Farmer heterogeneity and differential livelihood impacts of oil palm expansion in Sumatra, Indonesia

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Abstract

We examine the impact of oil palm expansion on smallholder livelihoods in Indonesia, using farm-household survey data. Treatment-effects and endogenous switching regression models suggest that smallholders benefit from oil palm adoption on average. Part of the benefit stems from the fact that oil palm requires less labour than rubber, the main alternative crop. This allows oil palm adopters to allocate more labour to off-farm activities and/or to expand their farmland. Households with a lower land-to-labour ratio are typically better-off with rubber. Depending on various social and institutional factors, households' access to land, labour, and capital varies, contributing to impact heterogeneity.

Keywords: *social heterogeneity, welfare impact, transmigrant programme, Jambi Province.*

1. Introduction

The global oil palm sector has witnessed accelerated area expansion over the last two decades, owing largely to the increased demand for vegetable oils and biofuels (Sayer *et al.*, 2012). The harvested area of oil palm expanded by 39% between 2004 and 2013, while the area of all other oil-producing crops combined only increased by 18% during the same period (FAOSTAT, 2014). Yet palm oil production is regionally quite concentrated: more than 80% of the global production comes from two countries, Indonesia and Malaysia. The rapid expansion of oil palm monoculture has led to significant land-use changes in these countries, affecting both the environment and human welfare. While environmental externalities associated with oil palm expansion have been widely examined, especially in the context of deforestation (Abood *et al.*, 2015; Barnes *et al.*, 2014; Margono *et al.*, 2014; Wilcove and Koh, 2010), the socio-economic implications remain understudied.

In Indonesia, the harvested area of oil palm increased from 2 million hectares in 2000 to 7 million hectares in 2013 (FAOSTAT, 2014). A few non-governmental organizations reported that this has resulted in social conflicts over land, further marginalization of the rural poor, and negative impacts on local communities (Overbeek, Kröger and Gerber, 2012; Sheil *et al.*, 2009; Anonymous, 2008). However, a closer look shows that most of these effects are rooted in institutional rather than crop-specific causes. Legal uncertainty over land rights and overlapping claims between the state and local communities were fundamental reasons for many of the social conflicts in the oil palm frontiers (Cramb and Curry, 2012; Fitzpatrick, 1997). Furthermore, especially during the 1990s oil palm was promoted by the Indonesian government as an instrument of integrated rural development in regions that were inhabited by indigenous communities (Rist, Feintrenie and Levang, 2010; McCarthy and Cramb, 2009). While these developments clearly contributed to negative social effects for certain population groups, oil palm cultivation may also be associated with benefits for those involved in growing this crop. An increasing share of oil palm cultivation in Indonesia takes place in the small farm sector (Gatto, Wollni and Qaim, 2015). Smallholders are expected to dominate overall production in Indonesia in the foreseeable future (Euler *et al.*, 2016). In Indonesia's masterplan for economic development till 2025, palm oil production is highlighted as one of the key economic activities contributing to growth in many regions, including Sumatra and Kalimantan (Kuncoro, 2013).

Given the uncertainty about the wider socio-economic impacts of oil palm expansion and the inclusiveness of recent and ongoing developments (Cramb and Curry, 2012; McCarthy, 2010), more systematic analysis of livelihood effects is required. Smallholder farmers may differ in their ability to get involved in oil palm cultivation. For instance, oil palm is relatively capital-intensive, so that access to finance is likely to play an important role for farmers' adoption decisions. On the other hand, oil palm is less labour-intensive than rubber, the main alternative cash crop in many parts of Sumatra (Drescher *et al.*, 2016; Euler *et al.*, 2016; Feintrenie, Chong and Levang, 2010). Labour saved through oil palm adoption may possibly be reallocated to other economic activities, when opportunities for such other activities arise. Hence, differences in households' factor endowments cannot only contribute to unequal adoption, but also lead to impact heterogeneity among those who decided to adopt. Budidarsono *et al.* (2012) suggested, for example, that impacts may differ between farmers depending on ethnicity and migration background.

In spite of the rapid uptake of oil palm by smallholder farmers in Indonesia, the micro-level determinants of adoption and the impacts on household livelihoods have received very limited attention in the empirical literature. The few studies that exist rely on comparisons of mean farm incomes between oil palm adopters and non-adopters (Budidarsono *et al.*, 2012; Lee *et* *al.*, 2014). Such simple comparisons may be misleading because of possible confounding factors and self-selection bias. The only study that tried to control for such bias is by Euler *et al.* (2015), who showed that oil palm adoption contributes to improved household living standards and nutrition. We add to this literature by focusing more explicitly on impact heterogeneity resulting from social diversity and differential factor endowments of smallholder households. We use survey data collected in Sumatra, Indonesia.

Mean impacts are analysed within a treatment-effects framework. The impact pathways through which oil palm adoption affects farmer livelihoods are examined by estimating regression models with and without the variables depicting households' relative access to factors of production in the set of regressors. As outcome variable we use per capita consumption expenditures, which is considered a reliable indicator of living standards in the development economics literature (Deaton, 1997). The treatment variable is oil palm adoption, which is defined as a dummy.[1] Instrumental variables are used to account for possible self-selection bias. However, even when possible biases are accounted for, standard treatment-effects models are not very suitable to analyse impact heterogeneity that may be caused by multiple factors. Such heterogeneity can be analysed more explicitly in endogenous switching regression (ESR) models, which we develop building on the same instrumental variables. Based on the ESR results, a counterfactual analysis is carried out for various groups of farmers.

The remainder of this article proceeds as follows. Section 2 describes the history and current status of oil palm adoption by smallholders in Sumatra, before presenting the survey data. Section 3 explains details of the analytical methods, whereas section 4 presents and discusses the estimation results. The last section concludes with a few policy and research implications.

2. Context and data

2.1 Background

We concentrate on Jambi Province, Sumatra Island, one of the hotspots of the recent oil palm boom in Indonesia. Deforestation of the tropical lowland rainforests in Jambi already started some 100 years ago, long before oil palm was introduced in this region. In the first half of the

[1] The term "treatment" comes from the experimental impact assessment literature in the medical sciences but has become common also in economics research. In our case, "treated" farmers are those who adopted oil palm.

twentieth century, rubber production in extensive agroforestry systems was an important economic activity of local communities. Increasing demand for rubber from international markets and other factors have contributed to intensified rubber production since the 1970s. Since the 1980s, oil palm has been introduced and promoted by the Indonesian government. Over the last 30-40 years, lowland rainforests in Jambi largely disappeared and agroforestry systems were downsized significantly, making space for rubber and oil palm monocultures (Krishna, Pascual and Qaim, 2014).

Oil palm was first introduced in Jambi by large public-sector companies. However, especially during the 1980s and 1990s, smallholder inclusion was promoted by the Indonesian government through the so-called “nucleus estate and smallholder” (NES) schemes (Euler *et al.*, 2016; Feintrenie and Levang, 2009; Sheil *et al.*, 2009). In these schemes, smallholders received financial and technical support to start oil palm cultivation and were contracted to supply their harvest to the company mills. The NES schemes were particularly relevant for the government’s transmigration programme, in which families from Java’s densely populated areas were relocated on a voluntary basis to Sumatra and other outer islands where they received land, credit, and technical support for agricultural production. In the early-1980s, transmigrants were supported in rice and rubber cultivation. Since the late-1980s, involvement in oil palm NES schemes became more relevant.

Transmigrants from Java predominantly settled in the newly created transmigrant villages in Sumatra, usually in isolation from the local population. After loan repayment, transmigrant families could obtain a formal title for their plot of land (Fearnside, 1997). From 1995, under a novel arrangement called *Koperasi Kredit Primer untuk Anggota* (KKPA; Primary Cooperative Credit for Members), the state handed over the functions of plantation planning and financing to the private sector (McCarthy and Cramb, 2009). The financial support for smallholders was reduced, but otherwise the conditions remained similar. One of the major shortcomings of NES and KKPA schemes was the undermining of customary land rights of the local population, which caused many social conflicts in the oil palm frontiers during the 1990s (Cramb and Curry, 2012; Fitzpatrick, 1997).

With the end of the Suharto era in 1999 and the resulting economic and policy reforms, state interventions in the oil palm sector declined significantly. Nevertheless, smallholder farmers – including both transmigrants and locals – continue adopting oil palm, often independent of company contracts. Yet, adoption rates are faster in villages where some farmers have or had oil palm production contracts in the past, which is likely due to better access to technical information and output markets in these locations (Euler *et al.*, 2016). By 2012, around 190 thousand households were cultivating oil palm in Jambi Province (DPPJ, 2012). Also in other parts of Indonesia, the role of smallholders in the oil palm sector has increased over time. Smallholders currently contribute to about 40% of Indonesia's total oil palm area, and their land expansion is faster than that of private companies and government estates (Euler *et al.*, 2016).

2.2 Data

Data for this study were collected during the second-half of 2012 through a survey of randomly selected farm households in Jambi Province. The survey aimed at understanding the micro-level determinants and impacts of recent land-use changes, mainly involving primary and secondary forests, extensive and intensive rubber, and oil palm plantations. For the selection of households, we used a multi-stage random sampling procedure. First, five regencies, which comprise most of the lowland systems in Jambi, were selected purposively. These regencies are Sarolangun, Bungo, Tebo, Batanghari, and Muaro Jambi, representing the large majority of smallholder oil palm producers in the province (Badan Pusat Statistik, 2012). Second, we randomly selected four districts per regency and two rural villages per district, resulting in 40 randomly selected villages. In addition, five villages near to the Bukit Duabelas National Park and the Harapan Rainforest, where supporting research activities were carried out (Drescher *et al.*, 2016), were purposively selected (we control for non-randomly selected villages in the regression models).

Third, we randomly selected households in the villages, based on household census data compiled by the village heads and village secretaries or by the enumerators. In each village, we selected between 12 and 24 households, with the number adjusted to the total number of households residing in a village. As village sizes vary significantly, selecting an equal number would have led to under-representation of households from large and over-representation of households from small villages. The total sample comprises 683 households. About one-third of these households have adopted oil palm, while the rest have not. Non-adopters primarily grow rubber. Food crop production is of minor importance in the regencies selected. The structured questionnaire focused on details of all cropping and livestock activities of the households in 2012. Further, socio-demographic characteristics, details of off-farm income activities, asset status, and consumption expenditures on food and non-food items were elicited. In addition, we use some village-level characteristics that were collected through community surveys in the same villages (Gatto, Wollni and Qaim, 2015).

2.3 Descriptive statistics

Farmers tend to adopt innovations based on the principle of comparative advantage. This means that the benefits of adoption may be larger for those who purposively decided to adopt than for a randomly chosen group of farmers (Suri, 2011). This is relevant in our context, because households differ in terms of their access to land, labour, and capital. Table 1 shows differences in the use of these production factors and specific returns between the two main cash crops in Jambi, rubber and oil palm. Since both are perennial crops, we differentiate between plantations of different age. Regardless of plantation age, notable differences can be observed. Labour use is significantly lower in oil palm, whereas capital use is significantly higher. Gross margins per hectare are similar for both crops, but returns to labour and capital differ considerably. Oil palm produces much higher returns to labour, while rubber produces much higher returns to capital. These differences are likely to be important drivers of farmers' land-use decisions and potential sources of impact heterogeneity of oil palm adoption. Households with good access to capital and high opportunity costs of labour are expected to adopt oil palm faster and to benefit more.

At the time of the survey in 2012, the international palm oil price was relatively low, while the rubber price was not, so the price ratio was more in favour of rubber than it usually is. To analyse how sensitive the comparisons in Table 1 are to price changes, we carried out the same calculations assuming a 10% higher price for oil palm fresh fruit bunches. As can be seen in the last column of Table 1, the general patterns remain unaffected. Of course, the picture could change with more drastic price changes.

Table 2 presents descriptive statistics for the variables used in the further analysis. A more detailed description of these variables is provided in Table A1 in the Appendix. We use per capita annual consumption expenditure (PACE) as the outcome variable in the regression models, as consumption is considered a better indicator of household living standard than income in the development economics literature (Deaton, 1997). First, consumption data are less influenced by measurement errors. Second, consumption data are less volatile and the

Table 1: Factor productivity of oil palm and rubber

	Input use per year		Gross margin ['000 IDR/AE] per input unit		
	Rubber	Oil palm	Rubber	Oil palm	
				at prevailing output price	with 10% increase in output price
Plantation age 6-15 years					
Land [plot size; ha]	1.50	2.00	11232.00	7603.50***	8649.00
Human labour [hours/ha]	708.00	173.50***	12.58	41.50***	46.83***
Capital outlay ['000 IDR/ha]	243.00	1966.50***	14.31	2.54***	2.90***
Number of observations	323	168			
Plantation age 16-25 years					
Land [plot size; ha]	1.50	2.00***	14640.00	13584.00	15443.00
Human labour [hours/ha]	818.00	222.00***	16.28	64.91***	72.94***
Capital outlay ['000 IDR/ha]	208.00	2344.00***	37.59	4.08***	4.58***
Number of observations	295	67			

Source: Household survey (2012).
Note: The unit of observation are farmers' plots. AE stands for adult equivalent. Due to a few extreme values, we report median values instead of means and use the Kruskal-Wallis equality of populations rank test to establish significant differences. *** Difference from rubber is statistically significant at the 0.01 level. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

distribution in the population is less skewed than that of most other welfare measures (Molini and Wan, 2008). Third, consumption expenditures are often a better proxy than income for household wellbeing in terms of nutrition and health. Several recent studies used changes in consumption expenditures to measure livelihood impacts of different technical or institutional innovations (e.g. Duflo *et al.*, 2013; Kathage and Qaim, 2012).

The mean PACE was about 15.7 million Indonesian Rupiah (IDR) (approx. USD 1668) among all sample households.[2] The PACE of oil palm adopters is significantly higher than that of non-adopters, although this does not necessarily imply a causal relationship. With respect to socio-cultural characteristics, more oil palm adopters have a migrant background and fewer of them belong to the Melayu ethnicity. Melayu is the most prominent ethnicity of the local population in Jambi. The variable "years since migration", which is also shown in Table 2, sheds some light on the history of the government's transmigration programme. Those who migrated to Jambi in the early-1980s are less likely to be oil palm farmers, as they were supported in the cultivation of rubber. However, since the late-1980s the government primarily supported transmigrants in the cultivation of oil palm.

[2] 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

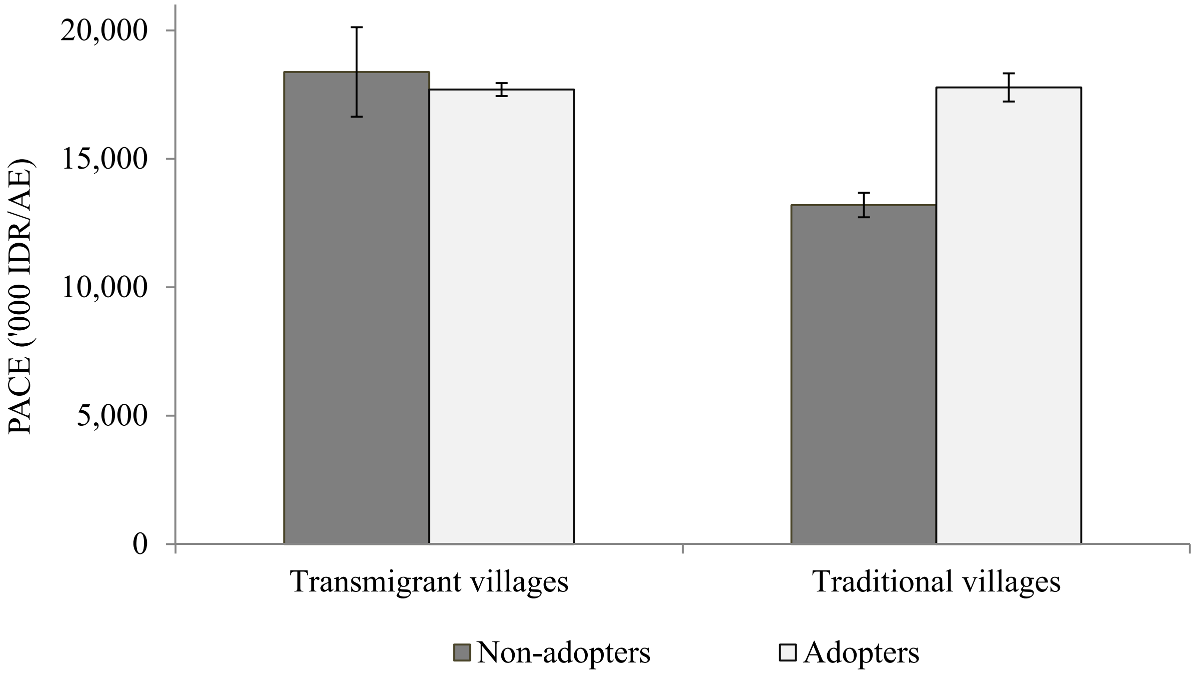
Table 2: Descriptive statistics

Variables [unit]	Full sample	Non-adopters of oil palm	Adopters of oil palm
Household characteristics			
Per capita annual consumption expenditure, PACE [‘000 IDR/AE]	15,662.99	14,591.73	17,731.94**
	(710.56)	(1009.67)	(715.80)
Ethnicity: Melayu [dummy]	0.49	0.55	0.37***
Migrant [dummy]	0.43	0.35	0.58***
Years since migration#	22.70	24.57	20.52***
	(0.60)	(0.92)	(0.71)
Distance to the market [km]	6.63	7.09	5.73**
	(0.28)	(0.35)	(0.49)
Group membership [dummy]	0.24	0.16	0.40***
Cultivated land [ha]	3.83	3.18	5.07***
	(0.17)	(0.18)	(0.34)
Number of adults in the household	3.02	3.06	2.95
	(0.05)	(0.06)	(0.07)
Employed or hiring out labour [dummy]	0.46	0.48	0.41*
Own business [dummy]	0.20	0.18	0.24*
Average age of adult members [years]	37.39	37.22	37.72
	(0.34)	(0.41)	(0.59)
Average education of adult members [years of schooling]	7.84	7.81	7.90
	(0.10)	(0.13)	(0.18)
Share of female adult members [0-1]	0.47	0.48	0.47
	(0.01)	(0.01)	(0.01)
Share of titled land [0-1]	0.45	0.39	0.58***
	(0.02)	(0.02)	(0.03)
Share of titled land, traditional villages [0-1]	0.30	0.27	0.38**
	(0.02)	(0.03)	(0.05)
Credit taken from formal sources [dummy]	0.24	0.18	0.36***
Years of farming in contract village	3.16	1.42	6.52***
	(0.23)	(4.09)	(7.30)
Altitude of place of residence [m]	54.22	56.00	50.79**
	(1.03)	(1.32)	(1.59)
Village characteristics			
Random village [dummy]	0.88	0.89	0.85
Transmigrant village [dummy]	0.37	0.27	0.57***
Number of observations	683	450	233

Notes: AE stands for adult equivalent. Figures in parentheses show standard errors. # Conditional on household being migrant. ***, **, * Difference from non-adopter group is statistically significant at the 0.01, 0.05, and 0.10 level, respectively. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

In terms of factor endowments, oil palm adopters cultivate significantly larger land areas than non-adopters, whereas we find no difference in the availability of family labour (number of adults in the household). Human capital endowments, which we capture by the average age, education, and gender of adult household members, are also similar between the two groups. Yet we observe some differences in the types of off-farm economic activities. Oil palm

Figure 1: Differences in mean household living standards by oil palm adoption status and village type



Note: PACE stands for per capita consumption expenditure and AE for adult equivalent. Error bars denote standard errors. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

adopters are more likely to have their own business (e.g., trading), whereas non-adopters are more likely to be employed. Furthermore, we observe that oil palm adopters take more credits from formal sources and are more likely to hold land titles. Land titles can be used as collateral and may therefore facilitate access to credit and thus oil palm adoption.[3]

Figure 1 shows a further breakdown of PACE not only by adoption status but also by the type of village. Interestingly, the difference in household living standards between adopters and non-adopters is significant only in traditional villages, not in transmigrant villages. The reason likely relates to the fact that rubber plots in transmigrant villages are often intensively managed and thus highly productive. Under such conditions, oil palm does not lead to higher returns to land in comparison. This does not mean that transmigrants do not benefit from oil

[3] Transmigrants could obtain a title for the land allocated to them after repayment of the loans received. Hence, the difference in land titles observed in Table 2 may be more related to transmigration than to the oil palm crop as such. However, our data show that even independent oil palm adopters living in traditional villages are more likely to hold land titles than non-adopters.

palm cultivation, but that the benefits from rubber cultivation are equally high. In traditional villages, the situation is different: rubber is often less intensively managed than in transmigrant villages, so that the comparative gains from oil palm adoption are larger. Moreover, lower labour requirements allow oil palm adopters to cultivate more land, and land is less scarce in traditional than in transmigrant villages. Obviously, differences in other conditions – including land property rights and off-farm income opportunities – may also contribute to heterogeneous impacts of oil palm adoption. Such aspects are analysed more formally in the following sections.

3. Analytical framework

3.1 Estimating the average impact of oil palm adoption

The decision of household i to adopt oil palm $(A_i = 1)$ or not $(A_i = 0)$ is assumed to be based on individual and farm-household characteristics $(\boldsymbol{z}_i)$, including those defining access to the factors of production. Hence, the adoption decision can be formulated as a binary choice model. The simplest way to examine the impact of oil palm adoption on farm household living standards is to regress PACE on a set of explanatory variables, including A_i as the adoption variable. The descriptive analysis in the previous section suggested that the impact of adoption may differ between traditional and transmigrant villages. Against this background, in addition to a pooled model with all observations, we estimate separate models where we split the observations by village type.

One problem in these models is that the adoption variable is likely to be endogenous. Farm households self-selected into the treatment group. This means that there may be unobserved factors that could affect both the adoption decision and PACE simultaneously, resulting in selection bias and inconsistent estimates in ordinary least squares regression (OLS) models. This problem can be tested and controlled through a treatment-effects model, using instrumental variables (Cameron and Trivedi, 2005). In the first stage, a selection equation is used, which includes a binary function modelling the adoption of oil palm. In the second stage outcome equation, the observed realization A_i of the dichotomous latent variable A_i^* captures the expected benefits from oil palm adoption:

Selection equation: $A_i^* = \boldsymbol{z}_i \alpha + \eta_i$ with $A_i = \begin{cases} 1 & if\ A_i^* > 0 \\ 0 & otherwise \end{cases}$ (1a)

Outcome equation: $PACE_i = \boldsymbol{x}_i \beta + \delta A_i + \varepsilon_i$ (1b)

The vectors $\boldsymbol{z}_i$ and $\boldsymbol{x}_i$ represent the covariates used to model A_i and $PACE_i$, respectively. These include household and village characteristics. α and β are vectors of parameters to be estimated, and δ is a scalar parameter. The error terms η_i and ε_i are bivariate normal with mean 0 and variance-covariance matrix $\boldsymbol{\Sigma_1}$,

$$\boldsymbol{\Sigma_1} = \begin{bmatrix} \sigma_\varepsilon & \sigma_\rho \\ \sigma_\rho & 1 \end{bmatrix}$$

For the treatment-effects model to be correctly specified, $\boldsymbol{z}_i$ should contain the same variables as $\boldsymbol{x}_i$ and additionally at least one suitable instrument that is correlated with oil palm adoption, but not directly correlated with $PACE_i$. We use two instruments. The first instrument is altitude of the household residence (meters above sea level), which is negatively correlated with oil palm adoption. This negative correlation is likely due to two factors: (i) most of the oil palm mills in Jambi are located in lower altitudes (DPPJ, 2012), (ii) land for oil palm is mostly converted from rubber agroforests and bush lands, both of which are more common in the lowlands (Villamor *et al.*, 2014). The second instrument is the number of years a household has farmed in a village with contractual ties to the oil palm industry, taking a value of zero for all villages with no contract at any time before the survey. Contractual ties at the village level do not necessarily imply that the household itself is involved in the contract, as contracted adopters, independent adopters, and non-adopters coexist in many of the villages. Nevertheless, if a contract exists at the village level, access to relevant input markets, technical information, and oil palm mills is facilitated, which is why we observe a positive correlation with individual oil palm adoption. In order to test whether these two instruments are valid, we use an approach suggested by Di Falco, Veronesi and Yesuf (2011). Table A2 in the Appendix shows the significance of both variables in the adoption model. At the same time, these variables are insignificant in the outcome equation for non-adopting households. We conclude that the instruments are valid.

3.2 Estimating heterogeneous impacts of oil palm adoption

One limitation of treatment-effects models with a simple adoption dummy is the underlying assumption that the impact is homogeneous and can be fully represented through an intercept shift on the outcome variable. Heterogeneous impacts could be tested through introducing interaction terms between the adoption variable and other covariates. A more elegant way is to use an endogenous switching regression (ESR) framework, where adoption is treated as a regime shifter. The ESR model accounts for observed and unobserved differences between farmers in the two adoption regimes. The ESR framework involves two stages. Similar to the standard treatment-effects model, the first stage is a selection equation, based on a dichotomous choice function, as was shown in equation (1a). In the second stage, two regime equations are specified explaining the outcome of interest (PACE in our context), based on the estimated selection function.

Regime 1: $PACE_{1i} = \boldsymbol{x}_{1i}\gamma_1 + \varepsilon_{1i} \;\; if \; A_i = 1$ (2a)

Regime 2: $PACE_{2i} = \boldsymbol{x}_{2i}\gamma_2 + \varepsilon_{2i} \;\; if \; A_i = 0$ (2b)

where γ_1 and γ_2 are parameter vectors to be estimated for regimes 1 and 2. The error terms in equations (1a), (2a), and (2b) are assumed to have a trivariate normal distribution with zero mean and variance-covariance matrix, $\boldsymbol{\Sigma_2}$

$$\boldsymbol{\Sigma_2} = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}$$

where σ_η^2 is the variance of the error term in equation (1a), which can be assumed to be equal to 1 since the coefficients are estimable only up to a scalar factor (Greene, 2008), σ_1^2 and σ_2^2 are the variances of the error terms in equations (2a) and (2b), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance between η_i and ε_{1i} and between η_i and ε_{2i}, respectively. Since $PACE_{1i}$ and $PACE_{2i}$ are not observed simultaneously, the covariance between ε_{1i} and ε_{2i} is not defined (Maddala, 1986). The expected values of ε_{1i} and ε_{2i} conditional on the sample selection are non-zero, because of the correlation between the error terms of the selection equation (1a) and regime equations (2a) and (2b). The expected values of the truncated error terms are:

$E[\,\varepsilon_{1i} \mid A_i = 1\,] = \sigma_{1\eta}\frac{\phi(\boldsymbol{z}_i\alpha)}{\Phi(\boldsymbol{z}_i\alpha)} = \sigma_{1\eta}\lambda_{1i}$ (3a), and

$E[\,\varepsilon_{2i} \mid A_i = 0\,] = -\sigma_{2\eta}\frac{\phi(\boldsymbol{z}_i\alpha)}{1-\Phi(\boldsymbol{z}_i\alpha)} = \sigma_{2\eta}\lambda_{2i}$ (3b)

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density function and the standard normal cumulative density function, respectively. The ratios of $\phi(.)$ and $\Phi(.)$ evaluated at $\boldsymbol{z}_i\alpha$ provide the Inverse Mills Ratios (IMR), λ_{1i} and λ_{2i} (Greene, 2008; Fuglie and Bosch, 1995). When there are unobserved factors that matter, the error terms of the selection and regime equations will be correlated. Estimates of covariance terms can therefore provide a test for endogeneity. This test is achieved by testing for significance of the correlation coefficients between η_i and ε_{1i} (indicated as $\sigma_{1\eta}$) and between η_i, and ε_{2i} (indicated as $\sigma_{2\eta}$) (Lokshin and Sajaia, 2004).

An efficient method to estimate ESR models is full information maximum likelihood. As in standard treatment-effects models, for the ESR model to be correctly specified $\boldsymbol{z}$ should contain at least one instrument in addition to $\boldsymbol{x}$ that is correlated with oil palm adoption but uncorrelated directly with PACE. We use the same two instruments that were already explained and tested for validity above.

A number of recent studies has modelled heterogeneous impacts of agricultural innovation adoption using the ESR framework (Abdulai and Huffman, 2014; Noltze, Schwarze and Qaim, 2013; Di Falco, Veronesi and Yesuf, 2011; Rao and Qaim, 2011; Alene and Manyong, 2007). Here, we use the ESR model to compare the expected PACE of oil palm adopters and non-adopters, and to investigate the expected consumption expenditures in the counterfactual hypothetical cases that adopter households had not adopted, and that non-adopter households had adopted oil palm. The conditional expectations in these four cases are defined as follows:

$$E[PACE_{1i} \mid A_i = 1] = \boldsymbol{x}_{1i}\gamma_1 + \sigma_{1\eta}\lambda_{1i} \quad \text{(real)} \qquad (4a)$$

$$E[PACE_{2i} \mid A_i = 0] = \boldsymbol{x}_{2i}\gamma_2 + \sigma_{2\eta}\lambda_{2i} \quad \text{(real)} \qquad (4b)$$

$$E[PACE_{2i} \mid A_i = 1] = \boldsymbol{x}_{1i}\gamma_2 + \sigma_{2\eta}\lambda_{1i} \quad \text{(hypothetical)} \qquad (4c)$$

$$E[PACE_{1i} \mid A_i = 0] = \boldsymbol{x}_{2i}\gamma_1 + \sigma_{1\eta}\lambda_{2i} \quad \text{(hypothetical)} \qquad (4d)$$

Cases (4a) and (4b) represent expectations of the actually observed regimes for adopters and non-adopters, whereas cases (4c) and (4d) represent the expected counterfactual outcomes. Following Greene (2008) and Fuglie and Bosch (1995), the net impact of adoption for adopters (average treatment effect on the treated, ATT) can be calculated as the difference between (4a) and (4c).

$$ATT = E[PACE_{1i} \mid A_i = 1] - E[PACE_{2i} \mid A_i = 1] = \boldsymbol{x}_{1i}(\gamma_1 - \gamma_2) + \lambda_{1i}(\sigma_{1\eta} - \sigma_{2\eta}) \qquad (5)$$

This equation controls for possible causes of income differences other than oil palm adoption. The procedure implies that unobserved factors have different effects depending on which regime applies. By holding λ_{1i} constant and taking the differences in variance $(\sigma_{1\eta} - \sigma_{2\eta})$, we eliminate the effects of unobserved factors. The ATT is the result of differences in the coefficients in equations (2a) and (2b). If self-selection is based on comparative advantage $(\sigma_{1\eta} - \sigma_{2\eta}) > 0$, adoption would produce bigger benefits under self-selection than under random assignment (Maddala, 1986). In that case, simple comparison of mean consumption expenditure levels between adopters and non-adopters would overestimate the real treatment effect. Such bias is controlled for in equation (5).

Similarly, we calculate the average treatment effect on the untreated (ATU) for the households that did not adopt oil palm as the difference between (4d) and (4b).

$$ATU = E[PACE_{1i} \mid A_i = 0] - E[PACE_{2i} \mid A_i = 0] = \boldsymbol{x}_{2i}(\gamma_1 - \gamma_2) + \lambda_{2i}(\sigma_{1\eta} - \sigma_{2\eta}) \quad (6)$$

We can use the expected outcomes described in equations (4a) to (4d) to calculate the heterogeneity effects. Following Carter and Milon (2005) and Di Falco, Veronesi and Yesuf (2011), the difference between (4a) and (4d) can be indicated as the 'base heterogeneity' (BH) effect for adopters, and the difference between (4c) and (4b) as the BH effect for non-adopters.

$$BH_1 = E[PACE_{1i} \mid A_i = 1] - E[PACE_{1i} \mid A_i = 0] = \gamma_1(\boldsymbol{x}_{1i} - \boldsymbol{x}_{2i}) + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}) \quad (7)$$

$$BH_2 = E[PACE_{2i} \mid A_i = 1] - E[PACE_{2i} \mid A_i = 0] = \gamma_2(\boldsymbol{x}_{1i} - \boldsymbol{x}_{2i}) + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}) \quad (8)$$

Finally, transitional heterogeneity (TH) is investigated, and the value denotes how large the differential effects of adoption are, as compared to the situation of non-adoption. As shown below, TH can be calculated as the difference between equations (5) and (6).

$$TH = ATT - ATU = (\boldsymbol{x}_{1i} - \boldsymbol{x}_{2i})(\gamma_1 - \gamma_2) + (\lambda_{1i} - \lambda_{2i})(\sigma_{1\eta} - \sigma_{2\eta}) \quad (9)$$

4. Estimation results and discussion

4.1 Average impact of oil palm adoption

We start the analysis by estimating the standard treatment-effects model, as explained in the previous section in equations (1a) and (1b). The dependent variable in the outcome equation (PACE) is log-transformed, which has two advantages. First, as expected, PACE has a notable positive skewness. The log-transformation contributes to a more symmetric distribution of the outcome variable. Second, the log-transformation facilitates interpretation, because the estimated coefficients can be interpreted more easily in percentage terms.

The model is estimated with different sets of explanatory variables. In the first specification, we include the treatment, adoption dummy, together with a vector of household and village variables but without controlling for land and labour availability. In this specification, the estimated treatment effect captures aggregate, both direct and indirect, impacts of oil palm adoption. Direct impacts are those related to possible profit gains on a given plot that is cultivated with oil palm instead of rubber or other alternative crops, whereas indirect impacts are those resulting from alternative uses of saved household labour. Such alternative uses, which are possible because of the lower labour requirements in oil palm, may involve off-farm activities as well as expansion of the cultivated land when such land is still available. In a second specification, we use the same explanatory variables but additionally control for household labour availability, off-farm activities, and cultivated land. Thus, the estimated treatment effect captures only the direct impact of oil palm adoption. Comparison of the effects in both specifications can help better understand relevant impact pathways.

Results of the model estimates with instrumental variables are shown in Table A3 in the Appendix. The signs of the estimated coefficients are reasonable, but some of them are not statistically significant. This is also true for the estimated treatment effects of oil palm adoption, which are positive but have relatively large standard errors. However, the associated likelihood ratio (LR) test reveals that there is no significant correlation between the error terms of the selection and outcome equations (σ). The standard Hausman test was also administered, but the model fitted failed to meet the asymptotic assumptions. The alternative, a generalized "seemingly unrelated estimation" test, yielded the same conclusion as the LR test. Hence, the null hypothesis that oil palm adoption is not correlated with the error term in the outcome equation (i.e., there is no self-selection bias due to unobserved factors) cannot be rejected. In that case, OLS estimation of the outcome equation leads to consistent and more efficient estimates.

The OLS results are shown in Table 3. The estimates are similar in magnitude to those with instrumental variables, but the standard errors are smaller and the treatment effects are now significant. The first two columns in Table 3 show model estimates using the full sample with and without the labour and land variables included. The estimated treatment effect of 0.189 in column (1) suggests that oil palm adoption increases PACE by 20.7%.[4] This implies that farm households benefit substantially in terms of higher living standards through oil palm adoption. However, once we control for labour and land, the treatment effect drops to 7.4% (column 2). This reduction suggests that a sizeable part of the total benefit is due to indirect effects related to labour reallocation. This is plausible given that labour is a constraining factor for many households in Jambi, so that the opportunity costs are high. The estimates in column (2)

[4] The percentage effect of a dummy variable in a semi-logarithmic specification is obtained as $100 \times \{e^{\hat{c}-0.5\hat{V}(\hat{c})} - 1\}$, where $\hat{c}$ is the estimated coefficient and $\hat{V}(\hat{c})$ is the estimated variance of $\hat{c}$ (van Jan Garderen and Shah, 2002; Kennedy, 1981).

confirm that expanding the land area and engaging in off-farm activities (especially own businesses) can add significantly to household living standards.

Looking at the other covariates in columns (1) and (2) of Table 3, we observe that distance to market has a negative effect on living standards, which is expected. On the other hand, education, age, and participation in group activities to reduce transaction costs contribute positively to living standards. Furthermore, the share of titled land has a positive effect on consumption expenditures.[5] The dummy for transmigrant villages in column (1) has a negative coefficient, which is striking because average living standards in transmigrant villages are often higher than in traditional villages. However, differences in average living standards are due to a variety of socio-demographic and institutional variables, many of which are controlled for in the models estimated here. The negative partial effect of transmigrant villages in column (1) seems to be driven by land scarcity that is more severe than in traditional villages. In column (2), where we control for land resources, the estimate for transmigrant villages turns insignificant.

This discussion implies that the impacts of oil palm adoption may differ between transmigrant and traditional villages, as was also suggested by the descriptive comparisons in Figure 1. We analyse this aspect further through splitting the sample by village type and estimating separate models. Without controlling for the opportunity costs of land and labour, oil palm adoption has significantly positive impacts on household living standards in transmigrant and traditional villages. However, once we control for availability of these factors of production, the treatment effect in transmigrant villages gets very small and insignificant, as can be seen in column (3) of Table 3. The effect in traditional villages, however, remains significant (column 4). Adoption of oil palm increases PACE by 12% in traditional villages, even after removing the indirect effects of land and labour reallocation. Possible reasons include higher gross margins from oil palm production in traditional villages, something that we do not observe in transmigrant villages.

[5] While land titles do not add to living standards directly, indirect effects through better access to formal credit can be expected (Deininger and Feder, 2001). While current credit access is included in the models, past credit access, which could also affect current welfare, is not. Better credit access potentially facilitates productivity-enhancing investments, which may contribute to positive livelihood effects over time.

Table 3. Mean livelihood impact of oil palm adoption: OLS estimates

	Overall		By village type	
	Model 1	Model 2	Transmigrant	Traditional
	(1)	(2)	(3)	(4)
Oil palm adoption [dummy]	0.189***	0.072*	0.013	0.119**
	(0.045)	(0.044)	(0.082)	(0.056)
Ethnicity: Melayu [dummy]	-0.065	-0.005	-0.149	0.060
	(0.058)	(0.054)	(0.111)	(0.067)
Migrant [dummy]	0.022	0.082	0.209	-0.012
	(0.083)	(0.078)	(0.133)	(0.100)
Years since migration [year]	0.001	-3.E-04	-0.005	0.006
	(0.003)	(3.E-03)	(0.004)	(0.004)
Distance to the market [km]	-0.005*	-0.005*	-0.014***	-0.003
	(0.003)	(0.003)	(0.006)	(0.003)
Group membership [dummy]	0.105**	0.116***	0.144*	0.095*
	(0.048)	(0.045)	(0.076)	(0.058)
Log of cultivated land [ha]		0.169***	0.181***	0.161***
		(0.020)	(0.034)	(0.026)
Number of adults in the household		-0.078***	-0.075**	-0.079***
		(0.015)	(0.031)	(0.018)
Employed or hiring out labour		0.036	-0.051	0.081*
[dummy]		(0.039)	(0.070)	(0.047)
Own business [dummy]		0.252***	0.249***	0.243***
		(0.045)	(0.075)	(0.057)
Average age of adult members	0.005**	0.001	-0.001	0.001
[years]	(0.002)	(0.002)	(0.004)	(0.003)
Average education of adult members	0.040***	0.027***	0.028**	0.024***
[years of schooling]	(0.008)	(0.007)	(0.014)	(0.009)
Share of female adult members [0-1]	-0.127	-0.125	0.120	-0.196
	(0.139)	(0.130)	(0.261)	(0.152)
Share of titled land [0-1]	0.085*	0.079*	-0.047	0.142***
	(0.046)	(0.043)	(0.078)	(0.052)
Credit taken from formal sources	0.066	0.012	0.045	-0.004
[dummy]	(0.048)	(0.045)	(0.067)	(0.063)
Random village [dummy]	-0.009	0.055	--	0.033
	(0.069)	(0.065)		(0.072)
Transmigrant village [dummy]	-0.110*	-0.062	--	--
	(0.060)	(0.056)		
Number of observations	683	683	253	430
Adj. R^2	0.14	0.27	0.25	0.25

Notes: The dependent variable is the log of per capita consumption expenditure (PACE). Figures in parentheses show standard errors. ***, **, * Significant at the 0.01, 0.05, and 0.10 level, respectively. Regency dummies are included in the estimation. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

Another interesting comparison between columns (3) and (4) in Table 3 is the role of land titles, which we measure in terms of the share of the farmers' individual land that is titled. In traditional villages, the effect is positive and highly significant, whereas in transmigrant villages it is not. We attribute this difference to a diminishing marginal effect when the share of titled land increases. When the household has no or only little land with titles, increasing the share can be associated with significant welfare gains, because the titles can be used as collateral for obtaining formal credit. Beyond a certain point, this effect becomes less relevant because access to credit is not a constraint anymore. Indeed, in transmigrant villages the average share of titled land is already quite high (71%), which is directly related to the transmigration program, as explained above.

4.2 Heterogeneous impacts of oil palm adoption

We now turn to the heterogeneous impacts of oil palm adoption by using the ESR framework. As before, we run the ESR models with and without controlling for labour and land. The results without the labour and land variables included are presented in Table A4 in the Appendix. The model estimates with these variables are shown in Table 4. Similar to the standard treatment-effects model, the correlation of the error terms (σ) is found to be insignificant, suggesting that there is no self-selection bias due to any unobserved factors.

We focus the discussion on the two regime equations, which are shown in columns (2) and (3) of Table 4. Structural differences can be observed, pointing at possible impact heterogeneity. For instance, the negative effect of market distance on PACE and the positive effect of group membership are more pronounced among oil palm adopters. Similarly, the land expansion and titling effects are larger for adopters than for non-adopters. As discussed above, land expansion is one of the indirect pathways how oil palm adoption contributes to higher living standards. Further, possession of land titles improves access to credit, which is more relevant in oil palm due to the crop's higher capital intensity. On the other hand, education has no significant effect for adopters, but a significantly positive effect for non-adopters.

Table 4. Endogenous switching regression estimates

	Selection equation	Log of PACE ['000 IDR/AE]	
		Non-adopters	Adopters
	(1)	(2)	(3)
Ethnicity: Melayu [dummy]	0.131	0.010	-3.E-04
	(0.175)	(0.071)	(9.E-02)
Migrant [dummy]	0.890***	0.079	0.211
	(0.248)	(0.106)	(0.164)
Years since migration [year]	-0.033***	3.E-04	-0.005
	(0.009)	(4.E-03)	(0.006)
Distance to the market [km]	-0.013	-0.004	-0.009*
	(0.008)	(0.003)	(0.005)
Group membership [dummy]	0.505***	0.095	0.180**
	(0.139)	(0.066)	(0.090)
Log of cultivated land [ha]	0.416***	0.165***	0.200***
	(0.073)	(0.029)	(0.066)
Number of adults in the household	-0.053	-0.072***	-0.098***
	(0.050)	(0.019)	(0.025)
Employed or hiring out labour	0.096	0.009	0.081
[dummy]	(0.128)	(0.047)	(0.064)
Own business [dummy]	0.149	0.245***	0.250***
	(0.147)	(0.059)	(0.068)
Average age of adult members [year]	-0.010	0.004	-0.004
	(0.008)	(0.003)	(0.004)
Average education of adult members	-0.012	0.045***	-0.010
[year of schooling]	(0.025)	(0.009)	(0.011)
Share of female adult members [0-1]	-0.464	-0.021	-0.464*
	(0.456)	(0.151)	(0.246)
Share of titled land [0-1]	0.133	0.052	0.131*
	(0.140)	(0.053)	(0.075)
Credit taken from formal sources	0.160	-0.044	0.107
[dummy]	(0.144)	(0.061)	(0.068)
Random village [dummy]	-0.219	0.050	0.087
	(0.202)	(0.083)	(0.121)
Transmigrant village [dummy]	0.612***	0.013	-0.138
	(0.181)	(0.083)	(0.135)
Years of farming in contract village	0.063***		
	(0.012)		
Altitude of place of residence [m]	-0.004		
	(0.003)		
σ		-0.017	0.172
		(0.212)	(0.499)
Log likelihood		-719.59	
Wald χ^2		91.74***	
LR test of independent eq. $\chi^2(1)$		0.14	
Number of observations		683	

Notes: Figures in parentheses are standard errors. PACE stands for per capita annual consumption expenditure, and AE for adult equivalent. ***, **, * Significant at the 0.01, 0.05, and 0.10 level, respectively. Regency dummies are included in the estimation. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

The average treatment effects on the treated and untreated (ATT and ATU) that we calculated based on the ESR estimates are shown in Table 5. The upper part of this Table shows the treatment effects without controlling for labour and land. The PACE predicted for oil palm adopters is about 15.8 million IDR, for non-adopters it is about 12.2 million IDR. When we compare these values that are based on farmers' real adoption decisions with the relevant counterfactuals, we see that the ATT and ATU are almost identical in relative terms. That is, oil palm adoption increases PACE by about 18% for both adopters and non-adopters. This effect is similar in magnitude to the average impact measured with the standard treatment-effects model in column (1) of Table 3. The similarity in ATT and ATU is also indicated by the transitional heterogeneity (TH) estimate in Table 5, which is not statistically significant. These estimated treatment effects include both the direct and indirect benefits of oil palm adoption.

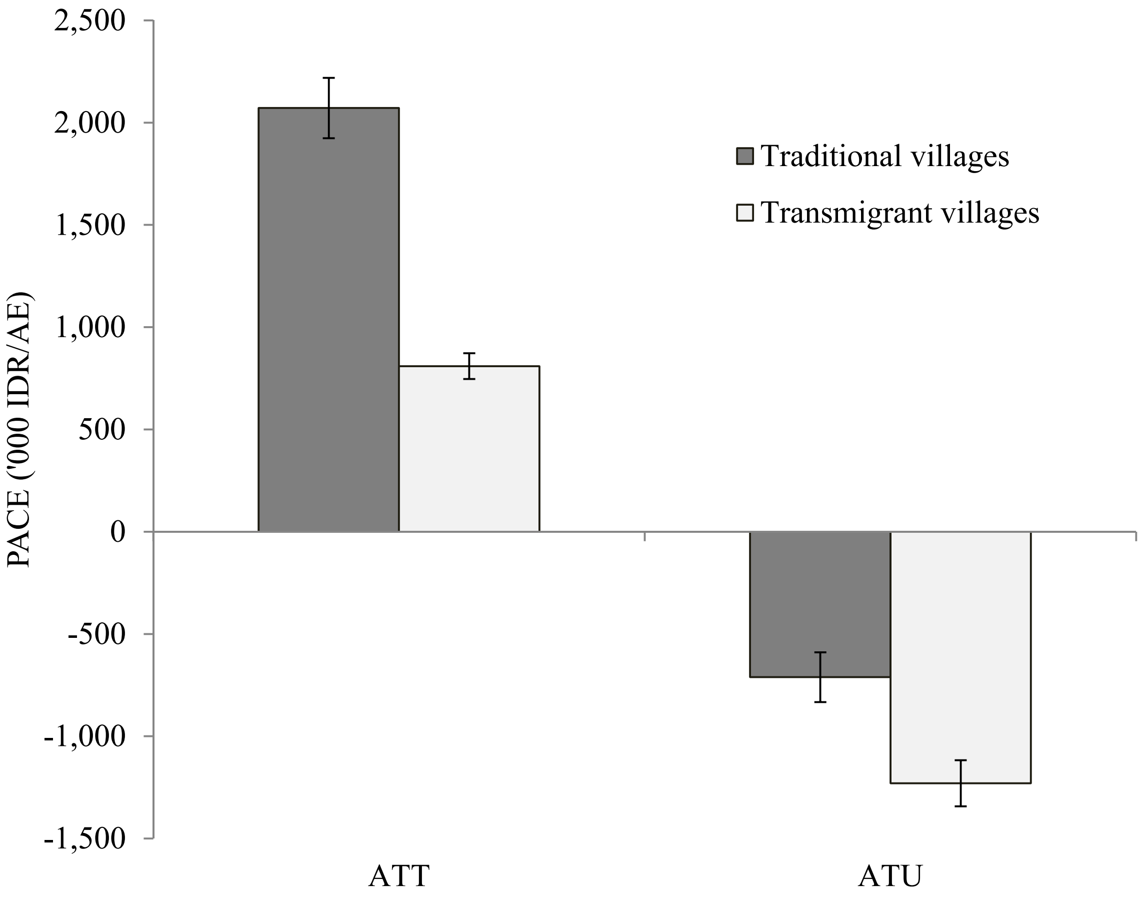
Table 5: Average treatment effect of oil palm adoption on PACE

Subsamples	Estimated PACE ['000 IDR/AE]		Average treatment effects and transitional heterogeneity effects	
	Adoption	Non-adoption	Value ['000 IDR/AE]	% over non-adoption
Without controlling for labour and land				
Adopters	15842.45	13443.82	ATT: 2398.63***	+17.84
[N = 233]	(213.45)	(168.40)	(271.88)	
Non-adopters	14306.07	12160.65	ATU: 2145.42***	+17.64
[N = 450]	(150.07)	(111.12)	(186.73)	
Heterogeneity effects	1536.38***	1283.17***	TH: 253.21	
	(259.00)	(196.29)	(324.98)	
Controlling for labour and land				
Adopters	16157.42	14800.86	ATT: 1356.57***	+9.17
[N = 233]	(315.21)	(268.29)	(192.15)	
Non-adopters	11531.12	12381.87	ATU: -850.75***	-6.87
[N = 450]	(170.21)	(164.24)	(110.45)	
Heterogeneity effects	4626.30***	2418.99***	TH: 2207.31***	
	(283.49)	(253.40)	(206.56)	

Notes: Estimates without controlling for labour and land are based on the ESR model shown in Table S2 in the online supplementary materials. Estimates controlling for labour and land are based on the estimates in Table 4. PACE stands for per capita annual consumption expenditure, AE for adult equivalent, ATT for average treatment effect on the treated, ATU for average treatment effect on the untreated, and TH for transitional heterogeneity, N for number of observations. Figures in parentheses are standard errors. *** Significant at the 0.01 level. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

This picture changes significantly when we only consider the direct effects of oil palm adoption by controlling for labour and land. These direct effects are shown in the lower part of Table 5. The ATT remains positive and significant, but the effects drop to about half its previous size. Without the possibility to reallocate labour and expand the cultivated land, oil palm adoption would increase PACE by about 9% for current adopters. More importantly, the ATU turns negative and significant. That is, if current non-adopters would adopt oil palm they would suffer from welfare losses in a magnitude of 7%, if they could not expand their cultivated land or use the saved labour through off-farm activities.

Figure 2: Average treatment effects of oil palm adoption by village type, controlling for labour and land availability



Notes: Derived from Table 4 estimates. PACE stands for per capita annual consumption expenditure, AE for adult equivalent, ATT for average treatment effect on the treated, and ATU for average treatment effect on the untreated. Error bars represent standard errors. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

As is shown in Figure 2, the negative ATU is particularly relevant in transmigrant villages. While many transmigrants are involved in oil palm cultivation, some of the early transmigrants were supported in cultivating rubber. Since additional cultivable land is hard to access in most transmigrant villages, adopting oil palm would mean that productive rubber plots had to be converted for the early transmigrants. Under the prevailing price conditions in 2012 this would only make sense when much more lucrative off-farm activities could be pursued through labour savings.

The observed impact heterogeneity emphasises that focusing on average effects alone may be inappropriate from a policy perspective. Land-use changes often affect factor-use ratios in farm production. Given varying factor endowments among farmers, this can lead to welfare gains for some, while making much less sense for others (Kathage *et al.*, 2016; Suri, 2011). Furthermore, our findings show that indirect effects related to factor reallocation can account for a sizeable part of the overall effect, so that impact estimates with plot level data alone may be misleading. Likewise, a focus on farm incomes may be insufficient, as off-farm activities are often equally important for household welfare. Indirect effects can also contribute to impact heterogeneity, as they depend on local infrastructure and institutions. While previous research has highlighted the importance of heterogeneity and the role of institutions in evaluating the impacts of agricultural technologies (Asfaw *et al.*, 2012; Kabunga, Dubois and Qaim, 2012; Rao and Qaim, 2011), we are not aware of much research that has analysed heterogeneity of livelihood impacts of land-use change in a developing country context.

5. Conclusion

The massive expansion of oil palm in Southeast Asia may have significant economic, social, and environmental implications. We have analysed economic and social impacts of oil palm adoption on the livelihoods of smallholder farmers in Sumatra, Indonesia. Previous publications by non-governmental organizations have highlighted negative social effects and conflicts between palm oil companies and local communities. While conflicts resulting from ambiguous land property rights occur, we have shown that rising numbers of smallholder farmers are involved in oil palm cultivation themselves. Oil palm adoption has helped these smallholders to significantly increase their household living standards. However, farmers benefit to varying degrees.

On average, oil palm does not contribute to higher profits per unit of land than rubber, which is the most important alternative cash crop. A major reason for many farmers' adoption decision is the fact that oil palm is less labour-intensive than rubber. This allows oil palm adopters to allocate more labour to off-farm activities. In some cases, adopters have also used the saved labour to expand their cultivated land area. Our estimates suggest that at least half of the total benefits from oil palm adoption are indirect gains resulting from such reallocation of household labour to other lucrative activities. Hence, living standard effects of oil palm adoption depend on individual factor endowments. Households with higher opportunity costs of labour and better access to land benefit over-proportionally. Furthermore, households with land titles have an advantage, because oil palm is capital-intensive and owning land titles facilitates access to formal credit. In terms of direct profit effects, farmers that substitute oil palm for extensive rubber benefit more than farmers with intensive and highly productive rubber plantations. This is also one of the reasons why we find significant direct adoption gains in traditional villages, but not in transmigrant villages. We argue that future research on land-use change should account for such heterogeneity in farmers' conditions and impacts. These results also suggest that emerging environment-friendly policies (e.g., Payment for Ecosystem Services) should more explicitly consider social heterogeneity and differential factor requirements for available production systems when designing strategies toward sustainable land-use and inclusive economic development.

One limitation of our study is that we only have cross-section data available, so that institutional responses to land-use change could not be analysed in detail. Farmers' crop adoption decisions depend on the nature of local institutions, but the opposite may also hold true to some extent. For instance, rising labour costs tend to increase the attractiveness of oil palm, but changing land and labour market arrangements may possibly dampen this effect over time. Sharecropping arrangements are typically observed in Sumatra, especially in rubber. Yet, in some cases the scope of sharecropping is affected by the lack of formal titles for the cultivated land. This may change with evolving land titling policies in Indonesia. Future research with panel data could help better understand the co-evolution of land use, factor markets, and other local institutions, and the resulting impacts on smallholder farmers. Beyond farming households, land-use change may also affect the welfare of rural non-farm households, especially through labour markets. Our survey concentrated on farm households, so that labour market spillovers could not be evaluated comprehensively. Poor non-farm households in particular depend on agricultural employment as sharecroppers or day laborers in rubber and oil palm cultivation. Increasing adoption of oil palm as the less labour-intensive crop may contribute to lower employment incomes and possibly also higher income variability. More research is reqired to analyse such spillovers and broader social effects.

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Appendix

Table A1: Description of variables

Variables	Description [unit of measurement]
PACE	Per-capita annual consumption expenditure of the household [thousand IDR per AE or adult equivalent]
Oil palm adoption	1 if household adopted oil palm; 0 otherwise [dummy]
Ethnicity: Melayu	1 if household belongs to Melayu ethnicity; 0 otherwise [dummy]
Migrant	1 if household is a migrant in the village; 0 otherwise [dummy]
Years since migration	Years between time of migration and 2012, the year of survey, if the household is a migrant [year]
Distance to the market	Distance from home to the local market of grocery purchase [km]
Group membership	1 if any of the adult members of the household has a group membership; 0 otherwise [dummy]
Cultivated land	Owned land under cultivation by the household [ha]
Number of adult members	Number of adult members in the household
Employed or hiring out labour	1 if any of the adult members of the household hires out labour; 0 otherwise
Own business	1 if any of the adult members of the household is self-employed outside the farm; 0 otherwise
Average age of adult members	Average age of the adult members in the household [year]
Average education of adult members	Average education of adults in the household [year of schooling]
Share of female adult members	Share of female adult members in all adults in household [0-1]
Share of titled land	Share of cultivated land with formal ownership titles [0-1]
Credit taken from formal sources	1 if household has taken any formal credit during the past one year; 0 otherwise
Random village	1 if the household is from a randomly selected village; 0 otherwise [dummy]
Transmigrant village	1 if the household is from a transmigrant village; 0 otherwise [dummy]
Years of farming in contract village	Number of years the household was farming in a village with contractual ties at the time of the survey (zero for all households in villages with no contract)
Altitude of place of residence	Altitude [meters above the mean sea level] of place of residence

Table A2: Verification of instrumental variables

	Dependent variable	
	Oil palm adoption [dummy, OLS]	Log of PACE ['000 IDR/AE, OLS] among non-adopters
Years of farming in contract village	0.020^{***}	-0.009
[years]	(0.003)	(0.006)
Altitude of place of residence [m]	-0.001^{*}	-0.001
	(7.E-04)	(0.001)
Adj. R^2	0.31	0.22
Number of observations	683	450

Notes: Figures in parentheses show standard errors. ***, * Significant at the 0.01 and 0.10 levels, respectively. Parameters for all the other variables are not reported.

Table A3: Mean impact of oil palm on PACE: treatment-effects model with instrumental variables

	Model 1		Model 2	
	Selection equation	Log of PACE ['000 IDR/AE]	Selection equation	Log of PACE ['000 IDR/AE]
	(1)	(2)	(3)	(4)
Oil palm adoption [dummy]		0.177		0.065
		(0.124)		(0.130)
Ethnicity: Melayu [dummy]	0.059	-0.064	0.131	-0.005
	(0.168)	(0.058)	(0.176)	(0.055)
Migrant [dummy]	0.742***	0.025	0.878***	0.084
	(0.237)	(0.088)	(0.247)	(0.084)
Years since migration [year]	-0.026***	0.001	-0.033***	-4.E-04
	(0.009)	(0.003)	(0.009)	(3.E-03)
Distance to the market [km]	-0.014*	-0.005*	-0.013	-0.005*
	(0.008)	(0.003)	(0.008)	(0.003)
Group membership [dummy]	0.496***	0.107**	0.504***	0.117**
	(0.134)	(0.053)	(0.139)	(0.049)
Log of cultivated land [ha]			0.410***	0.170***
			(0.070)	(0.025)
Number of adults in the household			-0.053	-0.079***
			(0.050)	(0.015)
Employed or hiring out labour [dummy]			0.098	0.036
			(0.128)	(0.038)
Own business [dummy]			0.156	0.252***
			(0.146)	(0.045)
Average age of adult members[years]	-0.003	0.005**	-0.010	0.001
	(0.008)	(0.002)	(0.008)	(0.002)
Average education of adult members [years of	0.017	0.040***	-0.012	0.027***
schooling]	(0.023)	(0.008)	(0.024)	(0.007)
Share of female adult members [0-1]	-0.626	-0.128	-0.483	-0.125
	(0.429)	(0.138)	(0.452)	(0.128)
Share of titled land [0-1]	0.182	0.085	0.132	0.079*
	(0.134)	(0.046)	(0.140)	(0.042)
Credit taken from formal sources [dummy]	0.234*	0.068	0.162	0.012
	(0.138)	(0.049)	(0.143)	(0.045)
Random village [dummy]	-0.343*	-0.012	-0.225	0.053
	(0.195)	(0.073)	(0.201)	(0.066)
Transmigrant village [dummy]	0.442***	-0.107	0.612***	-0.060
	(0.174)	(0.065)	(0.181)	(0.064)
Years of farming in contract village	0.073***		0.064***	
	(0.011)		(0.011)	
Altitude of place of residence [m]	-0.004		-0.005	
	(0.003)		(0.003)	
σ	0.015		0.010	
	(0.152)		(0.173)	
Log likelihood	-811.33		-733.68	
Wald χ^2	116.18***		277.27***	
LR test of independent eq. $\chi^2(1)$	0.01		0.00	
Number of observations	683		683	

Notes: PACE stands for per capita annual consumption expenditure, and AE for adult equivalents. Figures in parentheses show standard errors. ***, **, * Significant at the 0.01, 0.05, and 0.10 level, respectively. Regency dummies are included in the estimation. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

Table A4: Endogenous switching regression estimates without land and labour variables

	Selection equation	Log of PACE [‘000 IDR/AE]	
		Non-adopters	Adopters
	(1)	(2)	(3)
Ethnicity: Melayu [dummy]	0.060	-0.048	-0.085
	(0.168)	(0.075)	(0.089)
Migrant [dummy]	0.741***	0.071	0.017
	(0.237)	(0.112)	(0.140)
Years since migration [year]	-0.026***	0.001	0.002
	(0.009)	(0.004)	(0.005)
Distance to the market [km]	-0.014*	-0.004	-0.009*
	(0.008)	(0.004)	(0.005)
Group membership [dummy]	0.494***	0.081	0.156**
	(0.135)	(0.070)	(0.078)
Average age of adult members	-0.003	0.007**	3.E-04
[year]	(0.008)	(0.003)	(0.004)
Average education of adult	0.017	0.058***	0.002
members [year of schooling]	(0.023)	(0.010)	(0.012)
Share of female adult members [0-	-0.637	-0.048	-0.362
1]	(0.434)	(0.162)	(0.263)
Share of titled land [share]	0.182	0.061	0.131*
	(0.134)	(0.057)	(0.078)
Credit taken from formal sources	0.235*	0.022	0.134*
[dummy]	(0.139)	(0.065)	(0.072)
Random village [dummy]	-0.344*	-0.020	0.009
	(0.195)	(0.091)	(0.126)
Transmigrant village [dummy]	0.442***	-0.050	-0.213**
	(0.174)	(0.087)	(0.107)
Years of farming in contract village	0.073***		
	(0.011)		
Altitude of place of residence [m]	-0.004		
	(0.003)		
σ		0.046	-5.E-04
		(0.195)	(0.243)
Log likelihood		-799.23	
Wald χ^2		45.16***	
LR test of independent eq. $\chi^2(1)$		0.05	
Number of observations		683	

Notes: PACE stands for per capita annual consumption expenditure, and AE for adult equivalents. Figures in parentheses are standard errors. ***,**,* Significant at the 0.01, 0.05, and 0.10 level, respectively. Regency dummies are included in the estimation. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).