	0.780 (0.494)	0.178
Credit					-0.137 (0.528)	-0.031
Association					0.039 (0.437)	0.009
Time						
Year 2004	-1.769 (0.940)*	-0.296*	-2.078 (1.060)**	-0.320**		
Year 2006	-2.705 (0.800)***	-0.453***	-2.840 (0.881)***	-0.437***		
Year 2013	-2.549 (0.950)***	-0.426***	-2.853 (1.111)***	-0.439***		
Constant	2.241 (1.346)*		2.323 (1.418)		0.336 (1.437)	

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

5.4 Productivity change

Table 6 shows the decomposition of the total factor productivity change into several sources: technical efficiency factors, technical change, scale and allocative efficiency effects, and additional factors connected to technology. Land allocative effects are not calculated because if the size of a cocoa farm was changed over the years, we consider it a different farm. Since the pooled and random-effect model results are similar, we discuss only the RE estimates.

The total productivity growth of the cocoa farms over the 12 years amounts to around 75 percent. This means about a 6 percent annual improvement, on average. The fastest productivity growth (more than 36 percent) was accomplished in the third observation period, between 2006 and 2013. In the first and second periods, cocoa farms experienced total factor productivity increases of about 13 and 27 percent.

Examining the individual components of TFP change, we find that the growth in the 2001–2004 period is primarily caused by technical efficiency change, especially by its TEC_{TC} component (30.4 percent increase). The distribution of this effect is shown in Figure A2. This improvement might be the result of the fact that cocoa production in our sample area started just in the 1990s and farmers needed to gain knowledge and experience in the early stages of cultivation. In our first sample period, the sharp decrease (−23.5 percent) of the standard technology component was counteracting this growth. This could be mainly due to the very dry 2004 cocoa growing season. The allocative effect of the intermediate inputs had an additional negative influence (−12.8 percent) on productivity. Finally, we find that changes in scale and labor allocative efficiency are relatively small compared with the other elements.

The TFP increase between 2004 and 2006 is dominated by the technical efficiency change (16.4 percent) and the allocative effects of the intermediate inputs (14.9 percent). The value of the former points to the slowdown of the technical efficiency increase, while the latter shows a tremendous improvement in the input allocation. The allocative effect induced by labor input and the technology effect of the input use had a further positive influence on productivity. Again, the technical change component was offsetting the improvement because of the unfavorable weather conditions (-17 percent).

In contrast to the first two periods, the main driver for productivity growth in the last observation period was technical progress (40.5 percent increase). This is due to the positive effect of the La Niña climate pattern. However, the distortion in the allocation of intermediate inputs (-33.1 percent change) was counterbalancing this improvement. We can also notice the increasing technology effect of input use and the Gernas Pro Kakao government program. However, technical efficiency growth continued to slow down. A possible explanation for this finding could be the deterioration of land infrastructure because of the heavy rains.

Table 6: Decomposition of the total factor productivity change in cocoa farming (percentages).

Time period	TEC_{EV}	TEC_{TC}	TEC_{UF}	TC	SEC	AEC_{LA}	AEC_{II}	$TFPC_1$	T_{IU}	T_{GK}	$TFPC_2$
Pooled model											
2001–2004	2.3	29.3	18.7	-20.1	-1.3	-3.5	-12.6	12.8	1.2	0.0	14.0
2004–2006	0.9	12.6	4.8	-20.9	-0.1	5.8	14.6	17.7	6.8	0.0	24.5
2006–2013	2.9	-2.1	3.7	41.0	-1.5	8.7	-32.4	20.3	10.5	6.1	36.9
2001–2013	6.1	39.8	27.2	0.0	-2.9	11.0	-30.4	50.8	18.5	6.1	75.4
Average annual	0.5	3.3	2.3	0.0	-0.2	0.9	-2.5	4.3	1.5	0.5	6.3
TRE model											
2001–2004	2.1	30.4	20.7	-23.5	-1.3	-3.5	-12.8	12.1	1.1	0.0	13.2
2004–2006	0.8	9.6	6.0	-17.0	0.0	5.8	14.9	20.1	6.5	0.0	26.6
2006–2013	2.6	0.2	3.0	40.5	-1.6	9.2	-33.1	20.8	10.0	5.3	36.1
2001–2013	5.5	40.2	29.7	0.0	-2.9	11.5	-31.0	53.0	17.6	5.3	75.9
Average annual	0.5	3.4	2.5	0.0	-0.2	1.0	-2.6	4.5	1.5	0.4	6.4

Notes: TEC_{EV} = technical efficiency change from the variable “age of household head”, TEC_{TC} = technical efficiency change from technical change, TEC_{UF} = technical efficiency change from unspecified factors, TC = technical change, SEC = scale efficiency change, AEC_{LA} = allocative efficiency change (labor), AEC_{II} = allocative efficiency change (intermediate inputs), $TFPC_1$ = standard total factor productivity change, T_{IU} = the effect of non-zero intermediate input use, T_{GK} = the effect of the Gernas Pro Kakao program, $TFPC_2$ = augmented total factor productivity change. Values are calculated according to Brümmer et al. (2002), and Zhu and Lansink (2010).

6. Conclusion

The surge in cocoa demand and price prompts us to search for sustainable ways to improve cocoa yields and thus, farmer income. We investigate the productivity and efficiency of the Indonesian cocoa production using a panel survey data of 1290 observations and a stochastic frontier model. The results indicate a decreasing return to scale in production. Given the small average cocoa farm size, this could reflect the impediments to growth.

According to our results, the productivity of Indonesian cocoa farming increased by 75 percent between 2001 and 2013. We decompose total factor productivity change into several sources: technical efficiency factors, technical change, scale and allocative efficiency effects, and additional factors connected to technology. The calculations show large distortions in input allocation. Hence, policies that encourage the adjustment of the cocoa farms’ input use would be highly beneficial. Furthermore, the technical change component points to a weather-induced volatility in cocoa production. Thus, policy makers should also promote investment in agricultural research and transfer of drought-resistant cocoa varieties to farmers. The estimates also show the important role of the increasing input use and the Gernas Pro Kakao government program in achieving productivity growth.

Finally, the biggest growth in cocoa productivity was caused by the increasing technical efficiency. However, the average technical efficiency in Indonesia is still under 50 percent, which is much smaller than the West African average. To sustainably boost cocoa productivity further, we have to look at the possible sources in our detailed technical efficiency results. The significant factors identified to have a positive influence on the efficiency levels are the smallholders' educational attainment and their experience in cocoa farming. Our findings also show that the extension services, the rural credit system, and the farmer groups do not have a significant effect on the efficiency of cocoa farms in our research area.

The limited effect of existing agricultural extension programs on efficiency can be due to the inherent deficiencies of public information systems, flawed service design, or bureaucratic inefficiency. Furthermore, the ineffectiveness of farmer groups can be attributed to the missing social capital, that is, the lack of assistance to each other in the times of need. Hence, policy should focus on adjusting the public extension programs, fostering the mutual benefits in the farmer groups, and developing viable credit institutions to expand the Indonesian cocoa output without increasing input use.

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Appendix

Table A1: Technical efficiencies in previous cocoa studies.

Country	No. of datasets	Weighted mean TE	Mean sample size	Total sample size
Ghana	10	56	313	3125
Ivory Coast	1	58	1372	1372
Cameroon	1	65	1003	1003
Nigeria	11	72	246	2701
Indonesia	1	81	98	98
World	24	63	346	8299

Sources: Own calculations from Aneani et al. (2011), Awotide et al. (2015), Besseah and Kim (2014), Danso-Abbeam et al. (2012), Kyei et al. (2011), Nkamleu et al. (2010), Ofori-Bah and Asafu-Adjaye (2011), Onumah et al. (2013a), Onumah et al. (2013b), Adedeji et al. (2011), Agom et al.(2012), Amos (2007), Ogundari and Odefadehan (2007), Ogunniyi et al. (2012), Oladapo et al. (2012), Oyekale (2012), and Effendi et al. (2013).

Notes: There are 24 datasets in 17 studies. We used the sample sizes as weights for the aggregation of the technical efficiency scores. TE = technical efficiency.

Table A2: Determinants of production and inefficiency in previous cocoa studies.

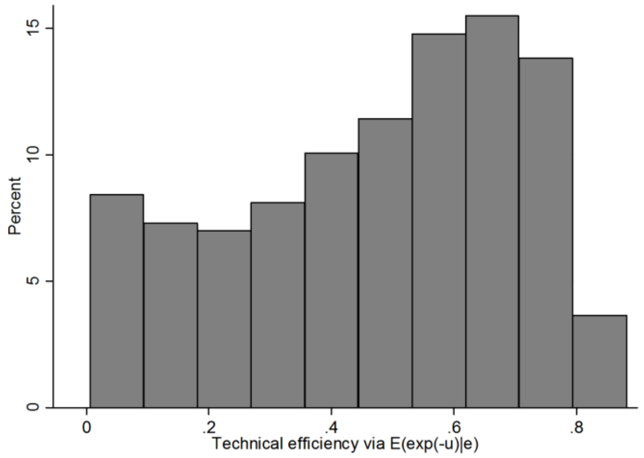
Variable	No. of positive effects	Number of negative effects	No. of insignificant effects	No. of datasets
Production				
Tree age	6	5	3	14
Farm size	19		2	21
Labor cost	20		3	23
Fertilizer cost	10	1	6	17
Pesticide cost	19	1	4	24
Processing cost	3		1	4
Transport cost	2			2
Pruning	1		2	3
Inefficiency				
Male	1	10	3	14
Farmer age	3	5	12	20
Educational level	3	11	9	23
Extension services	1	8	8	17
Credit access		6	4	10
Association member	1	5	4	10
Intercropping		1	1	2
Shade cover	1	2	2	5

Sources: Own calculations from Aneani et al. (2011), Awotide et al. (2015), Besseah and Kim (2014), Danso-Abbeam et al. (2012), Kyei et al. (2011), Nkamleu et al. (2010), Ofori-Bah and Asafu-Adjaye (2011), Onumah et al. (2013a), Onumah et al. (2013b), Adedeji et al. (2011), Agom et al.(2012), Amos (2007), Ogundari and Odefadehan (2007), Ogunniyi et al. (2012), Oladapo et al. (2012), Oyekale (2012), and Effendi et al. (2013).

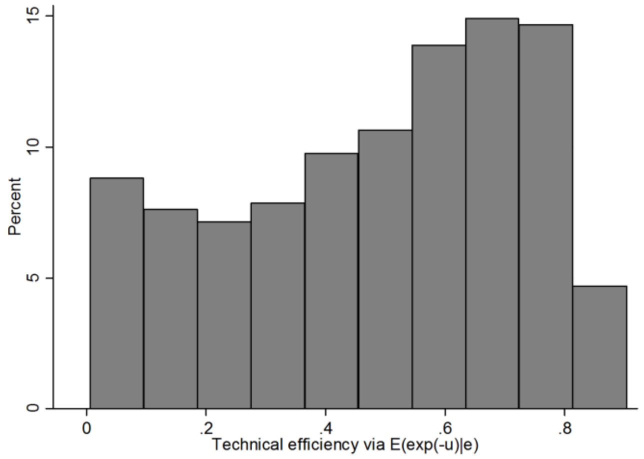
Notes: There are 24 datasets in 17 studies.

Figure A1: Distribution of efficiencies in the cocoa production models.

a) Pooled panel model, 2001-2013



b) TRE panel model, 2001-2013



c) 2013 model

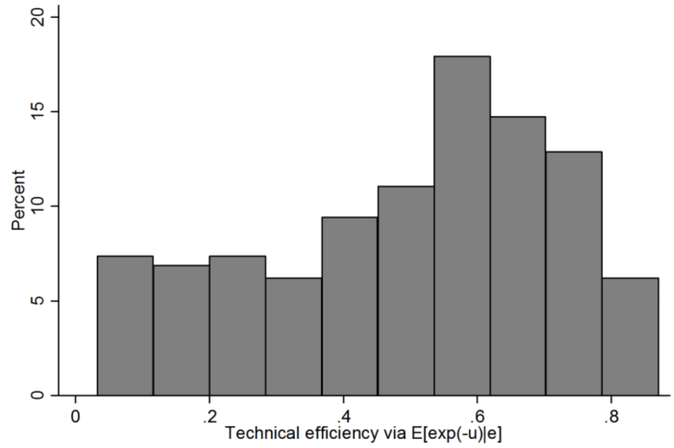
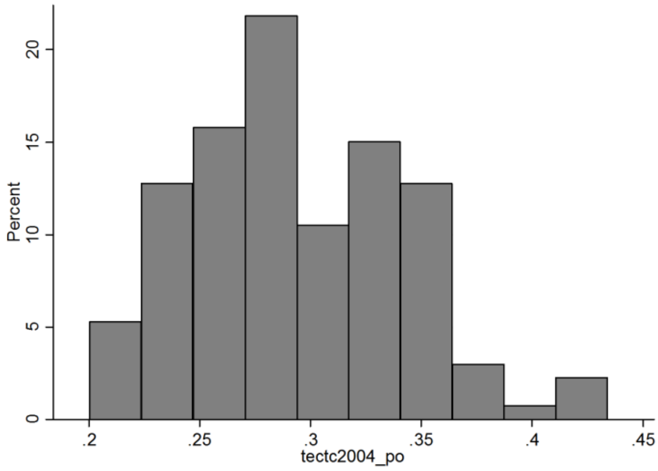


Figure A2: Distribution of the TEC_{TC} productivity change component in 2004.

a) Pooled panel model



b) TRE panel model