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RESEARCH ARTICLE

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How can the productivity of Indonesian cocoa farms be increased?

Andras Tothmihaly[1] | Verina Ingram[2]

[1]Department of Agricultural Economics and Rural Development, University of Goettingen, Goettingen, Germany

[2]Forest & Nature Conservation Policy Group, Environmental Sciences Group and Wageningen Economic Research, Social Science Group, Wageningen University & Research, Wageningen, The Netherlands

Correspondence
Andras Tothmihaly, Department of Agricultural Economics and Rural Development, University of Goettingen, Blue Tower, Room 9.148, 37075 Goettingen, Germany.
Email: atothmi@gwdg.de, andras.tothmihaly@gmail.com

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Abstract

This study investigates the Indonesian cocoa production to reveal the possibilities for poverty alleviation. We estimate, using 1,290 panel observations from 722 households and stochastic frontier analysis, the technical efficiency of cocoa production and disaggregate productivity growth. Our results indicate that the average efficiency of the cocoa farmers is 50%. Farmers' educational attainment and their experience in cocoa farming are significant factors increasing efficiency. We also find that the productivity of Indonesian cocoa farms increased by 75% 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, large distortions in input allocation were found. Hence, policies that encourage the efficient use of farm inputs would be highly beneficial. Weather- and pests-induced volatility in cocoa production could be decreased by promoting agricultural research on drought- and disease-resistant cocoa varieties (EconLit citations: D24, O13, Q12).

KEYWORDS
cocoa, Indonesia, productivity change disaggregation, technical efficiency

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 & Fountain, 2012). After the Ivory Coast and Ghana, Indonesia is the third largest cocoa producer in the world with 10% 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-third of Indonesia's cocoa production (Ministry of Agriculture, 2015), 60% of cocoa farmers were living below the World Bank poverty threshold of 1.90 US dollar per day in 2009 (van Edig, Schwarze, & Zeller, 2010). Cocoa is consumed mainly in developed countries, such as the US and Germany (21% and 13% of the total net imports in 2012). Global demand for cocoa grew steeply over the last 15 years. This growth was primarily due to the Asian and African countries (Squicciarini & Swinnen, 2016). However, cocoa growing countries can barely meet the current increasing demand due to inappropriate production systems and low level of resources (ICCO, 2016). This situation has generated an imbalance between the global cocoa supply and demand and, because of the low price elasticity of both cocoa supply and demand (Tothmihaly, 2017), an increase and high volatility in world cocoa prices (Onumah, Onumah, Al-Hassan, & Brümmer, 2013).

Three main ways exist to improve cocoa farmers' income and meet global demand for cocoa: (a) increasing the cocoa growing area; (b) increasing intermediate input use; or (c) increasing technical efficiency (Onumah, Onumah, et al., 2013). Both in Indonesia and Africa, expanding cocoa cultivation has mainly been achieved via the first route (Nkamleu, Nyemeck, & Gockowski, 2010). Increased cocoa prices, together with the incentives provided by government subsidies for the sector, have triggered farmers to increase cocoa production by raising cultivated land. This has led to an ongoing conversion of primary tropical forests to cocoa plantations worldwide (Teal, Zeitlin, & Maamah, 2006). In Indonesia, 80% of the rainforests were gone by 2010 in Sulawesi, the main area of cocoa production.

Second, enhancing yields through input intensification is relevant given that average yields in Indonesia are just above 400 kg/ha. This is much lower than the potential 1,500 kg/ha based on the best performance of Indonesian cocoa farmers (ICCO, 2012). Given this context, the Indonesian Government announced the 3 years, 350-million US dollar Gernas Pro Kakao revitalization program (KKPOD, 2013) for the cocoa industry in 2009. The program was established to boost productivity. However, intensification toward low shade systems can also cause environmental deterioration, in particular decreasing biodiversity (Asare, 2005).

For environmental sustainability, the third method to increase cocoa production is the most desirable option, improving technical efficiency. According to the Indonesian 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 financial capital (high bank interest rates). To tackle these issues, the government introduced a number of measures such as agricultural extension services and later an expansion of access to credit (Ministry of Agriculture, 2015). Negating the adverse environmental outcomes of low cocoa productivity systems requires investments from both the private and public sectors and farmers. A key question for decision makers is to what extent and how cocoa cultivation can be made more technically efficient.

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 the technical efficiency of production and disaggregate total factor productivity changes, based on household, agricultural, and environmental surveys and stochastic frontier analysis (Battese & Coelli, 1995). We determine the magnitude of the attainable efficiency increases and the methods that can be used to attain them.

We extend previous research on the technical efficiency of cocoa farming. Technical efficiency estimations have been conducted for the large producing countries such as Ghana (Aneani, Anchirinah, Asamoah, & Owusu-Ansah, 2011; Besseah & Kim, 2014; Danso-Abbeam, Aidoo, Agyemang, & Ohene-Yankyera, 2012; Kyei, Foli, & Ankoh, 2011; Nkamleu et al., 2010; Ofori-Bah & Asafu-Adjaye, 2011; Onumah, Al-Hassan, & Onumah, 2013; Onumah, Onumah, et al., 2013) and Nigeria (Adedeji, Ajetomobi, & Olapade-Ogunwole, 2011; Agom, Ohen, Itam, & Inyang, 2012; Amos, 2007; Awotide, Kehinde, & Akorede, 2015; Nkamleu et al., 2010; Ogundari & Odefadehan, 2007; Ogunniyi, Ajao, & Adeleke, 2012; Oladapo, Shittu, Agbonlahor, & Fapojuwo, 2012; and Oyekale, 2012). However, they all use cross-sectional data. Our panel data, in contrast, contains observations from four different years (2001, 2004, 2006, and 2013) over a 13-year period, allowing us to characterize inefficiencies more realistically. The use of panel data brings four key advantages to our econometric estimations (Hsiao, 2007). First, the large number of observations reduce the multicollinearity among independent variables thus making our estimates more efficient. Second, the information on both the heterogeneity of farms and the changes through time allows us to reduce the omitted (unobserved) variable bias. If the effects of unobserved variables are the same for farms at a given point in time or remain constant for a given farm over time, we can eliminate the estimation bias by using dummy variables (fixed-effects method) or assuming a conditional distribution of unobserved effects (random-effects method). Third, we can reduce the mismeasured variable bias. Measurement errors could lead to under-identification of our models but the availability of multiple observations at a given time or for a given farm allows us to identify an otherwise unidentified model. Fourth, we are able to calculate and disaggregate total factor productivity changes (TFPC) through the years. We decompose TFPC not only into the usual four components (technical efficiency change, scale efficiency change, allocative efficiency change, and technical change) but also augment it with multiple technological and efficiency factors.

Previous studies have analyzed the effect of shade trees and intercropping only in the efficiency equation, which has led to inconclusive results (Besseah & Kim, 2014; Nkamleu et al., 2010; Ofori-Bah & Asafu-Adjaye, 2011). We include these variables in the production frontier equation because we assume they have a direct effect on cocoa production. In Indonesia, Effendi, Hanani, Setiawan, and Muhaimin (2013) assessed the technical efficiency of cocoa smallholders. However, as well as the previous limitations noted, they did not include the effect of the Gernas Pro Kakao government program and used a small sample of 98 farm plots. The Supporting Information Table A1 summarizes the estimated average technical efficiencies and sample sizes of previous cocoa studies. With 1,290 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

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 as it can differentiate between technical inefficiency and the effects of random shocks (Battese & Coelli, 1995). It is used by various researchers, including, Brümmer, Glauben, and Lu (2006).

Based on Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), we can write the basic frontier model the following way:

$$\ln\ y_i = \ln\ f(\mathbf{x}_i;\beta) + v_i - u_i, \tag{1}$$

where y_i represents the output, $f(\mathbf{x}_i;\beta)$ denotes the production function at complete efficiency with $\mathbf{x}_i$ as input vectors and β 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 nonnegative unobservable term assumed to be independently and identically half-normally 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

$$TE_i = \exp(-u_i). \tag{2}$$

The parameters of the production function in Equation (1) must theoretically satisfy the regularity conditions: monotonicity and curvature (Battese & Coelli, 1995). 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 Battese and Coelli (1995), which models the technical inefficiency (u_i) as a function of several variables

$$u_i = \varphi Z_i + e_i, \tag{3}$$

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 look at four issues of the statistical inference, the estimation method of the frontier and inefficiency models, estimation with panel data and endogeneity.

We base the parameters on maximum likelihood (ML) estimation. 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 (Battese & Coelli, 1995).

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 of the predicted inefficiency values. This approach can lead to severely biased results because of possible correlations between the first- and second-stage variables. Furthermore, the identical distribution assumption of the inefficiencies in the first stage is contradicted by the functional relationships in the second stage. These two problems are addressed by using a simultaneous estimation that includes the efficiency effects in the production frontier estimation (Battese & Coelli, 1995).

Pooled-panel models can generate a misspecification bias in presence of unobserved time-invariant variables (Belotti & Ilardi, 2012). Greene (2008) addressed this problem with unit-specific intercepts. His true fixed-effect (TFE) and true random-effect (TRE) panel specifications differentiate between time-varying inefficiency and unit-specific unobservable time-invariant heterogeneity. The TFE model assumes the nonrandomness whereas the TRE model the randomness of the unobserved unit-specific heterogeneity. The ML estimation of TFE models presents two issues. First, one has to solve the incidental parameters problem, which appears when the panel length is small compared with the number of subjects, causing inconsistent estimation. As Belotti and Ilardi (2012) show, the dummy variable approach for estimation is only suitable when the panel length is over 10. Our sample is highly unbalanced because of the attrition of farmers and contains observations only at four points in time. The common solutions to this problem are based on the elimination of the individual effects through within transformation (Belotti & Ilardi, 2012): For each panel i and the respective variables (z_i), the individual mean ($\bar{z}_i$) is subtracted from the observation in period t (z_{it})

$$\bar{z}_{it} = z_{it} - \bar{z}_i. \tag{4}$$

Another issue and the big disadvantage of within TFE methods is that they do not permit the use of time-invariant variables, like gender and education, which we assume are important determinants of inefficiency. Thus, we plan to use the

TRE specification and check the assumption that our sample was randomly selected (otherwise the estimation is biased) with the Mundlak (1978) test. The TRE variant is more efficient than the TFE model if this assumption holds. Only if the test fails, we are forced to estimate the TFE specification, leaving out some important variables. Greene (2008) points out that neither the "true" nor the pooled model is entirely satisfactory. Although the "true" specification may seem the more flexible choice, it can be argued that part of the time-invariant unobserved heterogeneity belongs to inefficiency or that these two elements should not be untangled. Therefore, we estimate both extremes: the Battese and Coelli (1995) model in which all time-invariant unobserved heterogeneity is treated as inefficiency and the "true" formulation in which all time-invariant unobserved heterogeneity is excluded from inefficiency.

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 (Battese & Coelli, 1995). We make the assumption 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 calculations of total factor productivity (TFP) change on Coelli, Estache, Perelman, and Trujillo (2003) observations. The TFP change is decomposed into technical efficiency change (TEC), scale efficiency change (SEC), allocative efficiency change (AEC), and time-fixed effects (TFE) to control for productivity adjustments connected to these factors

$$TFPC_1 = TEC + SEC + AEC + TFE. \tag{5}$$

Scale efficiency is a measure of the degree to which a farm is optimizing the volume of operations. Its change is calculated the following way for farm i in the time period t:

$$SEC_i^t = 0.5 \sum_k \left[\left(SF_i^t E_{ki}^t + SF_i^{t-1} E_{ki}^{t-1} \right) \bullet \left(x_{ki}^t - x_{ki}^{t-1} \right) \right], \tag{6}$$

where E_{ki}^t are the production elasticities, $E_i^t = \sum_k E_{ki}^t$ is the returns to scale, and $SF_i^t = (E_i^t - 1)/E_i^t$ is the scale factor.

Allocative efficiency is the farmer's capability to choose the input mix that produces a given amount of output at minimum cost. Its change for farm i in the time period t is computed as follows:

$$AEC_i^t = 0.5 \sum_k \left[\left(E_{ki}^t / E_i^t - s_{ki}^t + E_{ki}^{t-1} / E_i^{t-1} - s_{ki}^{t-1} \right) \cdot \left(x_{ki}^t - x_{ki}^{t-1} \right) \right], \tag{7}$$

where s_{ki}^t is the cost share of the input k.

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

$$TEC = \sum_j TEC_{Z_j} + TEC_{TFE} + TEC_{UF}, \tag{8}$$

where TEC_{Z_j}, TEC_{TFE}, and TEC_{UF} are effects of the change in various inefficiency model variables, time-fixed effects of the inefficiency component, and unspecified factors in the inefficiency model. We calculate the contribution of the explanatory variable Z_j for farm i in the time period t as

$$TEC_{Z_{ji}}^t = \frac{1}{TE_i^{t-1}} \frac{\partial TE_i^t}{\partial Z_{ji}^t} \left(Z_{ji}^t - Z_{ji}^{t-1} \right). \tag{9}$$

Furthermore, the unspecified factors can be computed as the residual

$$TEC_{UF} = TEC - \sum_j TEC_{Z_j} - TEC_{TFE}. \tag{10}$$

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

$$TFPC_2 = TFPC_1 + T_{IU} + T_{GK}, \tag{11}$$

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

$$TFPC_2 = \sum_j TEC_{Z_j} + TEC_{TFE} + TEC_{UF} + SEC + AEC + TFE + T_{IU} + T_{GK}. \tag{12}$$

3 | EMPIRICAL SPECIFICATION

3.1 | Production frontier model

The translog production function (Battese & Coelli, 1995) for the cocoa farm *i* with four inputs and seven dummy variables is specified as

$$\ln\ y_i^t = \alpha_0 + \sum_{k=1}^{4} \beta_k \ln\ x_{ki}^t + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln\ x_{ki}^t \ln\ x_{ji}^t + \sum_{j=1}^{7} \delta_j D_{ji}^t + \sum_{j=1}^{3} \theta_j T_j^t + v_i^t - u_i^t \tag{13}$$

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, the α, β, δ, and θ's are unknown parameters to be estimated, v is a random error term, and finally u is a nonnegative unobservable variable describing inefficiency. For a TRE model (Greene, 2008), a $w_i \sim iidN(0,\sigma_w^2)$ unit-specific random constant term uncorrelated with v_i^t and u_i^t should be added to the production function, whereas for a within TFE model (Belotti & Ilardi, 2012), formula (4) in Section 2.2 should be applied. 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 (Table 1). The variables used in these and other cocoa technical efficiency studies are summarized in the Supporting Information Table A2. According to the classical model, with a given technology, the 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 acres, whereas labor is calculated in Rupiah and involves all harvest and maintenance tasks on the cocoa farm.[1] 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 & Brümmer, 2012). Cocoa tree age (x_4) influences the cocoa output. Cocoa trees begin to produce pods about 3 years after planting, reach full capacity at around 10-year-old, after which their output starts to diminish gradually (Dand, 2010). In some studies (Supporting Information Table A2), the sign of this variable is positive and in other studies (Supporting Information Table A2), negative depending on the average tree age in the sample.

We enhance the basic production frontier with seven dummy variables to describe the cocoa cultivation process (Wollni & 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). Thus, this dummy indicates a technological factor of production. The second dummy variable is equal to one if the smallholder participated in the Gernas Pro Kakao government program (KKPOD, 2013). The third dummy variable equals one if the hybrid cocoa variety is cultivated by the farmer. We anticipate that hybrids produce higher yields than the local varieties (Dand, 2010).

[1] 1 ha equals 100 ares. During the last 15 years, 1 euro fluctuated between 10,000 and 17,000 Indonesian Rupiahs.

TABLE 1 Description of the cocoa farm variables

Variables	Description
Output	
Cocoa	Cocoa quantity harvested on the farm (kg)
Input	
Tree age	Average cocoa tree age (years)
Land	Total area planted with cocoa, farmer-estimated (acres)
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%
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).

Pruning 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 spread of pests (Amos, 2007; Danso-Abbeam et al., 2012; Effendi et al., 2013). A dummy for yield loss is used to reflect the effect of pests, disease and adverse weather on cocoa harvest quantity (Bowers, Bailey, Hebbar, Sanogo, & Lumsden, 2001; Schwendenmann et al., 2010).

Some cocoa is grown in an agroforestry or an intercropping system (Ofori-Bah & 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. Some papers report the advantages of shade trees as decreasing plant stress, others provide evidence that shade can limit cocoa yields (Frimpong, Asase, & Yelibora, 2007). The current consensus on this issue implies that shade starts to reduce cocoa yields beyond a level of around 30%. Following Bentley, Boa, and Stonehouse (2004), a sixth dummy variable captures the influence of the high shade (larger than 60%) production system and expect the sign to be negative.

To assess the effect of crop diversification on cocoa production (Ofori-Bah & Asafu-Adjaye, 2011), a seventh dummy variable for intercropping is used. 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). Crop diversification has 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 (Gockoswki & Sonwa, 2011; Scherer-Lorenzen, Korner, & Schulze, 2005). 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

The following inefficiency equation for cocoa farm i is used:

$$u_i^t = \varphi_0 + \sum_{j=1}^{6} \varphi_j Z_{ji}^t + \sum_{j=1}^{3} \omega_j T_j^t + e_i^t, \tag{14}$$

where u are the inefficiency estimates that follow a truncated normal distribution (Battese & Coelli, 1995), 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. For a TRE model (Greene, 2008), a $\theta_i \sim iidN(0,\sigma_\theta^2)$ unit-specific random constant term uncorrelated with e_i^t should be added to the inefficiency equation, whereas for a within TFE model (Belotti & Ilardi, 2012), formula (4) in Section 2.2 should be applied. 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 & Brümmer, 2012).

The first two explanatory variables reflect the household structure (Wollni & 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, Onumah, et al., 2013). As a result, we expect female-headed households to display lower efficiency levels (Supporting Information Table A2).

Farmer age is assumed to increase technical inefficiency partly because older smallholders are less likely to take up the latest technologies (Battese & Coelli, 1995). Although less energetic than, their younger counterparts, Onumah, Onumah, et al. (2013), Waarts, Ge, Ton, and Mheen (2013), and Ingram et al. (2014) suggest that older farmers might develop a higher technical efficiency than younger farmers because of their longer farming experience.

The inner capabilities of the household head (Ofori-Bah & Asafu-Adjaye, 2011) are shown in the education dummy equaling 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, research shows that smallholders with higher educational attainment have 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; Ofori-Bah & Asafu-Adjaye, 2011). Contacts with extension agents are considered to influence efficiencies positively as the information circulated in extension services should enhance farming methods (Dinar, Karagiannis, & Tzouvelekas, 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, Murgai, & Quizon, 2004; Supporting Information Table A2).

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 be optimized. The failure of credit markets as a cause of nonprofit maximizing behaviors and poverty traps has been proposed (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, the spread of feasible agricultural credit services is seen as crucial to increase labor and land productivity (Zeller, Diagne, & Mataya, 1997).

The dummy variable for membership in a cocoa association assumes that associations assist smallholders in reducing transaction costs and, therefore improving their access to various resources and increasing their technical efficiency (Binam, Tonye, Wandji, Nyambi, & Akoa, 2004; Hafid, Neilson, Mount, & McKenzie, 2013).

3.3 | Data sources

Survey data from the STORMA (Stability of Rainforest Margins in Indonesia) project was used. This data set consists of an unbalanced panel of four rounds of household and agricultural surveys in 2001, 2004, 2006, and 2013, with 1,290 observations collected from 722 cocoa farmer households in 15 randomly selected villages near the Lore Lindu National Park in Central Sulawesi province. This province is the second largest cocoa producer in Indonesia with 17% of production in 2014 (Ministry of Agriculture, 2015). The park provides habitat for unique animal and plant species, however, conversion to farmland, in particular, cocoa, threatens its integrity (Ebersberger, 2016; Sodhi et al., 2005).

The researchers first edited the questionnaire in English, then translated it into Indonesian and tested it in a pilot survey. In each sample village, the head of the village listed the names of every household head in that village. Sample households were then randomly selected from these lists and interviewed using the structured questionnaire. The interviews lasted on average 2 hours. Because some farmers cultivate several cocoa plots simultaneously, output and input details were collected at the plot level. In the four rounds, those panel and split-off households were tracked who was still living in those 15 villages.

4 | RESULTS AND DISCUSSION

4.1 | Descriptive statistics

Table 2 shows the summary statistics of our model variables. Over the 12-year period, the average output of the cocoa farms rose almost two-fold, whereas the average farm size remained almost constant at around 0.75 ha, which is about one-third of the African average (ICCO, 2012; Nkamleu et al., 2010). The average cocoa yield almost doubled to around 600 kg/ha by 2013, which is above the world average of 500 kg/ha and well above the Indonesian average of about 400 kg/ha (ICCO, 2016). Two reasons are proposed for this productivity change. 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 increased more than three-fold and the ratio of cocoa farms that used both increased from 15% to 42%. The Gernas Pro Kakao government program implemented in 2009 could have contributed to this phenomenon by providing easier access to intermediate inputs (KKPOD, 2013). Furthermore, cocoa in our sample area is cultivated mostly in a full-sun monoculture system, in common with much of Indonesia (Rajab, Leuschner, Barus, Tjoa, & Hertel, 2016), and in contrast to Africa (Gockoswki & Sonwa, 2011; Nkamleu et al., 2010). The ratio of intercropping decreased to 8% in 2013, whereas the share of high shade farms stood at 2%. Similar to the world average, 43% of the cocoa farms experienced significant yield losses due to adverse weather and pests (Dand, 2010).

The inefficiency variable statistics point to a slow cultural change in our sample area, with an increase in female household heads to 10% in 2013, which is consistent with past studies that show cocoa cultivation as a male-dominated livelihood (Maytak, 2014; Nkamleu et al., 2010). 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). No increase in extension services from the initial 25% is seen, but credit access rose dramatically from almost 0% to 23%. In 2013 about every third household was a member of a cocoa farmer group. The last three values are close to the African averages (Nkamleu et al., 2010).

TABLE 2 Summary statistics of the cocoa farm variables

Variable	2001 Mean	2001 *SD*	2004 Mean	2004 *SD*	2006 Mean	2006 *SD*	2013 Mean	2013 *SD*	Pooled Mean	Pooled *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
International 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	

4.2 | Production frontier estimations

Table 3 displays the parameter estimates of the production frontiers.[2] Because the Mundlak (1978) test confirms the assumption of the random-effect (RE) specification (Greene, 2008), we do not estimate the inefficient within the fixed-effect model (Belotti & Ilardi, 2012) missing important variables. In the RE panel model, the output elasticities of land, labor, and intermediate inputs are 0.616, 0.123, and 0.081, which means that the elasticity of scale is 0.820 at the sample mean. According to *t*-test results, cocoa production exhibits diminishing returns to scale. Normally, farms with these 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).

The dummy variable "No input" is negative and significant at the 1% level. This suggests that, as anticipated, farms not using intermediate inputs have lower cocoa output levels. The variable "Gernas" indicates that smallholders who participated in the Gernas Pro Kakao government program had higher cocoa output.

Finally, the negative values of the 2004 and 2006 year dummies reflect much lower cocoa production levels in these 2 years compared with the other years. Time-effect dummies capture unobserved heterogeneity such as policy effects,

[2]We have used the SFPANEL Stata module (Belotti, Daidone, Atella, & Ilardi, 2013) with its built-in likelihood function for estimation and for adapting the Mundlak (1978) test to the stochastic frontier framework.

TABLE 3 Parameter estimates of the cocoa production frontier models

Variables	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			
σu	2.258 (0.377)***	2.301 (0.411)***	1.633 (0.313)***
σv	0.535 (0.039)***	0.475 (0.048)***	0.493 (0.065)***
RTS	0.819	0.820	0.850

Notes. Generalized LR tests show that the stochastic frontier models represents the data better than the OLS models. LR and AIC tests also suggest that the Cobb–Douglas production function is most appropriate for our panel data and the translog function for the 2013 data. Furthermore, the regularity conditions are satisfied for most of the observations. The first-order coefficients are interpreted as partial output elasticities at the sample mean because each variable is mean-corrected. Robust standard errors computed according to White (1980) are in the parentheses.
TRE: true random-effect.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

technical change, and weather and disease effects. After reviewing the possible policy impacts, we assume that the Gernas program was the only one considerably affecting cocoa production and this was already incorporated into the production frontier as a dummy. Similarly, we assume that the most important factor connected to technological change is already captured in our input use dummy variable. According to UNCTAD (2006) and Dand (2010), droughts and pests cause by far the greatest variation in cocoa production between years. Thus, because no accurate direct variables for these impacts are available for most of the years, we presume that the vast part of time-fixed effects are caused by the exceptionally strong negative El Niño weather between 2004 and 2006 (Keil, Zeller, Wida, Sanim, & Birner, 2008)

TABLE 4 Descriptive statistics of the cocoa farm efficiency estimates (percentages)

	Pooled panel model				TRE panel model				2013 model			
Year	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	–	–	–	–

Note. TRE: true random-effect.

and the high incidence of the cocoa pod borer pest (Juhrbandt, Duwe, Barkmann, Gerold, & Marggraf, 2010). The outcomes of the pooled-panel model are similar to the true random-effect model.

Additionally, we estimate a model based only on the 2013 data because many variables (such as tree age, shade, crop loss, and association) were not measured at earlier points in time. In the 2013 model, the square of the tree age variable is significant and negative. This result 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 *t*-test results, the scale elasticity amounts to 0.850 and significantly differs from one. The output elasticities indicate that cocoa farms exhibit decreasing returns to scale. Finally, all dummy variables of the 2013 model confirm the expected signs, but two of them (hybrid and intercrop) are not significant. Our findings show the positive effect of intermediate input use, pruning and the Gernas Pro Kakao program, and the negative effect of high shade on cocoa production.

4.3 | Efficiency estimations

Table 4 documents the average annual rates of technical efficiency, and Supporting Information Figure A1 presents the efficiency distributions of the sample farms. Based on the panel models, the mean technical efficiency of cocoa farmers is estimated at around 50%. Low values such as this tend to indicate a less specialized and less competitive market (Kumbhakar & Lovell, 2000). We can interpret the low efficiency as a result of the characteristics of the smallholder cocoa market in Sulawesi, where many producers do not pay much attention to the quality of the raw product (Neilson, 2007). Another potential reason for the poor efficiency is the high incidence of the cocoa pod borer (CPB) pest, because its control is expensive and difficult, and not many farmers are getting it right (Juhrbandt et al., 2010). The range of estimated efficiencies is very wide (1–90%) and many efficiency scores are lower than 25%. This means that most cocoa farmers have an ample scope to expand cocoa output without increasing input use. African cocoa farmers (Supporting Information Table A1) seem to have higher technical efficiencies, which can be partly explained by the much longer history of African cocoa cultivation In terms of technical efficiency change over time, we find an overall increasing trend. This is not surprising as the rapid growth in the Indonesian cocoa production was in the 1990s and farmers had to learn to how to cultivate it.

Table 5 presents the results of the inefficiency model estimations. 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% increase in technical efficiency, on average. Furthermore, the significant year dummies identify an overall increasing trend in technical efficiency. The 2013 model indicates an additional significant factor: educational attainment. As expected, a higher educational level enhances an individual's understanding of farming.

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 (Supporting Information Table

TABLE 5 Estimates and average marginal effects of the cocoa farm inefficiency models

	Pooled panel model		TRE panel model		2013 model	
Variables	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. 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. Based on LR tests, we reject that all inefficiency variables are insignificant for all three models. Robust standard errors computed according to White (1980) are in the parentheses.
TRE: true random-effect.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

A2). For example, feasible agricultural credit services have been seen as crucial to raise technical efficiency (Zeller et al., 1997). Hafid et al. (2013) also report that farmers in certification programs in West Sulawesi were positive about credit, training and extension received. The limited effect of agricultural extension programs on efficiency may be due to the inherent deficiencies of public information systems, a "top-down" design, or bureaucratic inefficiency (Nkamleu et al., 2010). Furthermore, the ineffectiveness of farmer groups can be attributed to a lack of social capital, that is, the lack of assistance to each other in the times of need (Ingram et al., 2014).

4.4 | Productivity change calculations

Table 6 shows the disaggregation of total factor productivity change. As the pooled and random-effect model results are similar, we discuss only the RE estimates. The total productivity growth of cocoa farms over the 12 years was around 76%, equal to on average a 6% annual improvement. The fastest productivity growth (over 36%) was accomplished in the third observation period, between 2006 and 2013. In the first and second periods, total factor productivity increased to 13% and 27%.

Growth in the 2001–2004 period was primarily caused by technical efficiency change, especially in the TEC_{TFE} component (30.4% increase), the distribution of which is shown in Supporting Information Figure A2. This improvement might be the result of the fact that cocoa production in our sample area started in the 1990s and farmers needed to gain knowledge and experience in the early stages of cultivation. In the first sample period, the sharp decrease (−23.5%) of the time-fixed effects component derived from the frontier estimation counteracted this growth. This could be mainly to the very dry 2004 cocoa growing season (Keil et al., 2008). The allocative effect of the intermediate inputs had an additional negative influence (−12.8%) on productivity.

The TFP increase between 2004 and 2006 is dominated by the technical efficiency change (16.4%) and the allocative effects of intermediate inputs (14.9%). The value of the former points to the slow down of technical efficiency increases, whereas the latter shows a major improvement in input allocation. The allocative effect induced by labor input and the technology effect of the input use had a further positive influence on productivity.

TABLE 6 Disaggregation of the total factor productivity change in cocoa farming (percentages)

Time period	TEC_Z	TEC_{TFE}	TEC_{UF}	TFE	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_Z: technical efficiency change from the variable "age of household head"; TEC_{TFE}: technical efficiency change from time-fixed effects in the inefficiency model; TEC_{UF}: technical efficiency change from unspecified factors; TFE: time-fixed effects in the production frontier; SEC: scale efficiency change; AECLA: allocative efficiency change (labor); AEC_{II}: allocative efficiency change (intermediate inputs); $TFPC_1$: standard total factor productivity change; T_{IU}: effect of nonzero intermediate input use, T_{GK} = effect of the Gernas program, $TFPC_2$: augmented total factor productivity change. Land allocative effects are not calculated because if the size of a cocoa farm changed over time, we consider it a different farm.

Again, the time-fixed effects component of the production frontier offset the improvement because of the unfavorable weather and pest conditions (−17%).

In contrast to the first two periods, the main driver for productivity growth in the last observation period was the time-fixed effects of the production frontier (40.5% increase). We attribute this to the positive effect of increased rain caused by the La Niña climate pattern in 2013. However, the negative allocative efficiency change for intermediate inputs (−33.1% change) counterbalanced this improvement. Also noticeable is 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 roads because of the heavy rains.

5 | CONCLUSION

The growing global demand and price for cocoa and the impact of converting forests into cocoa farms has led to a quest for more sustainable ways to improve cocoa yields and farmer income. We investigate the productivity and efficiency of cocoa production using a panel survey data of 1,290 observations in Indonesia and stochastic frontier analysis. The results indicate a decreasing return to scale in production. Given the small average cocoa farm size (0.75 ha), this could reflect the impediments to growth.

According to our results, the productivity of Indonesian cocoa farming increased by 75% between 2001 and 2013. To examine the source of changes in productivity, we investigate 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. The analysis also highlights the high, weather- and pests-induced volatility of cocoa production. Thus, promoting investment in agricultural research and the transfer of drought- and disease-resistant cocoa varieties to small farmers would be important to cope with weather vagaries and climatic changes.

The biggest growth in cocoa productivity was due to increasing technical efficiency. However, the average technical efficiency in Indonesia is still under 50%, which is much smaller than the West African average. To sustainably boost cocoa productivity further, the factors identified as having a significant, positive influence on efficiency levels are smallholders' educational level and their experience in cocoa farming. This corresponds with other experiences related to improving farmer's awareness and knowledge through training in Indonesia (Hafid et al., 2013) and in West Africa (Ingram et al., 2014; Waarts et al., 2013).

However, our findings also show that extension services, the rural credit system, and farmer groups did not have a significant effect on the efficiency of cocoa farms in our research area. This is in contrast to findings in other major cocoa production countries in West Africa and points to the need for well-designed interventions that are local-context specific and fit well with public information systems (Binam, Gockowski, & Nkamleu, 2008; Nkamleu et al., 2010). As the membership of farmer groups have been positively associated with increased production in other cocoa production countries, the ineffectiveness of farmer groups in our sample might be attributed to the low social capital, that is, the lack of assistance to each other in the times of need. Hence, policies aimed at increasing efficiency could focus on adjusting the public extension programs, fostering the mutual benefits in the farmer groups, and developing viable credit institutions.

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ORCID

Andras Tothmihaly http://orcid.org/0000-0002-4475-2146

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AUTHOR'S BIOGRAPHIES

Andras Tothmihaly has just finished his Ph.D. in International Food and Development Economics at the University of Goettingen in 2017 and has been a research assistant there. His main research interest is the technical and environmental efficiency analysis of production.

Verina Ingram is Assistant Professor with the Forest & Nature Conservation Group, Wageningen University and Senior Adviser with Wageningen Economic Research. Verina's Ph.D. (2014) concerned the governance of forest product value chains from the University of Amsterdam. Her main research focus is on value chains of forest products and agrocommodities from tropical landscapes and the impacts of different governance arrangements at multiple scales.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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