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Technical efficiency and farmland expansion: Evidence from oil palm smallholders in Indonesia

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Abstract

This study asks whether innovation in smallholder production reduces or accelerates land expansion. Even though innovation in agriculture has reduced land expansion globally, rebound effects can occur locally and often at the expense of vital ecosystem functions. In contrast to other studies that investigate rebound effects in response to technological innovation, our study focuses on technical efficiency, the remaining component of total factor productivity. We use a short panel dataset from smallholder oil palm farmers in Sumatra, Indonesia, and develop a two-stage approach in which we estimate technical efficiency and determine its land expansion effect. Our findings suggest that technical efficiency and in particular land efficiency are low, indicating that 50% of the currently cultivated land could be spared. However, the land-sparing effect of increasing technical efficiency is at risk of being offset by about half due to a rebound effect. To maximize the conservation potential from increasing smallholder efficiency, policies need to simultaneously incentivize well-functioning land markets and stricter protection measures for land with high ecological value to mitigate local rebound effects.

KEYWORDS
error in variables, farmland expansion, linear mixed models, palm oil production, rebound effect, smallholder production, stochastic production frontier, technical efficiency

JEL CLASSIFICATION
D22, Q12, Q15, Q24, Q28, Q56

1 | INTRODUCTION

In recent decades, the unprecedented global growth in population and income has led to a constantly growing demand for agricultural output. Although the rise in demand has been partly met by increases in productivity, agricultural output growth has also induced the expansion of farmland, often at the expense of natural ecosystems and related ecosystem functions (Hooper et al., 2012; Rasmussen et al., 2018; TEEB, 2010). Particularly tropical forests were affected by the expanse of agricultural production having substantially receded during recent decades (Curtis et al., 2018).

Perhaps the most promising remedy is innovation in agriculture, which in the past saved large swaths of land from conversion into agricultural production. Borlaug (2007) demonstrated that increasing total factor productivity (TFP) in agriculture significantly reduces the pressure on agricultural land. In opposition to Borlaug's hypothesis stands the backfire-type rebound effect—also referred to as the Jevons paradox—describing a situation in which TFP in agriculture leads to increased profitability and eventually further agricultural expansion. Empirical evidence shows that increasing productivity—one component of TFP—can lead to sizable land-sparing effects in the long term (Balmford et al., 2005; Balmford et al., 2018; Feniuk et al., 2019; Folberth et al., 2020; Phalan et al., 2014; Villoria, 2019). However, most studies on land sparing effects of innovation rely on aggregates at the country, or even continental level and often span over decades, as opposed to short-term and micro-level perspectives. One reason for the lack of a local focus in the literature might stem from global balancing effects. Villoria et al. (2014), Hertel (2018), and Taheripour et al. (2019) argue that rebound effects in one region can be offset by disproportionately higher savings in another, given that barriers to trade are negligible. However, the comparison of local expansion versus global sparing is conditional on the substitutability between ecosystem functions or services. This assumption is fairly reasonable in the case of greenhouse gas (GHG) emissions but highly questionable regarding other ecosystem functions and services. For example, reducing biodiversity in one part of the world cannot be compensated with higher levels of biodiversity in another part as many species are endemic to regional environments. Thus, for ecosystem functions that are no spatial substitutes, global savings cannot offset local rebounds. Indeed, as farms become more profitable, some evidence suggests that rising marginal products exacerbate instead of mitigate the pressure on land and thereby often also on the reliant ecosystem functions either in the short term (e.g., Desquilbet et al., 2017; Foster et al., 2011; García et al., 2020; Garrett et al., 2013) or depending on the type of technology (Maertens et al., 2006).

Besides technical change, technical efficiency (TE)—or managerial skill—is another important component of TFP change. In contrast to the relationship between technology and land expansion, the link between TE and demand for land is not well researched at the micro level. Whereas new technologies exogenously increase land productivity and induce additional costs for producers, often with ambiguous short-term effects on farm profitability, managerial skill leads to endogenous increases of productivity and thereby is directly linked to improved profitability. The gap in the literature is particularly striking as numerous extension service and outreach programs aim to improve the managerial skills of farmers in an effort to improve rural livelihoods. In the absence of respective land use policies, such measures can have unintended ecologically detrimental effects by setting powerful incentives for farmers to extend their farmland and expand further into natural ecosystems, at least in the short run.

This paper asks whether TE of oil palm smallholder farmers reduces or accelerates land expansion in Indonesia. With about 34%, smallholders contribute remarkably to national palm oil output (Indonesian Ministry of Agriculture, 2016). Accordingly, recent evidence shows that palm oil production has contributed to reduce rural poverty as well as food insecurity (Chrisendo et al., 2020; Edwards, 2019; Qaim et al., 2020; Sayer et al., 2012). However, at the same time smallholders fall short of nearly 40% of yield compared with large estates (Indonesian Ministry of Agriculture, 2016). Closing this yield gap could lead to improved livelihoods in conjunction with mitigated area-related environmental externalities, including deforestation (e.g., Jelsma et al., 2017; Soliman et al., 2016; Wiebe et al., 2019).

Our empirical approach is organized in two stages. First, we estimate the TE of smallholder oil palm farmers based on a short panel dataset from Jambi province on the island of Sumatra. We model the production technology relying on a translog functional form and employ a random effects model that accommodates the hierarchical structure of the data. The distance of farmers to the best-practice frontier constitutes the farmers' inefficiency scores and determines the extent to which they fall short of the maximum attainable output considering their input use. Second, we estimate an error-in-variables (EIV) land use model to test if higher efficiency levels lead to farmland expansion.

Our contributions to the empirical literature on the link between TFP change and natural resource use are threefold. First, in contrast to most other studies, our analysis focuses on TE as opposed to technical change, and it directly estimates and classifies its rebound effect. Second, to our best knowledge, the only similar study that estimates the effect of TE on land use expansion, employs a Tobit model (Marchand, 2012) that could potentially neglect the measurement error stemming from the parametrically estimated efficiency score. Here, we apply an EIV approach to address the attenuation bias and compare its performance to its ordinary least squares (OLS) counterpart. Finally, we contribute to the evidence base of the linkage between TFP change in smallholder farming and farmland expansion, and our findings have implications for conservationist and development policies.

The key finding of this study is that TE is an important junction within the land-sparing debate. Although we show that closing the yield gap provides remarkable land-sparing opportunities, we also find that about half of the land-sparing effect is at risk of being offset by increased land demand. We conclude that outreach and extension services as well as agricultural cooperatives that target the managerial skill of farmers should be combined with land use policies that impede further encroachments of natural ecosystems to limit the unintended consequences of increasing TE in the smallholder sector. These include policies that enable well-functioning land markets, improve farmers' land rights and protect areas of high conservation value.

The remainder of this paper is organized as follows. In the next section, we define our conceptual framework and provide a brief discussion of key findings from the literature with regard to the rebound effect in agriculture. Then we describe the smallholder oil palm sector in Indonesia and our data. The following section explains our two-stage empirical approach and the empirical specifications of the stochastic frontier and land expansion models. FInally, we present the results and calculate the rebound effect and conclude the paper.

2 | LAND SPARING AND REBOUND EFFECTS

The role of TE within the land sparing versus land expansion debate is not well understood. Before approaching the problem empirically, we briefly discuss some key literature and revisit essential empirical and theoretical aspects. Subsequently, we set the stage for our case study and provide relevant insights into the smallholder oil palm sector in Indonesia.

During recent decades, two distinct views regarding the role of intensified agriculture in mitigating land-use change (LUC) induced deforestation or other externalities have emerged. The Borlaug hypothesis (Borlaug, 2002) states that more than one billion hectares of land have been spared from agricultural production since the 1950s as a result of intensified cereal production. During the *Green Revolution*, most of the growing demand for food was met by technological innovation and the resulting higher yields as opposed to further area expansion of agriculture. From a policy perspective, the land sparing view postulates that deforestation—and other environmental externalities—around the world can be mitigated by increasing productivity through the invention and adoption of new technologies as well as more efficient management of resources.
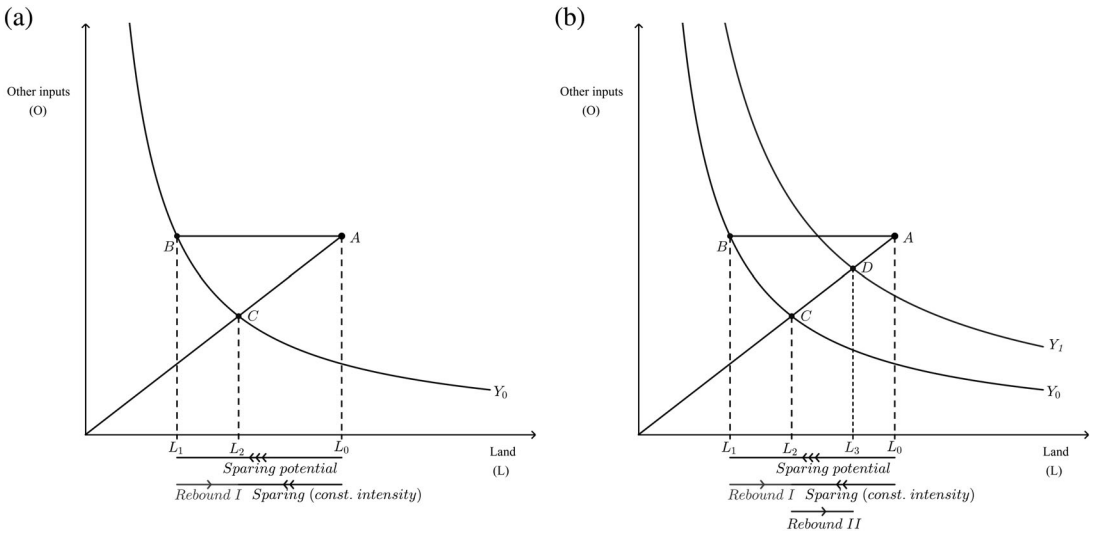
FIGURE 1   Rebound effects

In sharp contrast to the Borlaug hypothesis stands the backfire-type rebound effect or Jevons paradox[1], which denotes a contrary situation where the intensification in agriculture leads to a further expansion of agricultural area (Desquilbet et al., 2017; García et al., 2020). In this view, innovation and more efficient management set further incentives to shift supply outwards as long as demand is elastic. Given such circumstances, any policy aiming at sparing land while relying solely on boosting innovation and performance is bound to backfire.

2.1 | Conceptual framework

In Figure 1, we illustrate land sparing and rebound effects using an input oriented representation of the technology, adapting similar considerations in Berkhout et al. (2000) to the land case. We assume technically inefficient production at A where output is produced using land (L_0) and other inputs (O). The maximum land saving potential occurs if the farmer becomes technically efficient by saving land, for instance through dedicated policy measures. In the left panel of the diagram, this is represented by a horizontal movement from A to B, which is on the isoquant Y_0. However, if producers keep factor intensities constant, input savings will not be achieved through the land factor alone, but savings will result along a constant factor intensity which is at C in the diagram. The total potential for land sparing is thus reduced, resulting in a first rebound effect (Rebound I).

The second part of the rebound effect depends on market features and is shown in the right panel of Figure 1. As the sector becomes more efficient, profitability will increase. Under perfect competition, output prices will decrease until the point where profits are equal as in the initial equilibrium. If consumer demand is price elastic, producers respond further and shift supply outward to Y_1, which supports a higher level of output at a higher level of input use. Thus, the final technically efficient equilibrium is at point D where the increased use of all factors of production then leads to a further rebound effect (Rebound II) and net land savings are $L_0 - L_3$. An exception is the case of perfectly inelastic demand, where producers will not respond with a supply shift and limit the

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[1]The hypothesis goes back to Jevons (1879) who observed that in response to the invention of more efficient coal ovens, overall coal consumption increased instead of declined.

rebound effect to $L_2 - L_1$ and land savings are $L_0 - L_2$. By contrast, if demand is highly elastic such that $L_3 > L_0$, net savings are negative and the efficiency gains backfire (Berkhout et al., 2000; Desquilbet et al., 2017; Hertel, 2018; Villoria et al., 2014).

2.2 | Empirical evidence

Villoria et al. (2014) provide a review of empirical evidence regarding rebound effects in agricultural production. The study finds that intensifying production is overwhelmingly associated with land sparing as opposed to land expansion, particularly in the long run. Furthermore, a number of recent studies confirm that innovation reduces biodiversity loss, GHG emissions, and deforestation (e.g., Abman et al., 2020; Abman & Carney, 2020; Balmford et al., 2005; Balmford et al., 2018; Feniuk et al., 2019; Folberth et al., 2020; Pelletier et al., 2020; Phalan et al., 2014; Villoria, 2019). Furthermore, Villoria et al. (2014) find that empirical support for the existence of backfiring rebound effects in agriculture is scarce. The few empirical examples refer to short-term horizons or very small datasets. One such example is provided in Gutiérrez-Vélez et al. (2011), who find overall land saving in response to increasing oil palm yields in Peru, albeit at the expense of increased deforestation. The authors furthermore highlight the importance of local policies to mitigate local leakage effects.

In a more recent study, García et al. (2020) confirm the long-term sparing effect of innovation in agriculture using global aggregate data over a 50-year period but nonetheless find strong rebound effects in middle-income countries for commodities with elastic consumer demand. Another case for the presence of rebound effects is found in Desquilbet et al. (2017), who consider global aggregate production and biodiversity conservation.

Strikingly, much of the existing work relies on remote sensing data and aggregates at the country, or even continental level while often also spanning over decades, as opposed to short-term and microlevel perspectives. Only a few studies take a local approach. For instance, Garrett et al. (2013), Birkenholtz (2017), and Song et al. (2018) find short-term rebound effects for country level soybean yields in Brazil, the introduction of drip irrigation in India, and agricultural water use in China, respectively. Also regarding water technology, Li and Zhao (2018) find rebound effects of farmers in the United States when granted more extensive water rights. In the case of oil palm, the literature does not offer any microlevel analyses on rebound effects. However, macrolevel analyses have shown that if TFP growth promotes deforestation and LUC resulting in accelerated GHG emissions in South-East Asia, global GHG emissions could still decline. As the comparably less resource intensive palm oil replaces other more resource intensive vegetable oils, GHG are saved in other parts of the world (Meyfroidt et al., 2013; Taheripour et al., 2019). Nonetheless, local expansion versus global sparing dynamics are conditional on the perfect substitutability between ecosystem functions or services. By contrast, many ecosystem functions are endemic and not substitutable across the globe, providing strong motivation for microeconomic approaches. Particularly biodiversity is a point in case as it is endemic and highly threatened by deforestation (Ando & Langpap, 2018).

At present, TE has received minimal attention in the land sparing versus expansion literature as opposed to technological innovation or aggregate TFP growth. To our knowledge, the only exception is Marchand (2012), who finds a quadratic relationship between TE and land expansion among farms in Brazil. All other relevant studies consider technical change as part of TFP change and refrain from distinguishing between TE and technology. This is fair enough in cases where technology is homogeneous, and all producers are operating close to the production frontier, namely in the absence of inefficiency. Such production systems are typically characterized by advanced technology as well as highly competitive producers. However, in developing countries, where technology adoption is still catching up and market inefficiencies are more severe, gains in TE could translate into large yield increases. Consequently, both considerable sparing as well as rebound potentials are conceivable.

Thus far we synthesize that despite a multitude of research on innovation in agriculture amid the land sparing and land expansion debate, the literature lacks (i) local microeconomic evidence on rebound effects in agriculture and (ii) approaches that assess innovation in farm performance as opposed to technology. As ecosystem services are not spatially substitutable and TE is a particularly important part of TFP growth—at least in low and middle-income countries—both shortcomings could manifest in a shaky evidence base for designing local conservation policies, particularly in the face of agricultural commodity booms.

3 | CASE STUDY AND DATA

Amid the oil palm boom and the related ecological crisis in South-East Asia, smallholder oil palm farmers in the Indonesian province of Jambi constitute a relevant case to explore how gains in performance affect factor demand for land from a microeconomic perspective. First, even though smallholder farmers in Indonesia significantly contribute to national palm oil output, they do so at low land productivity compared with large estates. On average, smallholders in Indonesia fall short of nearly 40% of potential oil palm output (Euler et al., 2016; Indonesian Ministry of Agriculture, 2016; Jelsma et al., 2017; Woittiez et al., 2017), which highlights the sizable potential of performance improvements from a production perspective. Second, the sector has been subject to heavy government intervention from its very beginning. From the 1970s onward, the government launched several development programs—often in conjunction with international organizations—aiming to promote smallholder palm oil production. The measures ranged from migration programs and allocation of land for oil palm cultivation (*trasmigrasi* program) to credit and fertilizer provision as well as extension services (Jelsma et al., 2017).

Although productivity boosts through technology and managerial performance are possible considering the large yield gap, oil palm cultivation is also closely connected to deforestation in the region. At present, the expected returns of land conversion in Indonesia are high and constitute a major barrier for conservation policy that intends to change incentive structures (Shah & Ando, 2016). Regarding land use policy, the Indonesian government has implemented several initiatives to halt deforestation. Most prominently, since 2011 a moratorium prohibiting the conversion of primary forest has been in place. Studies evaluating the efficacy of the policy find mixed results. Although some studies have found remarkable reduction rates of deforestation associated with the introduction of the moratorium (e.g., Busch et al., 2015; Chen et al., 2019), others find relative inefficacy of the ban (e.g., Suwarno et al., 2018). Additionally, Miyamoto (2006) and Krishna et al. (2017) find that weak property rights favor the direct appropriation of forestland. Similarly, despite such regulatory efforts, Kubitza, Krishna, Urban, et al. (2018) and Krishna et al. (2017) find that direct forest appropriation has been common regardless of such institutional developments among smallholder farmers. More precisely—and relevant to our case study—Krishna et al. (2017) find that 18% of existing oil palm plantations were acquired through direct forest land appropriation among smallholder farmers in Jambi province. Moreover, the study finds that in 2012, 9% of land expansion occurred at the direct expense of forests. At present, lowland forests are limited and few opportunities to appropriate forest land exist, whereas direct forest land appropriation rates have plummeted. Nevertheless, the smallholder experience in Jambi province during the past decade could be similar to that of other parts of Indonesia, where oil palm cultivation started more recently (e.g., in Kalimantan or Papua) or other regions in the world where agricultural commodity booms are closely linked to deforestation (Kubitza, Krishna, Urban, et al., 2018).

Our case study relies on a farm survey conducted in Jambi province on Sumatra island, Indonesia. A multistage random sampling approach was used, stratifying at the regency, district, and village level to reflect geographical and regional differences. The survey was first conducted in 2012 and repeated in 2015 and 2018, resulting in a short panel dataset.[2] The data are hierarchical as

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[2]A more detailed description of the data is available in Krishna et al. (2017) and Kubitza et al. (2018a). Although the survey also included other types of farmers, we only selected oil palm farmers for our analysis.

farmers own one or more plots. All plots of a farmer were sampled during the first round in 2012. In the subsequent rounds only one randomly selected plot per farmer and per crop was recorded due to time and budget constraints. In addition to the unbalanced plot dimension, the sample is also unbalanced as some farms of the random sample became only productive after 2012. Moreover, the sample is subject to attrition at 4.4% and 5% in 2015 and 2018, respectively. Overall, the dataset comprises 363 observations (plots), which belong to 181 unique groups (farm households). In 2012, a total of 131 farms that cultivate 187 plots were surveyed. In 2015, the sample includes 163 farms and 175 plots. This results in a multilevel dataset with small and heterogeneous groups that is unbalanced in both the time and group dimensions.

For our second stage, we use detailed data on farm households' land acquisition and LUCs from all three survey rounds to construct our land expansion variable between 2012 and 2018. All 181 unique farms surveyed in 2012 and 2015 were also surveyed in an additional wave in 2018 and were asked in all rounds to report each single change in farm size over time. They reported the year of change and type of acquisition, such as a land purchase, inheritance, or forest encroachment. If ownership changed, the original land cover was also recorded, such as forest, grass land, or agriculture.

Table 1 presents descriptive statistics of our sample. On average, farm households own two oil palm plots that are on average 1.9 ha large and yield a harvest of 14 tons of fresh fruit bunches per year per ha. This is in line with other studies but well below occasionally observed maximum yields of about 40 tons/ha (Euler et al., 2016). The farms cultivate on average 5.3 ha of land as they partly also cultivate rubber and less than 2.5% of the sampled households own more than 15 ha. The distribution of the farm size matches other surveys on Sumatra that focus on small-scale farms (Jelsma et al., 2017). Farm households expanded their oil palm land by 0.8 hectares on average between 2012 and 2018, which results in a share of 0.2 of the landholding size in 2012.

4 | METHODS

The methodology to measure the rebound effect of performance innovation of smallholder oil palm farmers is organized in two main stages. In the first stage, we estimate TE scores of oil palm smallholders and employ a translog production function in a hierarchical random intercepts model. In the second stage, we predict the land expansion of farmers based on TE scores by means of an EIV model that accounts for the measurement error in the estimated efficiency score introduced in stage one.

4.1 | Technical efficiency and production frontier

Since the seminal works of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), empirical production frontiers have been widely used to model production processes of firms and determine their TE. In essence, production functions aim to evaluate the provision of outputs against the usage of inputs and determine how well individual units perform compared with each other. Critically, they enable distinguishing the production technology from TE, which ultimately is a measure of managerial skill. We define the latter as the ratio between an individually realized outcome and a best practice outcome. From an output perspective, TE designates the difference between the maximum attainable output and individually achieved, that is,

$$TE_i = \frac{y_i}{y_i^*}, \tag{1}$$

TABLE 1   Descriptive statistics

Statistic	Unit	Mean	SD	Min	Pctl(25)	Pctl(75)	Max
2012–2015							
Plot level (*n* = 363)							
Production	kg	28,133.1	31,851.2	900	9600	36,000	240,000
Size	ha	1.9	1.6	0.3	1.0	2.0	12.0
Labor	Working hours year^{-1}	2807.0	5887.2	45	1260.5	2868	100,500
Agrochemicals	kg	789.9	1108.4	0	67	1085.5	12,050
Palm age	Years	12.6	6.4	4	7	18	25
Palm density	No. palms ha^{-1}	119.4	26.2	30	105	130	234
Yield	kg ha^{-1} year^{-1}	14,414.2	7946.1	900	8400	19,680	38,860
Farm level (*n* = 181)							
No. plots	No.	2.06	1.1	1	1	2	10
2012							
Farm level (*n* = 181)							
Landholding	ha	5.3	5.2	0	2.0	6.0	45.5
Age (household head)	Years	45.4	12.1	23	36	55	77
Gender (household head)	Binary	0.02	0.1	0	0	0	1
Education (household head)	Years	3.5	1.2	0	3	4	6
Transmigrant	Binary	0.3	0.5	0	0	1	1
Household size	No. people	4.1	1.4	2	3	5	10
Employed	Binary	0.4	0.5	0	0	1	1
Self-employed	Binary	0.2	0.4	0	0	0	1
Wealth index	Quintiles	2.7	1.5	1	1	4	5
Rubber	Binary	0.6	0.5	0	0	1	1
Farmer group	Binary	0.1	0.3	0	0	0	1
Cooperative	Binary	0.2	0.4	0	0	0	1
Credit formal	Binary	0.3	0.5	0	0	1	1
Credit informal	Binary	0.1	0.3	0	0	0	1
Distance to palm oil mill	Distance (m) in log	9.4	0.7	8.0	8.7	9.9	11.7
Village level (*n* = 40)							
Transmigrant village	Binary	0.4	0.5	0	0	1	1
Land title share	Share	0.7	0.4	0	0	1	1
Migrant share	Share	0.5	0.3	0.002	0.2	0.9	1.0
Nearby large estate	Binary	0.8	0.4	0	1	1	1
Non-random village	Binary	0.1	0.4	0	0	0	1
Suitability for oil palm	Max. att. yield (kg) in log	7.7	0.02	7.6	7.7	7.7	7.7
2012–2018							
Farm level (*n* = 181)							
Change of oil palm area	Share	0.2	0.5	−1.0	0	0.3	3.7
Non-agricultural land change	Share	0.1	0.3	0	0	0	2.0
Agricultural land change	Share	0.2	0.4	−1.0	0	0.2	2.7
Inherited land change	Share	0.02	0.2	−1.0	0	0	1.0
Purchased land change	Share	0.1	0.4	−1.0	0	0	2.7

Note: Change of oil palm area is calculated as oil palm area change in hectares between 2012 and 2018 divided by landholding size in hectares in 2012.

where y_i and y_i^* designate the output of firm i and the best-practice scenario respectively.[3] However, aside from TE, output is conditional on a set of inputs and the transformation process, which—in contrast to TE—is not adjustable and in the short term and exogenous to the manager. The stochastic version of the production function is generally expressed as

$$ln(y_i) = lnF(\mathbf{x}_i, \boldsymbol{\beta},) - u_i + v_i, \tag{2}$$

where $\mathbf{x}_i$ are inputs used in the production process and $\boldsymbol{\beta}$ is a vector of technological parameters (O'Donnell, 2018; Parmeter & Kumbhakar, 2014). The error components u_i and v_i capture inefficiency and statistical noise, respectively. Estimating the production frontier parametrically requires choosing (i) an appropriate functional form for the production process $F(x)$, and suitable distributions for (ii) the efficiency term and (iii) the random error term.

4.2 | Random intercept frontier

The productivity and efficiency literature provides a variety of parametric and non-parametric frontier models to empirically determine both the production technology and efficiency scores of decision-making units fitting a vast set of data types (O'Donnell, 2018; Parmeter & Kumbhakar, 2014). Multilevel data are common as panel datasets where the levels result from the time dimension are typically modeled making use of fixed and random effects. For instance, the "true" random effects model of Greene (2005a, 2005b) allows to disentangle time-invariant unobserved heterogeneity of the production technology from inefficiency. By contrast, the problem of hierarchical data where heterogeneity arises from within production units has received little attention in the literature, even though data aggregation can result in biased estimates of efficiency scores (Brorsen & Kim, 2013; Cook et al., 1998; Mehta & Brümmer, 2020). In the case of smallholder farms in Jambi, such heterogeneity could arise from distance to the house, to other plots, or differences in the accessibility of the plots. However, separating the random and time-invariant fixed effects on both the time and unit levels from inefficiency requires sufficiently large numbers of observations in both dimensions. Given the limitations of the data, we express the production frontier as a random intercept model[4] and allow for group-specific effects to vary between as well as across groups, whereas the technology is homogeneous across units (e.g., Gelman & Hill, 2006; Mehta & Brümmer, 2020).

$$y_{ic} = \alpha_0 + \mathbf{x}'_{ic}\boldsymbol{\beta} + (u_c + v_{ic}) \tag{3}$$
$$y_{ic} = \alpha_c + \mathbf{x}'_{ic}\boldsymbol{\beta} + v_{ic}$$
$$v_{ic} \sim \mathcal{N}\left(0, \sigma^2_{v_{ic}}\right).$$

Where $\mathbf{x}$ and y are now logarithmized and individuals i are clustered in groups c. The errors v_{ic} are assumed to be normally distributed with mean zero and variance σ^2_v. The group intercepts $\alpha_c = \alpha_0 + u_c$ and u_c captures the group level errors, which are also $\mathcal{N}\left(0, \sigma^2_{u_c}\right)$ by assumption. In contrast to asymmetric distributional assumptions that are often employed in the SFA literature, this specification allows for the possibility of only few efficient firms as opposed to assuming that the

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[3]One could also define efficiency from an input perspective. In this case efficiency refers to the difference between individually used inputs and minimum level of input use.

[4]In context of the Stochastic Frontier Analysis (SFA) literature, this model is discussed and extended in Greene (2005a).

majority of producing units are relatively efficient (Almanidis et al., 2014). The model accommodates small and heterogeneous group sizes for multiple levels, whose aggregation could otherwise introduce severe bias, for instance resulting from rotating sampling schemes or missing observations. We model u_c and thereby α_c as time invariant because of the unbalanced structure of the data and the fact that palms are perennial crops where management and input use take prolonged effects. TE can be retrieved following the transformation proposed in Schmidt and Sickles (1984) where

$$TE_c = \exp(-max\{\alpha_c\} - \alpha_c). \tag{4}$$

Efficiency is hence expressed in relation to the best performer. One of the drawbacks of the model is that in case of correlation between inputs and the group level predictor, the estimator is biased as the Gauss-Markov assumption of independence is violated. To overcome the problem, we make use of the modification proposed in Bafumi and Gelman (2006), and allow for correlation between inputs and group effects by introducing group level predictors.[5]

$$\alpha_c = \alpha_0 + \mathbf{z}'_c \boldsymbol{\gamma} + u_c. \tag{5}$$

Here z_c are predictors at the group level (c). If no additional group characteristics are available, simple group means of the next level predictors (x_{ic}) could be employed to resolve the correlation problem. Besides addressing the potential correlation between individual-level predictors and group effects, the group-level predictors can also be interpreted as determinants of efficiency.

Accordingly, we implement the first-stage production frontier as a mixed linear estimator in a multilevel model. Farm plots represent the lower level i and farms the group level c. We express the production of fresh fruit bunches of oil palm in kg (y_{ict}) as a function of plot size in ha (x_{1ict}), labor in working hours (x_{2ict}), agrochemical application in kg (x_{3ict}), the age of the palms (x_{4ict}), as well as the density of the palms (x_{5ict}).[6] Based on conventional tests for nested models, we choose the translog functional form that offers more flexibility as opposed to Cobb–Douglas or quadratic production functions, and we thereby estimate output as

$$y_{ict} = \alpha_c + \sum_{j}^{5} \beta_j x_{jict} + \frac{1}{2} \sum_{j} \sum_{k} \beta_{jk} x_{jict} x_{kict} + \rho t + v_{ict}. \tag{6}$$

The group intercept is modeled as described in Equation (5) where the specific independent variables ($z_1, \ldots, z_4$)$'$ are the age of the farm manager in years, education of the farm manager in years, the household size, migration status, rubber cultivation, presence of a formal land title, membership in cooperatives or farmers groups, and credit access. Moreover, we include a time trend t to capture technical change between the two periods. All variables enter the equation in mean scaled form such that we can interpret the coefficients as elasticities at the sample mean. We estimate Equation (6) by means of restricted maximum likelihood (REML).

4.3 | Land expansion model

After estimating the TE of smallholder farmers in the first stage, we model the effect of TE on farmers' land expansion in a second stage. The most pertinent issue we need to specifically account

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[5]Note that this is similar to the Mundlak (1978) correction in panel models.
[6]Note that with regard to capital, the oil palm smallholders own land and palm trees, which we include explicitly in the production model. None of the farms operate machinery or storage facilities.

for is confoundedness that is likely to arise from simultaneity between TE and land expansion, measurement error from the efficiency estimates, and other unobserved confounders.

To begin with, it is conceivable that both inputs and the intercepts reversely cause each other in the first stage model. In other words, farms that are efficient are likely to expand and conversely, expanding farms are also likely to become less efficient. To address input endogeneity in production frontier models, Kumbhakar et al. (2009), Amsler et al. (2016), Tran and Tsionas (2015),[7] and Kutlu et al. (2019) propose joint estimation with a selection equation, instrumental variables, copula function, and time-varying true individual effects combined with an additional decomposition of the irregular error term, respectively. However, such approaches build on binary technology variables, questionable assumptions on the distribution of potential endogeneity, the presence of proper instruments, or the availability of data with cross-sectional units observed at multiple points in time.

Another solution is lag identification. Even though lagged variables have been shown to often not solve identification problems, they are still valid under some explicit assumptions (Bellemare et al., 2017; Reed, 2015). Bellemare et al. (2017) establish three specific scenarios under which lagged explanatory variables identify a causal effect: first, in case of no reverse causality and no contemporaneous causality from TE to land expansion; second, in presence of only contemporaneous reverse causality and no contemporaneous causality; third, in presence of reverse causality and contemporaneous causality only from TE to land expansion. For valid lag identification in this scenario, it must be the case that there are dynamics in TE but not in the land expansion variable.

We confidently assume no contemporaneous causality from TE to land expansion, given the time that it takes to either establish new oil palm area or purchase existing plantations. Second, we assume no reverse causality also because of the prolonged effects in oil palm production. The data allow to test this assumption, which we discuss in detail in the results section. The third assumption is the absence of unobserved confounding variables (Bellemare et al., 2017), which is perhaps the most questionable one to make. Yet again, we report several empirical tests and specifications that allow us to at least mitigate the issue of unobserved confounding variables.

Altogether, under the assumptions of (i) no reverse causality, (ii) lagged causality, and (iii) no unobserved confounding, we specify the land expansion model as follows:

$$(A_{iv2018} - A_{iv2012})/F_{iv2012} = \mathbf{w}'_{iv2012}\boldsymbol{\delta} + TE'_{iv}\tau + d_v + e_{iv}, \tag{7}$$

where $A_{iv2018} - A_{iv2012}$ is the change in farmers' oil palm area between 2012 (t) and 2018 ($t + 1$) relative to the total farm size F_{iv2012} of farmer i in village v in year t. TE_{iv} is TE from the first stage and d_v is a village fixed effect. The matrix $\mathbf{w}_{iv2012}$ gathers additional control variables. In particular, we include variables on age, education, gender, rubber production, migratory status, household size, employment status, wealth, cooperative membership, and credit access. For other specifications than the village fixed-effects models, we include as further controls the village-level share of land titles and migrants, villages' oil palm suitability and vicinity to large estates, as well as regency fixed effects. The error term e_{iv} is assumed to be normally distributed with mean zero and variance σ_e^2.

Finally, we need to address the attenuation bias arising from the stochastically estimated variable u_c. However, we obtain TE_c from α_c, which is modeled depending on group-specific covariates as well as a measurement error. Thus, Equation (7) can be interpreted as an EIV model (e.g., Fuller, 2009) where land use expansion is the observed dependent variable and TE_{iv} the measured variable with known deviation u_c and variance $\sigma_{u_c}^2$. Consequently, we estimate Equation (7) as an EIV model by means of total least squares (TLS) adjusting the estimator by $\sigma_{u_c}^2$.

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[7]The online supplementary appendix C.4 provides an application of the approach by Tran and Tsionas (2015) on the two cross sections as a robustness check of the main model.

5 | RESULTS

The two-stage empirical approach delivers several layers of results.[8] First, we examine the parameter of the production frontier and assess the technology of smallholder oil palm farmers. Second, we evaluate the TE scores of the farmers and their determinants. Third, we assess the validity of the assumptions that govern the identification strategy. Fourth, we gauge the land expansion effect resulting from the land expansion model of the second stage and calculate the rebound effect.

5.1 | Production technology

With regard to model choice, likelihood ratio (LR) tests of nested models confirm the translog functional form to be superior to the Cobb–Douglas specification and the use of random intercepts compared to an alternative plot-level specification. Moreover, the intra-class correlation is 0.41 suggesting that the random intercepts are useful in explaining overall variation.

   Table 2 details the REML estimates and associated standard errors of the first- and second-order terms as well as the group predictors, which we can interpret as drivers of efficiency.[9] The first-order coefficients can be interpreted as elasticities at the sample mean as the variables have been scaled by their means. The parameters associated with the first-order terms of the productive inputs are significant with expected sign. Notably, the model reveals a considerable effect of land size, although the elasticity of agrochemical use is quite low, confirming the experimental findings of Darras et al. (2019). The effect of labor is also comparably small yet reasonable as both direction and magnitude find support in the relevant literature on the low labor intensity of oil palm cultivation (Chrisendo et al., 2021; Kubitza, Krishna, Alamsyah, & Qaim, 2018). Palm age and density exhibit first-order nonsignificant and second-order significant negative coefficients and thereby only partly confirm the quadratic relationship with output of both variables that is often found in the plant growth literature (e.g., Corley et al., 2003). However, the sample includes only productive plots that are older than 3 years, which leads to an omission of the growth patterns at the early stage of oil palm plantations.

   The time trend coefficient is quite large and negative, which we attribute to a particularly strong El Niño–Southern Oscillation (ENSO) that induced a severe drought and widespread fires and haze that negatively affected yields throughout the region (Meijide et al., 2018; Stiegler et al., 2019).

   Another notable finding of the production function is increasing returns to scale of smallholder oil palm farming. The sum of the size, labor, and agrochemical use coefficients amounts to a scale elasticity of 1.15. In other words, average farm size is smaller than the equilibrium size where marginal returns to scale are constant. Increasing returns to scale could manifest in strong incentives for smallholders to expand their farm.

5.2 | Technical efficiency

The TE scores are illustrated in Figure 2. The mean TE is 0.59, implying that palm oil output falls short by 41%, on average. Interestingly, mean TE, which describe shortfalls compared with the best-practice benchmark, aligns well with the size of the yield gap of 40% between smallholders and large estates that has been reported by the Indonesian Ministry of Agriculture (2016) and in the literature (Woittiez et al., 2017). Although generally TE is rather low, in combination with the production function parameter estimates, which suggest the relatively strong importance of land size as a

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[8]The econometric analysis is carried out in R (R Core Team, 2019). We estimate the random intercept model using the `lme4` package (Bates et al., 2015) and the EIV model using the `eivtools` package (Lockwood, 2018).

[9]The full results of the estimated translog production function—including the cross-terms—are reported in the online supplementary Appendix A.

TABLE 2 First and second order terms and group predictors of the linear mixed model (LMM)

	Production
Technology	
β_0 (Intercept)	0.18 (0.49)
β_1 (Size)	0.87 (0.07)***
β_2 (Agrochemicals)	0.15 (0.04)***
β_3 (Labor)	0.13 (0.05)***
β_4 (Palm age)	0.07 (0.09)
β_5 (Palm density)	−0.17 (0.20)
β_{11} (Size^2)	0.40 (0.14)***
β_{22} (Agrochemicals^2)	0.04 (0.02)**
β_{33} (Labour^2)	−0.10 (0.05)**
β_{44} (Palm age^2)	−0.80 (0.22)***
β_{55} (Palm density^2)	−1.50 (0.41)***
ρ (Time)	−0.20 (0.09)**
Group predictors	
γ_1 (Rubber)	−0.17 (0.07)**
γ_2 (Age)	−3e−3 (0.02)
γ_3 (Age^2)	4e−5 (2e−4)
γ_4 (Education)	0.01 (0.01)
γ_5 (Gender)	−0.08 (0.20)
γ_6 (Household size)	−0.03 (0.02)
γ_7 (Transmigrant)	0.17 (0.09)*
γ_8 (Land title)	0.05 (0.04)
γ_9 (Farmer group [= 1])	0.03 (0.09)
γ_{10} (Cooperative [= 1])	0.18 (0.09)**
γ_{11} (Formal credit [= 1])	−0.03 (0.07)
γ_{12} (Informal credit [= 1])	−0.05 (0.08)
Num. obs.	362
Num. groups:	181
σ_{α_c}	0.12
σ_v	0.17
Mean TE	0.59

Note: Standard errors are in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

productive input, we additionally note further evidence for the apparent low land productivity of smallholder farmers.

With regards to the drivers of inefficiency, we find that being member of a cooperative as well as being part of the transmigrant program is associated with higher efficiency (Table 2). These findings suggest that institutional efforts to support smallholder yield growth have been effective to some extent. Farmers that also cultivate rubber exhibit significantly lower efficiency in palm oil production compared with those who do not. The remaining coefficients of the intercept model exhibit relatively large standard errors, failing to result in statistical significance.
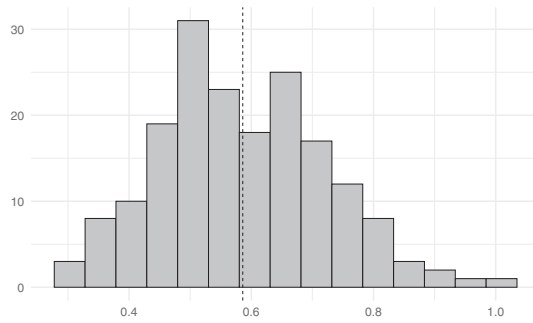
FIGURE 2 Distribution of technical efficiency scores of smallholder oil palm farmers Notes: The TE scores have a mean of 0.59 with standard deviation of 0.14 and range from 0.29 to 1. The 25th percentile is 0.5 and the 75th percentile is 0.68

5.3 | Land expansion

The efficiency scores obtained from the first-stage estimation serve as an explanatory variable in the land expansion model. We estimate the effect of efficiency jointly with other control variables on land expansion between 2012 and 2018 relative to farm size in 2012 by means of OLS and EIV models.

Table 3 juxtaposes the OLS estimates and associated standard errors in column (1) with the EIV parameter estimates in column (2), where we additionally correct for attenuation bias in the TE variable.[10] In column (3), we additional control for village fixed effects. Except for the error-prone variable, the coefficients of the other covariates are of comparable dimension in both the OLS and EIV models. Nevertheless, the OLS model shows a considerably smaller estimate of the effect of TE due to attenuation bias. Both the lower precision of estimates as well as the bias of the error-prone variable are in line with the relevant theory (Nelson, 1995). The difference in parameter estimates highlights the importance of EIV estimation in the case of variables measured with error as OLS results can lead to different outcomes and thus misguided coefficient interpretation.

Aside from these methodological considerations, all models suggest a significant positive effect of TE on oil palm area expansion. With TE being bounded between 0 and 1, real unit changes hardly occur and the coefficients can be interpreted in percentage point changes. For instance, based on the models in Table 3, an efficiency improvement of 10% points is associated with an area expansion of 7%, 8%, and 6.7%, on average in the OLS, EIV, and village fixed effects EIV models, respectively.

Tables 4 and 5 report the effect of TE on land expansion while only considering land that has already been under agricultural production and on land expansion into non-agricultural land such as forests and grass and bush land, respectively. Again, we employ OLS, EIV, and village fixed effects EIV models. The results show that increasing TE is mostly related to farmers acquiring land that is already used for agricultural production. Given that most of the research region's lowland forests already disappeared before 2012, this is not a surprising result. Nonetheless, we still find a positive effect of TE on non-agricultural area change. Moreover, underreporting of farmers on deforestation could additionally downward bias our estimates. The positive effect of rubber cultivation on oil palm expansion on agricultural land could indicate a shift from rubber to oil palm within farms. In online supplementary Appendix C.3 we show, however, that mainly land purchases are driving the effect of TE on oil palm expansion.

Another concern is the sample attrition of 4.4% per round. We provide however three pieces of evidence that attrition is unlikely to affect our results. First, we elicited the reasons for attrition in 2015, which suggest that these farmers did not fall out due to lower or higher levels of efficiency.

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[10]The standard errors of the OLS model are bootstrapped with 1000 repetitions.

TABLE 3 Effect of TE on oil palm area (2012–2018)

	Change of oil palm area (share)		
	(1)	**(2)**	**(3)**
TE	0.71 (0.29)**	0.81 (0.36)**	0.68 (0.32)**
Landholding (ha)	−0.03 (0.01)***	−0.03 (0.01)**	−0.03 (0.01)*
Age (years)	−1e-3 (3e-3)	−1e-3 (3e-3)	−1e-3 (3e-3)
Gender (male = 1)	0.15 (0.27)	0.15 (0.15)	0.16 (0.17)
Education (years)	0.04 (0.04)	0.04 (0.03)	0.04 (0.03)
Rubber (= 1)	0.03 (0.10)	0.03 (0.10)	0.11 (0.12)
Transmigrant (= 1)	0.04 (0.13)	0.04 (0.10)	0.05 (0.10)
Household size (No.)	−0.04 (0.03)	−0.04 (0.02)	−0.04 (0.03)
Employed (= 1)	−0.05 (0.09)	−0.04 (0.08)	−0.03 (0.08)
Self-employed (= 1)	0.06 (0.10)	0.06 (0.10)	0.08 (0.10)
Wealth quintile	0.03 (0.03)	0.03 (0.03)	0.05 (0.03)*
Farmer group (= 1)	−0.16 (0.15)	−0.16 (0.09)*	−0.24 (0.11)**
Cooperative (= 1)	0.05 (0.12)	0.05 (0.10)	0.06 (0.11)
Formal credit (= 1)	0.05 (0.09)	0.05 (0.08)	0.01 (0.10)
Informal credit (= 1)	−0.12 (0.12)	−0.12 (0.10)	−0.14 (0.12)
Distance to palm oil mill (log)	−1e-3 (0.08)	−1e-5 (0.07)	0.17 (0.10)
Transmigrant share	−0.06 (0.17)	−0.06 (0.15)	
Land title share	0.13 (0.10)	0.13 (0.08)	
Migrant share	−0.18 (0.17)	−0.17 (0.15)	
Non-random (= 1)	0.20 (0.17)	0.20 (0.14)	
Suitability for oil palm	0.83 (3.00)	0.74 (1.55)	
Vicinity to large estate (= 1)	0.23 (0.12)*	0.23 (0.09)**	
Intercept	−6.63 (23.19)	−5.99 (12.12)	
Regional dummies	Yes	Yes	
Num. obs.	181	181	181

Note: Column (1) lists the OLS estimator with bootstrapped standard errors in parentheses, columns (2) and (3) list the total least squares (TLS) estimators of the errors-in-variable model with and without village fixed effects respectively and associated standard errors in parentheses. Significant at ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Attrition was mainly related to the sudden death of the household head or migration due to marriage or migrant farmers returning to their homelands. Second, we do not find any significant effect of attrition in 2018 in our first-stage model. Third, although we do find a significant and negative effect of attrition in 2018 on oil palm area expansion between 2012 and 2015, we do not find that the effect of efficiency on land expansion is changing across the models with (see online supplementary Appendix D) or without attritors (see online supplementary Appendix C.2).

5.4 | Robustness checks

Our identification strategy builds upon the assumptions of no reverse causality from land expansion to TE, only lagged causality from TE to land expansion, and no unobserved confounders.

We investigate the validity of the first assumption of no reverse causality using data on historical land use change that was collected in 2012 and test whether the expansion of farm area between

TABLE 4   Effect of TE on oil palm area (2012–2018): agricultural land

	Agricultural area change (share)		
	(1)	**(2)**	**(3)**
TE	0.54 (0.26)[**]	0.62 (0.25)[**]	0.49 (0.23)[**]
Landholding (ha)	−0.02 (0.01)	−0.02 (0.01)[**]	−0.02 (0.01)[*]
Age (years)	−4e−4 (3e−3)	−3e−3 (2e−3)	1e−3 (3e−3)
Gender (male = 1)	0.06 (0.20)	0.06 (0.14)	0.04 (0.16)
Education (years)	0.05 (0.03)[*]	0.05 (0.02)[**]	0.04 (0.03)
Rubber (= 1)	0.15 (0.07)[**]	0.15 (0.06)[**]	0.25 (0.07)[***]
Transmigrant (= 1)	−0.02 (0.10)	−0.02 (0.09)	−0.03 (0.09)
Household size (No.)	−0.04 (0.02)[**]	−0.04 (0.02)[**]	−0.05 (0.02)[**]
Employed (= 1)	−0.08 (0.07)	−0.08 (0.06)	−0.05 (0.06)
Self-employed (= 1)	0.07 (0.09)	0.07 (0.08)	0.09 (0.08)
Wealth quintile	−0.01 (0.03)	−0.01 (0.03)	−0.00 (0.03)
Farmer group (= 1)	−0.10 (0.08)	−0.09 (0.06)	−0.12 (0.08)
Cooperative (= 1)	−0.01 (0.09)	−0.01 (0.07)	0.02 (0.09)
Formal credit (= 1)	0.05 (0.08)	0.05 (0.06)	0.01 (0.08)
Informal credit (= 1)	−0.07 (0.12)	−0.07 (0.10)	−0.15 (0.11)
Distance to palm oil mill (log)	−0.01 (0.07)	−0.01 (0.07)	0.19 (0.09)[**]
Transmigrant share	0.06 (0.14)	0.06 (0.12)	
Land title share	0.11 (0.07)	0.11 (0.06)[*]	
Migrant share	−0.06 (0.17)	−0.06 (0.15)	
Non-random (= 1)	0.19 (0.13)	0.19 (0.12)	
Suitability for oil palm	1.54 (2.13)	1.47 (1.31)	
Vicinity to large estate (= 1)	0.13 (0.09)	0.13 (0.07)[*]	
Intercept	−11.96 (16.58)	−11.47 (10.35)	
Regional dummies	*Yes*	*Yes*	
Num. obs.	180	180	180

Note: Columns (1) lists the OLS estimator with bootstrapped standard errors in parentheses, columns (2)–(3) list the total least squares (TLS) estimators of the errors-in-variable model with and without village fixed effects respectively and associated standard errors in parentheses.
[***]$p < 0.01$; [**]$p < 0.05$; [*]$p < 0.1$.

2006 and 2012 affects the technical efficiencies scores. We do not find any significant effect of past land expansion on contemporaneous TE (online supplementary Appendix C.2). Next, we test if results differ if we use land expansion between 2012 and 2015, and land expansion from 2015 to 2018. Although TE can have a lagged effect if we only consider land expansion between 2012 and 2015, the effect of TE is even further lagged with respect to land expansion between 2015 and 2018 making contemporaneous reverse causality unlikely. The coefficients are as expected smaller for both periods but still positive and significant for part of the specifications (online supplementary Appendix C.3). Finally, the endogenous stochastic frontier specification by Tran and Tsionas (2015) as applied and discussed in the online supplementary Appendix C.4 reveals no contemporaneous endogeneity in the two separate cross sections, which is in further support of no contemporaneous reverse causality.

    The assumption of lagged effects of TE is more difficult to test. As TE is time invariant in the modeling framework, we cannot empirically distinguish lagged effects from contemporaneous ones. However, the assumption still finds support in the experimental literature on oil palm cultivation and management. For instance, Darras et al. (2019) show in an experiment that changes in management practices and quantity of agronomic inputs have potentially lagged effects on oil palm yields, which

TABLE 5 Effect of TE on oil palm area (2012–2018): Non-agricultural land

	Non-agricultural area change (share)		
	(1)	**(2)**	**(3)**
TE	0.14 (0.17)	0.16 (0.17)	0.11 (0.16)
Landholding (ha)	−0.01 (0.01)	−0.01 (0.00)*	−0.01 (0.01)*
Age (years)	−3e–3 (−2e–3)	−3e–3 (−2e–3)	2e–3 (2e–3)
Gender (male = 1)	−0.03 (0.08)	−0.03 (0.05)	0.02 (0.04)
Education (years)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)
Rubber (= 1)	−0.18 (0.07)**	−0.18 (0.07)***	−0.18 (0.08)**
Transmigrant (= 1)	−0.03 (0.07)	−0.03 (0.06)	−2e–2 (0.07)
Household size (No.)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Employed (= 1)	−3e–3 (0.05)	−4e–3 (0.04)	8e–4 (0.04)
Self-employed (= 1)	0.00 (0.06)	0.00 (0.06)	−0.01 (0.06)
Wealth quintile	0.02 (0.02)	0.02 (0.01)	0.02 (0.02)
Farmer group (= 1)	−0.03 (0.09)	−0.03 (0.08)	−0.09 (0.10)
Cooperative (= 1)	0.06 (0.08)	0.06 (0.07)	0.08 (0.08)
Formal credit (= 1)	−1e–3 (0.07)	−1e–3 (0.06)	−0.03 (0.07)
Informal credit (= 1)	−0.09 (0.04)**	−0.09 (0.03)***	−0.12 (0.05)**
Distance to palm oil mill (log)	−0.03 (0.04)	−0.03 (0.04)	0.04 (0.05)
Transmigrant share	−0.05 (0.11)	−0.05 (0.10)	
Land title share	0.04 (0.06)	0.04 (0.05)	
Migrant share	0.08 (0.12)	0.08 (0.11)	
Non-random (= 1)	0.11 (0.09)	0.11 (0.08)	
Suitability for oil palm	−2.36 (2.24)	−2.38 (1.18)**	
Vicinity to large estate (= 1)	0.09 (0.05)*	0.09 (0.04)**	
Intercept	18.32 (17.27)	18.45 (9.26)**	
Regional dummies	*Yes*	*Yes*	
Num. obs.	180	180	180

Note: Columns (1) lists the OLS estimator with bootstrapped standard errors in parentheses, columns (2)–(3) list the total least squares (TLS) estimators of the errors-in-variable model with and without village fixed effects respectively and associated standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^*p < 0.1$.

can span even over several years. With our sampling structure at hand, we conclude that the effect of changes in management practices can only be measured in terms of TE during the subsequent wave.

The final overarching concern of our identification strategy is that our set of observable variables is too limited leading to an omitted variables bias. Although we control for a large set of variables and employ village fixed effects, unobserved heterogeneity within villages could still be present. In particular, some households could settle in areas with little additional land available, whereas others settle closer to forests or shrub land, which could change the available land accessible for farmland expansion. We report two pieces of evidence that challenge this assumption. First, we find little evidence that expansion in non-agricultural land is driving the effect of efficiency on farmland expansion (Tables 4 and 5). Second, we additionally conduct a robustness check with land availability in 2013 based on LandSat satellite imagery for a more limited subsample. The effect of TE remains robust (online supplementary Appendix C.2). The different modes of land acquisition allow us to further test the validity of our results. For instance, land purchases are driven by farmers own decision and characteristics, including potentially TE, whereas other modes of land acquisitions such as inheritance depend mostly on independent events that should not be related to the farms' TE but to

family structures of the farming households. We find that TE is only influencing land expansion driven by land purchases but not land expansion based on inheritance, which is line with our expectations (online supplementary Appendix C.1). In contrast to the assumptions of no reverse causality and lagged causality, which we are confident to be reasonable given the empirical evidence in conjunction with literature insights, the assumption of no unobserved confounding could be challenged by unobservables that have not been accounted for in the model and the robustness checks.

Altogether, the main findings of the two-stage approach are that (i) TE is a good predictor of future land expansion, and thus its improvements are likely to result in increasing demand for land expansion; and (ii) the sector on average exhibits relatively low mean, as well as heterogeneous levels of TE. This implies ample room to increase output without additional use of inputs. Moreover, we also find that (iii) the output of smallholder oil palm farmers is overwhelmingly area driven, and (iv) increasing returns to scale in turn suggest the presence of strong expansion incentives.

6 | LAND SPARING VERSUS LAND EXPANSION

In this section, to better understand the effects of development policies that focus on management practices, we simulate the potential aggregate outcome of increasing smallholder TE and compare it with the sector's potential land savings.

First, we determine the overall potential of land saving resulting from improvements in efficiency only. In other words, we ask how much less land farmers would require to produce the given level of output. One way of disentangling the technologically feasible minimum land input from our production frontier is to follow Reinhard et al. (1999) and derive a single-input efficiency measure by equating a hypothetical minimum input use frontier with the output oriented production frontier. Reinhard et al. (1999) define input (environmental) efficiency as the ratio of the minimum level of input use and observed input, which is a convenient measure of land efficiency for our case at hand. Hence, we apply their formula to our production function.[11]

$$LE_{ict} = \frac{\left[-\left(\beta_1 + \sum_{j}^{4} \beta_{1j} \mathbf{x}_{ictj} + \beta_{11} x_{1ict} \right) \pm \left\{ \left(\beta_1 + \sum_{j}^{4} \beta_{1j} \mathbf{x}_{ictj} + \beta_{11} x_{1ict} \right)^2 - 2\beta_{11} u_{ict} \right\}^{.5} \right]}{\beta_{11}}. \quad (8)$$

The resulting measure can be interpreted as the minimum amount of land required to provide the given level of output, holding all other parts of the technology constant. Applied to our data at hand, a hypothetical elimination of land inefficiency results in the sparing of 297 ha. In terms of Figure 1, this corresponds to $L_3 - L_1$, which is the maximum land saving potential. Put in perspective, this is 54% of the oil palm area under cultivation of the whole sample. The large land inefficiency of smallholder oil palm farmers is unsurprising in light of the inherent yield gap compared with larger estates. If farms return to constant intensities and thereby only save land by the elimination of the radial technical efficiency measure, the land saving still amounts to 280 ha, which corresponds to 51% of oil palm plantation area of the sample and is represented by $L_3 - L_2$ in Figure 1.

Second, we turn to quantifying the land expansion potential as the aggregated effect from increased TE. Just like in the land sparing case, we conversely simulate a hypothetical elimination of technical inefficiency and calculate the resulting additional area demand of the smallholders. Relying on the estimated coefficients from the second-stage expansion models, we calculate the corresponding demand for area expansion as $\sum_{i=1}^{N} \tau * (1 - TE_i)$. Table 6 details the expansion and rebound effects of all reported

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[11]A detailed derivation of this measure is provided in the online supplementary Appendix B.

TABLE 6 Aggregated land expansion and rebound effects

	Total land			Agricultural land			Non-agricultural land		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expansion (ha)	163	186	155	133	155	122	37	42	30
Expansion (%)	28	34	30	24	28	22	7	8	5
Rebound effect	0.55**	0.62**	0.51*	0.45**	0.51**	0.41*	0.12	0.14	0.10
	(0.27)	(0.32)	(0.32)	(0.19)	(0.23)	(0.25)	(0.12)	(0.14)	(0.15)

Note: The land-sparing effects are derived from the first-stage model are 297 ha or 54% of existing cultivated land. For columns (1) to (3), the coefficients for the rebound effect are derived from Table 3. For columns (4) to (9), coefficients for the rebound effect are derived from Tables 4 and 5. Accordingly, results in columns (1), (4) and (7) are derived from OLS estimators, (2), (5) and (8) from TLS and (3), (6) and (9) from TLS that controls for village fixed effects. The standard errors of the rebound effects are bootstrapped at 1000 repetitions and given in parentheses. Significance at **$p < 0.05$ and *$p < 0.1$.

models. For instance, the EIV model in column (2) of Table 6 implies a demand for area expansion of 186 ha, which represents 34% of the currently cultivated oil palm area of the sampled farmers.

Comparing land sparing and expansion demand, we calculate rebound effects between 0.51 and 0.62 from the total land models (columns [1]–[3]). The implication is that about half the potentially spared land could be offset by increased land demand. In other words, each hectare of land that is saved through efficiency gains could actually translate into only 0.51–0.62 ha based on our estimates. Regarding exclusively agricultural land, we find slightly lower rebound effects, and for non-agricultural land, rebound effects are substantially lower. Nonetheless, altogether we find a substantial drag of efficiency induced land sparing.

Moreover, Figure 1 allows to classify the rebound effect into two components that are driven by returning to given input intensities and by responses to market incentives, respectively. The first rebound (Rebound I in Figure 1) is designated by the difference between land-efficiency savings and TE savings, and in our case amounts to 11%. The remaining rebound effect (Rebound II in Figure 1) can be attributed to a supply shift in response to elastic demand, which makes up for 89% of the total simulated rebound effect in our sample.

However, the hitherto-found effects should be interpreted with some caution. First, the land saving potential derives from a scenario in which other production factors are disregarded, and hence it constitutes a maximum solution that is likely to be different under consideration of inevitable by-effects from other inputs. Second, thus far we have not accounted for non-linear expansion effects. The reason here is that we cannot adequately correct—for instance—a squared effect of a error-prone variable having at disposal only errors of the linear variable. By contrast, Marchand (2012) find concave effects of TE on land expansion of farms in the Brazilian amazon, albeit without correcting for measurement errors.

In terms of policy, our results have two main implications. (i) The yield gap between smallholder farmers and large estates is characterized by substantial inefficiency, including regarding land use. Therefore, outreach and extension programs that target managerial skill—in particular cooperatives—could be promising avenues to increase smallholder productivity, which in turn is likely to show positive impacts on livelihoods. (ii) We join Kubitza, Krishna, Urban, et al. (2018) and Gawith and Hodge (2019) in advocating that such policies must be accompanied by changes in land and forest governance to obtain the maximum of land savings from increasing TE.

7 | CONCLUSION

Although deforestation due to agricultural expansion remains a major local and global environmental concern, commodity booms also provide opportunities to promote rural development. Palm oil production on Sumatra in Indonesia is a point in case where ecologically invaluable forest land has

made way to more than 7 million ha of oil palm plantations. In order to halt further deforestation, it is essential to shift the increase in palm oil production from area expansion to the intensification of existing cultivation using both technological innovation and improvements of production management. However, in light of the elastic demand for palm oil, such measures could in turn accelerate local land demand and fuel further deforestation, at least in the short term.

In Indonesia, smallholder farmers cultivate nearly half of the national oil palm area and provide nearly 34% of aggregate output. Nonetheless, they are also subject to informal land regulations and often encroach forest land. Addressing the smallholder sector is hence key for both forest conservation as well as sustainable rural development. Although the adverse effects of technological innovation within the land-sparing debate are well researched, the equivalent mechanism for TE has been empirically opaque. This study aims at placing the TE of smallholder oil palm farmers in the context of the land-sparing controversy. Our empirical approach contains two stages. First, relying on a random intercept model, we estimate the production frontier of smallholder oil palm farmers in Indonesia in a translog specification and determine their TE. Based on the estimated technology parameters, land specific efficiency can be calculated, and we determine the overall land saving potential. Second, we regress area expansion on past efficiency scores by means of an EIV model to reveal the extent to which farmers expand if their efficiency increases.

Our main results are threefold. First, we find that smallholders are considerably technical and land inefficient. Additionally, land is by far the most decisive factor of production. Therefore, remarkable opportunities for optimizing the sector persist, including sizable savings potentials. Second, we find that efficiency is associated with land expansion, whereby the problem is amplified by overall increasing returns to scale. Third, consolidating the first two results, we find that potential land savings achieved through gains in TE—for instance by means of extension and outreach—are at risk of being offset by about half due to rebound effects.

In the context of our study region, more efficient farmers acquired additional land mostly through land markets. The new land was also mostly already used for agricultural production. Deforestation still occurred, albeit to a lesser extent as Sumatra's low land forests have already mostly disappeared. This relation might very well shift in favor of deforestation in other regions, particularly in future agricultural frontier areas such as Kalimantan and Papua, but also Africa, where well-developed land markets are less frequent and (ecologically valuable) land to expand agricultural production is available.

Closing the smallholder yield gap is an effective measure to promote rural development. However, our results imply that policy makers should be aware of partial rebound effects that threaten conservation efforts. Policies that increase agricultural efficiency should hence be matched with complementary strategies to reduce deforestation. Such policies could include further releases of land to local communities through social forestry schemes and stricter forest protection that prohibits the conversion of primary forest land. Customary land rights need also to be acknowledged to allow for functioning land markets. On the other hand, in order to increase efficiency, policies could legalize agricultural land ownership of local farming communities as well as improve extension services. Our study underlines that reconciling both of these efforts is crucial.

Owing to the complexity of the topic, some aspects have to be considered while interpreting our results. First, the internal validity of our study could still be compromised by unobserved confounders that were not addressed by the village fixed effects models and alternative specifications and tests. Second, regarding the external validity, we recognize that the rebound effect is highly context specific. With differing demand elasticities for other commodities or countries, the rebound effect is also likely to change. In addition, increasing efficiency and agricultural profitability could induce migration into rural areas, whereby in-migration could potentially increase the pressure on forest land. Although this is generally a valid argument, in the specific context of the research region, mostly autochthonous farmers obtain land through direct deforestation or they buy encroached land. Finally, although not the focus of our study, increasing efficiency could lead to a further consolidation of the farming sector

with more efficient farmers buying up land from their less efficient counterparts. However, the implications for inequality and welfare are beyond the scope of the present study.

Overall, our study suggests that managerial skill in agriculture is a critical junction within the land-sparing debate. However, the policy relevance is not matched by empirical evidence, particularly regarding potential rebound effects. Although Sumatra has already experienced the loss of most its lowland forests, a better understanding of the land-sparing effects of TE and potential rebound effects could help to protect forests in the present as well as future deforestation hotspots with similar institutional and economic characteristics.

REFERENCES

Abman, Ryan, and Conor Carney. 2020. "Agricultural Productivity and Deforestation: Evidence from Input Subsidies and Ethnic Favoritism in Malawi." *Journal of Environmental Economics and Management* 103: 102342.

Abman, Ryan, Teevrat Garg, Yao Pan, and Saurabh Singhal. 2020. Agriculture and Deforestation. Working paper, available at SSRN: https://ssrn.com/abstract=3692682 or https://doi.org/10.2139/ssrn.3692682.

Aigner, Dennis, C.A. Knox Lovell, and Peter Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6: 21–37.

Almanidis, Pavlos, Junhui Qian, and Robin C. Sickles. 2014. "Stochastic Frontier Models with Bounded Inefficiency." In *Festschrift in Honor of Peter Schmidt*, edited by Robin C. Sickles and William C. Horrace, 47–81. New York: Springer.

Amsler, Christine, Artem Prokhorov, and Peter Schmidt. 2016. "Endogeneity in Stochastic Frontier Models." *Journal of Econometrics* 190: 280–8.

Ando, Amy W., and Christian Langpap. 2018. "The Economics of Species Conservation." *Annual Review of Resource Economics* 10: 445–67.

Bafumi, Joseph, and Andrew Gelman. 2006. "Fitting Multilevel Models When Predictors and Group Effects Correlate." Working paper, available at SSRN: https://ssrn.com/abstract=1010095 or https://doi.org/10.2139/ssrn.1010095.

Balmford, Andrew, Tatsuya Amano, Harriet Bartlett, Dave Chadwick, Adrian Collins, David Edwards, Rob Field, et al. 2018. "The Environmental Costs and Benefits of High-Yield Farming." *Nature Sustainability* 1: 477–85.

Balmford, Andrew, Rhys E. Green, and Jörn P.W. Scharlemann. 2005. "Sparing Land for Nature: Exploring the Potential Impact of Changes in Agricultural Yield on the Area Needed for Crop Production." *Global Change Biology* 11: 1594–605.

Bates, Douglas, Martin Mächler, Ben Bolker, and Steve Walker. 2015. "Fitting Linear Mixed-Effects Models Using lme4." *Journal of Statistical Software* 67: 1–48.

Bellemare, Marc F., Takaaki Masaki, and Thomas B. Pepinsky. 2017. "Lagged Explanatory Variables and the Estimation of Causal Effect." *Journal of Politics* 79: 949–63.

Berkhout, Peter H.G., Jos C. Muskens, and Jan W. Velthuijsen. 2000. "Defining the Rebound Effect." *Energy Policy* 28: 425–32.

Birkenholtz, Trevor. 2017. "Assessing India's Drip-Irrigation Boom: Efficiency, Climate Change and Groundwater Policy." *Water International* 42: 663–77.

Borlaug, Norman E. 2002. "Feeding a World of 10 Billion People: The Miracle Ahead." *In Vitro Cellular & Developmental Biology. Plant* 38: 221–8.

Borlaug, Norman E. 2007. "Feeding a Hungry World." *Science* 318: 359.

Brorsen, B. Wade, and Taeyoon Kim. 2013. "Data Aggregation in Stochastic Frontier Models: The Closed Skew Normal Distribution." *Journal of Productivity Analysis* 39: 27–34.

Busch, Jonah, Kalifi Ferretti-Gallon, Jens Engelmann, Max Wright, Kemen G. Austin, Fred Stolle, Svetlana Turubanova, et al. 2015. "Reductions in Emissions from Deforestation from Indonesia's Moratorium on New Oil Palm, Timber, and Logging Concessions." *Proceedings of the National Academy of Sciences of the United States of America* 112: 1328–33.

Chen, Bin, Christina M. Kennedy, and Xu. Bing. 2019. "Effective Moratoria on Land Acquisitions Reduce Tropical Deforestation: Evidence from Indonesia." *Environmental Research Letters* 14: 044009.

Chrisendo, Daniel, Vijesh V. Krishna, Hermanto Siregar, and Matin Qaim. 2020. "Land-Use Change, Nutrition, and Gender Roles in Indonesian Farm Households." *Forest Policy and Economics* 118: 102245.

Chrisendo, Daniel, Hermanto Siregar, and Matin Qaim. 2021. "Oil Palm and Structural Transformation of Agriculture in Indonesia." *Agricultural Economics* 52: 849–62. https://doi.org/10.1111/agec.12658

Cook, Wade D., Dan Chai, John Doyle, and Rodney Green. 1998. "Hierarchies and Groups in DEA." *Journal of Productivity Analysis* 10: 177–98.

Core Team, R. 2019. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Corley, R., V. Hereward, and Peter B.H. Tinker. 2003. *The Oil Palm*. Oxford: Blackwell Science Ltd.

Curtis, Philip G., Christy M. Slay, Nancy L. Harris, Alexandra Tyukavina, and Matthew C. Hansen. 2018. "Classifying Drivers of Global Forest Loss." *Science* 361: 1108–11.

Darras, Kevin F.A., Marife D. Corre, Greta Formaglio, Aiyen Tjoa, Anton Potapov, Fabian Brambach, Kibrom T. Sibhatu, et al. 2019. "Reducing Fertilizer and Avoiding Herbicides in Oil Palm Plantations—Ecological and Economic Valuations." *Frontiers in Forests and Global Change* 2: 65.

Desquilbet, Marion, Bruno Dorin, and Denis Couvet. 2017. "Land Sharing Vs Land Sparing to Conserve Biodiversity: How Agricultural Markets Make the Difference." *Environmental Modeling & Assessment* 22: 185–200.

Edwards, Ryan B. 2019. Export Agriculture and Rural Poverty: Evidence from Indonesian Palm Oil. Working paper, Hanover, NH: Dartmouth College.

Euler, Michael, Munir P. Hoffmann, Zakky Fathoni, and Stefan Schwarze. 2016. "Exploring Yield Gaps in Smallholder Oil Palm Production Systems in Eastern Sumatra, Indonesia." *Agricultural Systems* 146: 111–9.

Feniuk, Claire, Andrew Balmford, and Rhys E. Green. 2019. "Land Sparing to Make Space for Species Dependent on Natural Habitats and High Nature Value Farmland." *Proceedings of the Royal Society B* 286: 20191483.

Folberth, Christian, Nikolay Khabarov, Juraj Balkovič, Rastislav Skalský, Piero Visconti, Philippe Ciais, Ivan A. Janssens, Josep Peñuelas, and Michael Obersteiner. 2020. "The Global Cropland-Sparing Potential of High-Yield Farming." *Nature Sustainability* 3: 281–9.

Foster, William A., Jake L. Snaddon, Edgar C. Turner, Tom M. Fayle, Timothy D. Cockerill, M.D. Farnon Ellwood, Gavin R. Broad, et al. 2011. "Establishing the Evidence Base for Maintaining Biodiversity and Ecosystem Function in the Oil Palm Landscapes of South East Asia." *Philosophical Transactions of the Royal Society B: Biological Sciences* 366: 3277–91.

Fuller, Wayne A. 2009. *Measurement Error Models*, Vol 305. New York: John Wiley & Sons.

García, Virginia R., Frédéric Gaspart, Thomas Kastner, and Patrick Meyfroidt. 2020. "Agricultural Intensification and Land Use Change: Assessing Country-Level Induced Intensification, Land Sparing and Rebound Effect." *Environmental Research Letters* 15: 085007.

Garrett, Rachael D., Eric F. Lambin, and Rosamond L. Naylor. 2013. "Land Institutions and Supply Chain Configurations as Determinants of Soybean Planted Area and Yields in Brazil." *Land Use Policy* 31: 385–96.

Gawith, David, and Ian Hodge. 2019. "Focus Rural Land Policies on Ecosystem Services, Not Agriculture." *Nature Ecology & Evolution* 3: 1136–9.

Gelman, Andrew, and Jennifer Hill. 2006. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge, UK: Cambridge University Press.

Greene, William. 2005a. "Fixed and Random Effects in Stochastic Frontier Models." *Journal of Productivity Analysis* 23: 7–32.

Greene, William. 2005b. "Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model." *Journal of Econometrics* 126: 269–303.

Gutiérrez-Vélez, Víctor H., Ruth DeFries, Miguel Pinedo-Vásquez, María Uriarte, Christine Padoch, Walter Baethgen, Katia Fernandes, and Yili Lim. 2011. "High-Yield Oil Palm Expansion Spares Land at the Expense of Forests in the Peruvian Amazon." *Environmental Research Letters* 6: 044029.

Hertel, Thomas W. 2018. "Economic Perspectives on Land Use Change and Leakage." *Environmental Research Letters* 13: 075012.

Hooper, David U., E. Carol Adair, Bradley J. Cardinale, Jarrett E.K. Byrnes, Bruce A. Hungate, Kristin L. Matulich, Gonzalez Andrew, J. Emmett Duffy, Lars Gamfeldt, and Mary I. O'Connor. 2012. "A Global Synthesis Reveals Biodiversity Loss as a Major Driver of Ecosystem Change." *Nature* 486: 105–8.

Indonesian Ministry of Agriculture. 2016. *Tree Crop Estate Statistics of Indonesia 2015–2017 Oil Palm*. Jakarta: Directorate General of Estates.

Jelsma, Idsert, G.C. Schoneveld, Annelies Zoomers, and A.C.M. van Westen. 2017. "Unpacking Indonesia's Independent Oil Palm Smallholders: An Actor-Disaggregated Approach to Identifying Environmental and Social Performance Challenges." *Land Use Policy* 69: 281–97.

Jevons, William S. 1879. *The Theory of Political Economy*. London: Macmillan and Company.

Krishna, Vijesh V., Christoph Kubitza, Unai Pascual, and Matin Qaim. 2017. "Land Markets, Property Rights, and Deforestation: Insights from Indonesia." *World Development* 99: 335–49.

Kubitza, Christoph, Vijesh V. Krishna, Zulkifli Alamsyah, and Matin Qaim. 2018. "The Economics behind an Ecological Crisis: Livelihood Effects of Oil Palm Expansion in Sumatra, Indonesia." *Human Ecology* 46: 107–16.

Kubitza, Christoph, Vijesh V. Krishna, Kira Urban, Zulkifli Alamsyah, and Matin Qaim. 2018. "Land Property Rights, Agricultural Intensification, and Deforestation in Indonesia." *Ecological Economics* 147: 312–21.

Kumbhakar, Subal C., Efthymios G. Tsionas, and Timo Sipiläinen. 2009. "Joint Estimation of Technology Choice and Technical Efficiency: An Application to Organic and Conventional Dairy Farming." *Journal of Productivity Analysis* 31: 151–61.

Kutlu, Levent, Kien C. Tran, and Mike G. Tsionas. 2019. "A Time-Varying True Individual Effects Model with Endogenous Regressors." *Journal of Econometrics* 211: 539–59.

Li, Haoyang, and Jinhua Zhao. 2018. "Rebound Effects of New Irrigation Technologies: The Role of Water Rights." *American Journal of Agricultural Economics* 100: 786–808.

Lockwood, J.R. 2018. eivtools: Measurement Error Modeling Tools. R Package Version 0.1–8. https://CRAN.R-project.org/package=eivtools.

Maertens, Miet, Manfred Zeller, and Regina Birner. 2006. "Sustainable Agricultural Intensification in Forest Frontier Areas." *Agricultural Economics* 34: 197–206.

Marchand, Sébastien. 2012. "The Relationship between Technical Efficiency in Agriculture and Deforestation in the Brazilian Amazon." *Ecological Economics* 77: 166–75.

Meeusen, Wim, and Julien van Den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18: 435–44.

Mehta, Yashree, and Bernhard Brümmer. 2020. Efficiency Aggregation in Stochastic Frontier Analysis with Hierarchical Data. Working paper No. 23, ZfS Working papers.

Meijide, Ana, Chandra Shekhar Badu, Fernando Moyano, Nina Tiralla, Dodo Gunawan, and Alexander Knohl. 2018. "Impact of Forest Conversion to Oil Palm and Rubber Plantations on Microclimate and the Role of the 2015 ENSO Event." *Agricultural and Forest Meteorology* 252: 208–19.

Meyfroidt, Patrick, Eric F. Lambin, Karl-Heinz Erb, and Thomas W. Hertel. 2013. "Globalization of Land Use: Distant Drivers of Land Change and Geographic Displacement of Land Use." *Current Opinion in Environmental Sustainability* 5: 438–44.

Miyamoto, Motoe. 2006. "Forest Conversion to Rubber around Sumatran Villages in Indonesia: Comparing the Impacts of Road Construction, Transmigration Projects and Population." *Forest Policy and Economics* 9: 1–12.

Mundlak, Yair. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica: Journal of the Econometric Society* 46: 69–85.

Nelson, Daniel B. 1995. "Vector Attenuation Bias in the Classical Errors-in-Variables Model." *Economics Letters* 49: 345–9.

O'Donnell, Christopher J. 2018. *Productivity and Efficiency Analysis*. Singapore: Springer.

Parmeter, Christopher F., and Subal C. Kumbhakar. 2014. "Efficiency Analysis: A Primer on Recent Advances." *Foundations and Trends® in Econometrics* 7: 191–385.

Pelletier, Johanne, Hambulo Ngoma, Nicole M. Mason, and Christopher B. Barrett. 2020. "Does Smallholder Maize Intensification Reduce Deforestation? Evidence from Zambia." *Global Environmental Change* 63: 102127.

Phalan, Ben, Rhys Green, and Andrew Balmford. 2014. "Closing Yield Gaps: Perils and Possibilities for Biodiversity Conservation." *Philosophical Transactions of the Royal Society B: Biological Sciences* 369: 20120285.

Qaim, Matin, Kibrom T. Sibhatu, Hermanto Siregar, and Ingo Grass. 2020. "Environmental, Economic, and Social Consequences of the Oil Palm Boom." *Annual Review of Resource Economics* 12: 321–44.

Rasmussen, Laura Vang, Brendan Coolsaet, Adrian Martin, Ole Mertz, Unai Pascual, Esteve Corbera, Neil Dawson, Janet A. Fisher, Phil Franks, and Casey M. Ryan. 2018. "Social-Ecological Outcomes of Agricultural Intensification." *Nature Sustainability* 1: 275–82.

Reed, William R. 2015. "On the Practice of Lagging Variables to Avoid Simultaneity." *Oxford Bulletin of Economics and Statistics* 77: 897–905.

Reinhard, Stijn, C.A. Knox Lovell, and Geert Thijssen. 1999. "Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms." *American Journal of Agricultural Economics* 81: 44–60.

Sayer, Jeffrey, Jaboury Ghazoul, Paul Nelson, and Agni Klintuni Boedhihartono. 2012. "Oil Palm Expansion Transforms Tropical Landscapes and Livelihoods." *Global Food Security* 1: 114–9.

Schmidt, Peter, and Robin C. Sickles. 1984. "Production Frontiers and Panel Data." *Journal of Business & Economic Statistics* 2: 367–74.

Shah, Payal, and Amy W. Ando. 2016. "Permanent and Temporary Policy Incentives for Conservation under Stochastic Returns from Competing Land Uses." *American Journal of Agricultural Economics* 98: 1074–94.

Soliman, T., F.K.S. Lim, J.S.H. Lee, and L.R. Carrasco. 2016. "Closing Oil Palm Yield Gaps among Indonesian Smallholders through Industry Schemes, Pruning, Weeding and Improved Seeds." *Royal Society Open Science* 3: 160292.

Song, Jianfeng, Yanan Guo, Pute Wu, and Shikun Sun. 2018. "The Agricultural Water Rebound Effect in China." *Ecological Economics* 146: 497–506.

Stiegler, Christian, Ana Meijide, Yuanchao Fan, Ashehad Ashween Ali, Tania June, and Alexander Knohl. 2019. "El Niño–Southern Oscillation (ENSO) Event Reduces CO_2 Uptake of an Indonesian Oil Palm Plantation." *Biogeosciences* 16: 2873–90.

Suwarno, Aritta, Meine van Noordwijk, Hans-Peter Weikard, and Desi Suyamto. 2018. "Indonesia's Forest Conversion Moratorium Assessed with an Agent-Based Model of Land-Use Change and Ecosystem Services (LUCES)." *Mitigation and Adaptation Strategies for Global Change* 23: 211–29.

Taheripour, Farzad, Thomas W. Hertel, and Navin Ramankutty. 2019. "Market-Mediated Responses Confound Policies to Limit Deforestation from Oil Palm Expansion in Malaysia and Indonesia." *Proceedings of the National Academy of Sciences of the United States of America* 116: 19193–9.

TEEB. 2010. *The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations.* London: Earthscan.

Tran, Kien C., and Efthymios G. Tsionas. 2015. "Endogeneity in Stochastic Frontier Models: Copula Approach without External Instruments." *Economics Letters* 133: 85–8.

Villoria, Nelson B. 2019. "Technology Spillovers and Land Use Change: Empirical Evidence from Global Agriculture." *American Journal of Agricultural Economics* 101: 870–93.

Villoria, Nelson B., Derek Byerlee, and James Stevenson. 2014. "The Effects of Agricultural Technological Progress on Deforestation: What Do We Really Know?" *Applied Economic Perspectives and Policy* 36: 211–37.

Wiebe, Keith D., Timothy Sulser, Pablo Pacheco, Alessandro De Pinto, Daniel Mason d'Croz, Ahmad Dermawan, Timothy S. Thomas, Man Li, Sherman Robinson, and Shahnila Dunston. 2019. *The Palm Oil Dilemma: Policy Tensions among Higher Productivity, Rising Demand, and Deforestation.* Washington, DC: International Food Policy Research Institute.

Woittiez, Lotte S., Mark T. van Wijk, Maja Slingerland, Meine van Noordwijk, and Ken E. Giller. 2017. "Yield Gaps in Oil Palm: A Quantitative Review of Contributing Factors." *European Journal of Agronomy* 83: 57–77.

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