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

Vijesh V. Krishna, Michael Euler, Hermanto Siregar,
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Abstract

The study examines the heterogeneous livelihood impacts of oil palm expansion among smallholder farmers in Jambi Province, Sumatra. Per-capita annual consumption expenditure (PACE) is chosen as a quantitative measure of livelihood status of farm-households. Its determinants are estimated using standard treatment-effect and endogenous switching regression models. After controlling for self-selection bias, adopters of oil palm are found increasing their PACE significantly in comparison to the counterfactual. On the other hand, most of the non-adopters are better-off without oil palm, presenting a strong case of comparative advantage. Differential consumption impacts of observed variables are evident across adoption and non-adoption regimes. In general, farm-households with higher opportunity cost of family labour benefit disproportionately more with oil palm adoption.

Key words: Adoption, agricultural development, endogenous switching, impact, Indonesia, farmer welfare.

JEL codes: O12, O33, Q12, P36, R14.

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1. INTRODUCTION

The global oil palm sector has witnessed an accelerated area expansion in 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 has grown by 39% between 2004 and 2013, while the corresponding growth rate for all other oil yielding crops together was only 18% (FAOSTAT, 2014). However, about 80% of the global oil palm cultivation is located in only three tropical countries – Indonesia, Malaysia and Nigeria. A combination of rapid growth in product demand and such highly localized production has led to significant land-use changes in the producing countries, and affected both the environment and human welfare. While the environmental externalities associated with oil palm expansion have been widely examined in the literature (Abood et al., 2014; 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 has increased from 2 million hectares to 7 million hectares between 2000 and 2013 (FAOSTAT, 2014). Here, most of the publicized effects of oil palm expansion on human welfare are associated with social conflicts over land, marginalization of the rural poor, and negative impacts on local communities (Overbeek et al., 2012; Anonymous, 2008). However, a closer look shows that these effects are rooted in institutional rather than crop-specific causes. During the 1980s and 1990s, oil palm was promoted by the Indonesian government as a major instrument of integrated rural development in regions that were long occupied by indigenous communities and governed by customary tenure systems (Rist et al., 2010; McCarthy et al., 2009). Legal pluralism in land rights and politico-legal undermining of customary claims to land were the fundamental reasons for many social conflicts in the oil palm frontiers during the 1990s (Cramb and Curry, 2012; Fitzpatrick, 1997). These well-publicized negative effects overshadow the possible livelihood benefits of oil palm adoption among smallholder farmers, who are increasingly adopting the crop and are expected to dominate overall production in the near future in Indonesia.

A systematic analysis of the livelihood impacts of oil palm in Indonesia is called for, as the expansion process may not be inclusive and impacts not homogeneous across the smallholder farmers (Cramb and Curry, 2012; McCarthy, 2010). Crop-specific attributes, such as higher capital and lower labour requirements for cultivation and sensitive agronomic management practices, might entail heterogeneous livelihood impacts of oil palm. Since the factor use in oil palm differs drastically from that of more traditional labour-intensive crops, like natural rubber and rice (Euler et al., 2015a; Lee et al., 2014; Feintrenie et al., 2010), those farmers having access to formal credit, possessing large areas of cultivable land with formal titles, and pursuing off-farm activities, are expected not only to adopt the crop faster, but also to realize significantly larger benefits. Further, there could be differential impacts of oil palm across the socio-ethnic groups. Budidarsono et al. (2012), for example, suggested differential effects for oil palm adoption between migrant and resident farmers.

Contrasting the widespread uptake by smallholder farmers, the micro-level determinants of oil palm adoption in Indonesia and its livelihood implications have received only limited attention in the empirical literature, especially pursuing a quantitative methodology. The few studies include Lee et al. (2014) and Budidarsono et al. (2012), which rely on comparisons of mean farm incomes between adopters and non-adopters of oil palm. Nevertheless, such simple mean comparison may offer biased estimates on the impacts because of farmer self-selection and exclusion of confounding factors from the analysis. In order to distinguish between the causal effect of oil palm adoption and the effect of unobserved heterogeneity, a systematic analysis of the livelihood impacts of the recent diffusion of oil palm among oil palm smallholders is needed. Euler et al. (2015b) examine the welfare and nutritional impacts of oil palm while controlling for the potential self-selection bias of adoption. This study goes a step ahead, explicitly addressing the heterogeneity of livelihood impacts that arises due to differential factor endowments of smallholder households.

Estimation of treatment and heterogeneity effects of oil palm adoption in Indonesia forms the primary focus of the paper. We can account for the endogeneity of the adoption decision by estimating a standard treatment-effect model, in which the effect of an endogenously chosen binary treatment (i.e., oil palm adoption) on another endogenous outcome variable (i.e., households' per capita consumption expenditure) is examined, conditional on two sets of independent variables (Greene, 2008). However, treatment-effect model does not capture the possible heterogeneous impacts of oil palm adoption. This drawback is especially relevant if there exists are known factors generating differential impacts across the adoption groups. Considerable variation around the mean effect of oil palm was observed in some previous studies (e.g., Budidarsono et al., 2012). In the present study, an endogenous switching regression (ESR) model is developed and estimated to accommodate the potential heterogeneity of oil palm adoption on farmer livelihoods. A counterfactual analysis is carried out and the expected livelihood outcomes of adoption are compared under the actual and counterfactual cases. For the analysis, we use farm survey data collected from Jambi Province of Sumatra, Indonesia.

The reminder of this paper proceeds as follows. Section 2 briefly describes the history and current status of oil palm cultivation by smallholders and presents the survey data. The analytical methods, highlighting how the impact of oil palm adoption can be estimated within the standard treatment-effect and ESR frameworks, are included in Section 3. Section 4 presents and discusses the empirical findings. The last section concludes and suggests policy implications and directions for future research.

2. CONTEXT AND DATA

2.1 Background

Oil palm was perceived as a vehicle for rural development and smallholder inclusion by the Indonesian government during the 1980s and 1990s (Feintrenie and Levang, 2009).

Smallholder adoption of oil palm started in Sumatra with the 'nucleus estate and smallholder' (NES) schemes, led by the Indonesian government and financially supported by the World Bank (Euler et al., 2015a). Families from densely populated areas of Indonesia (e.g., Java) were supported to migrate to sparsely populated islands (e.g., Sumatra) (Gatto et al., 2015; 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). Once the participating smallholders complete the repayment of the costs for plantation establishment and initial management to the plantation company, they would eventually own the landholding, obtaining formal land titles. One of the major shortcomings of these schemes was the undermining of customary claims to land by state authorities, which caused many social conflicts in the oil palm frontiers during 1990s (Cramb and Curry, 2012; Fitzpatrick, 1997).

With the end of the Suharto era in 1999 and the resulting economic reforms and political decentralization, state interventions in the oil palm sector declined. Even in the absence of direct government support, oil palm expansion among smallholders was reported as the fastest, with annual growth rate around 7%, compared to private companies (4%) and government estates (<1%), during the last decade (ISPOC, 2012). A study by Euler et al. (2015a) shows that oil palm expansion has moved beyond government designed supported schemes and is being driven by independently operating smallholders in Jambi Province of Sumatra. The same study further demonstrates that independent oil palm adoption follows the path of past supported schemes and contract farming arrangements, being fastest in those villages in which formal contracts between smallholders and private sector plantations are in place and access to output markets is secured. Currently, smallholder farmers contribute to 41% of oil palm area and 36% of production in Indonesia (ISPOC, 2012).

2.2 Data

The present study examines the impact of oil palm adoption on the per-capita annual consumption expenditure (PACE) of smallholder farmers in Jambi Province of Sumatra, Indonesia. Over the past few decades, tropical lowland rainforest areas in Jambi have experienced a dramatic change in land-use. While forestland largely disappeared and agroforestry systems significantly downsized, rubber and oil palm monocultures rapidly expanded (Krishna et al., 2014). The transmigration program by the Indonesian government was instrumental for the start and initial spread of oil palm in the province during 1980s and 1990s, from where it has been spreading to autochthonous villages (Euler et al., 2015a; Gatto et al., 2015). Based on the recent estimates, oil palm is second only to natural rubber with respect to the number of cultivating households. By 2012, about 187 thousand farm-households were cultivating oil palm in the Province (DPPJ, 2012).

Primary data were collected during the second-half of 2012 through a farm household survey among 683 smallholder farmers. 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. In a first step, five regencies, which comprise most of the lowland transformation systems in Jambi province, were selected purposively. These regencies are Sarolangun, Bungo, Tebo, Batanghari and Muaro Jambi, and represent the main share of smallholder oil palm producers and area share under oil palm in the province (Badan Pusat Statistik, 2012). In order to capture geographical disparity and regional diversity, a stratified random sampling approach was followed, fixing the number of districts per regency and the number of villages per district *a priori*. A total of forty villages – two rural villages per district and four districts per regency – were selected randomly. In addition, five villages near to the Bukit Duableas National Park and the Harapan Rainforest, where supporting research activities were carried out, were purposively selected.

A complete list of households was prepared from each of the selected villages. We found a significant diversity with respect to village population size – ranging from about 100 to more than 2000 households residing in a single village. Sampling a constant number of households per village was expected to under-represent households residing in larger and over-represent households residing in smaller villages. To reduce this bias, we divided randomly selected villages into four quarters based on population size. About 6 households were selected from each of the 10 villages in the lowest size quartile, 12 per village from the second quartile, 18 per village from the third, and 24 per village from the largest village size quartile, resulting in a total sample of 600 households. One-third of these households are found cultivating oil palm. From each of the five purposively selected villages, about 17 households were selected for the survey, generating a sample size of 683 households. Details of sampling, alongside a list of sample villages and number of sample households per village are available in Faust et al (2013; pp. 16-19). Information on crops and livestock managed by the households in 2012, socio-demographic characteristics, details of off-farm income, asset status, and consumption expenditure on food and non-food items were elicited in the survey. We further draw on information gathered through village surveys that were carried out by a different team of researchers but in close coordination with the household survey (Gatto et al., 2015).

2.3 Descriptive statistics

Table 1 presents the differences in land, labour and capital use, alongside the average productivity of these factors in monetary terms for 2012, between oil palm and rubber, the major land use alternative. In both younger (6-15 years) and older (16-25 years) plantations, significant inter-crop differences are observed with respect to labour and capital use. Notably, the annual labour use in oil palm plantations is only about 25% of the level of labour input in rubber plantations. In contrast, the average capital input in oil palm plantations is around 8-times higher compared to rubber in younger plantations, while for older plantations it is 11-times higher. Whereas the average plot sizes and gross margins per hectare are comparable between the crops, returns to labour are much higher (42 to 65 thousand Indonesian rupiah or IDR per hour) for oil palm than for rubber (13 to 16 thousand IDR per hour). There is also a significant difference with respect to capital productivity. One IDR spent on productive oil palm returns 3 to 4 IDR as gross margin per year. Since rubber cultivation is less capital-intensive, the return to working capital is much higher (14 to 38 IDR per year). These contrasting factor productivities are likely to be the key drivers of oil palm adoption, and potential sources of impact heterogeneity of oil palm adoption among smallholders. In other words, households with easy access to working capital (e.g., having possession of formal land titles that facilitates access to formal credit) but having severe labour constraints (e.g., involved in an off-farm activity) are expected not only to adopt oil palm faster, but also to benefit more from its adoption.

Table 2 presents mean values and standard deviations for our dependent variable, household consumption expenditure per adult equivalent (PACE) along with a set of key variables. Values are shown for the full sample, as well as for the sub-groups of oil palm adopters and non-adopters. The description of these variables is given in Appendix I.

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 the 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***
Paid-out cost [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***
Paid-out cost [000 IDR/ha]	208.00	2344.00***	37.59	4.08***	4.58***
Number of observations	295	67			

Source: Household survey (2012).

Note: Unit of observation is plantation plots. Due to extreme values (farms with limited use of capital and labour are associated with high factor productivity values), median values are provided and the statistical significance was tested using Kruskal-Wallis equality of populations rank test. ***: difference with rubber is statistically significant at 0.01 level. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

Table 2: Descriptive statistics

Variables (unit)	Full sample [n = 683]	Non-adopters of oil palm [n = 450]	Adopters of oil palm [n = 233]
Dependent variable			
Per capita annual consumption expenditure, PACE [000 IDR/AE]	15,662.99 (710.56)	14,591.73 (1009.67)	17,731.94** (715.80)
Explanatory variables			
Socio-economic attributes of household			
Ethnicity: Melayu [dummy]	0.49	0.55	0.37***
Migrant [dummy]	0.43	0.35	0.58***
Years since migration#	22.70 (0.60)	24.57 (0.92)	20.52*** (0.71)
Distance to the market [km]	6.63 (0.28)	7.09 (0.35)	5.73** (0.49)
Group membership [dummy]	0.24	0.16	0.40***
Cultivated land [ha]	3.83 (0.17)	3.18 (0.18)	5.07*** (0.34)
Number of adults in the household	3.02 (0.05)	3.06 (0.06)	2.95 (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 (0.34)	37.22 (0.41)	37.72 (0.59)
Average education of adult members [years of schooling]	7.84 (0.10)	7.81 (0.13)	7.90 (0.18)
Share of female adult members [0-1]	0.47 (0.01)	0.48 (0.01)	0.47 (0.01)
Titled land [share]	0.45 (0.02)	0.39 (0.02)	0.58*** (0.03)
Titled land in autochthonous villages [share]	0.30 (0.02)	0.27 (0.03)	0.38** (0.05)
Credit taken from formal sources [dummy]	0.24	0.18	0.36***
Years of farming till contract signing	3.16 (0.23)	1.42 (4.09)	6.52*** (7.30)
Altitude of place of residence [m]	54.22 (1.03)	56.00 (1.32)	50.78** (1.59)
Village attributes			
Random villages [dummy]	0.88	0.89	0.85
Transmigrant villages [dummy]	0.37	0.27	0.57***

Notes: n refers to the number of households included in the analysis. Figures in parentheses show std. errors.
Conditional on household being migrant.
***, **, *: Difference from non-adopter group is statistically significant at 0.01, 0.05 and 0.10 levels respectively.
1 US$ = 9,387 IDR in 2012 (World Bank, 2015).

We have selected consumption expenditure to represent household livelihood due to three major of reasons. First, it is usually a more reliable measure than income in developing countries, as the variable is less influenced by measurement errors (Deaton, 1997). Second, consumption data show less volatility, are less vulnerable to idiosyncratic shocks and their distribution in the population is less skewed than other measures of welfare (Molini and Wan, 2008). Third, consumption often represents finer concepts of living standard, like nutrient intake, as is in the present study (cf. Appendix II, which shows a positive correlation between PACE and micronutrient intake by the household). In the literature, there are a number of examples where changes in consumption expenditure were used to measure rural livelihood impacts (e.g., Duflo et al., 2013; Kathage and Qaim, 2012).

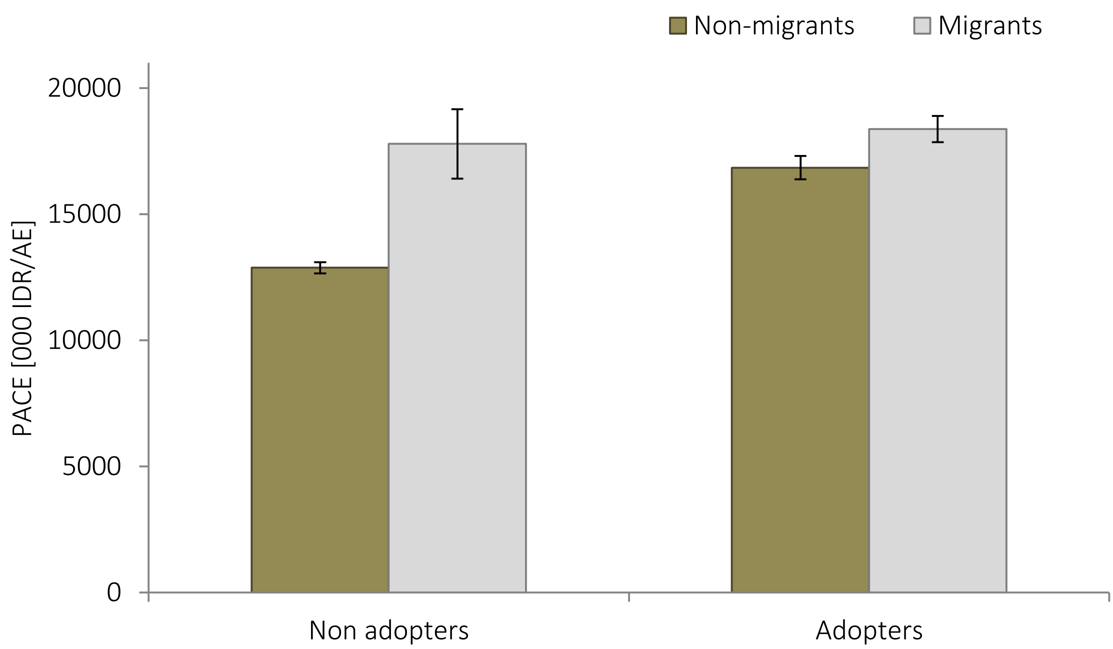
According to descriptive statistics, the mean PACE was about 15.7 million IDR (approx. USD 1668) among all sample households. PACE of adopters is found 21.5% higher than for non-adopters in the study area. However, there could be many confounding factors other than adoption status that influence PACE. In particular, we expect socio-cultural household characteristics and factor scarcity to determine PACE levels. With respect to socio-cultural characteristics, we find adopters of oil palm to have migrated to the current place of residence more often and to commonly have a non-Melayu background; Melayu is the most prominent autochthonous ethnicity in Jambi province. In contrast to earlier migrants, recent migrants are widely adopting oil palm.[2] Non-adopters live in more remote villages and their participation in group activities is minimal. With respect to factor endowments, we find that the farms managed by adopters are 59% larger than those of non-adopters. However, there is no significant difference between groups in labour availability, represented by the total number of adult members in the household. We do not find significant difference also with respect to the average age and education status of adult members. Adopters are found to be more actively involved in entrepreneur activities (e.g., trading), while non-adopters are hiring-out labour more often. Further, there are significant differences with respect to utilization of formal credit and holding of formal land titles between adopters and non-adopters, which imply the crucial role of capital availability for oil palm adoption.[3] Unsurprisingly, households residing in villages associated with transmigrant programme are found cultivating the crop more frequently. Oil palm adoption is prevalent in the lower altitude regencies (e.g., Muaro Jambi) than in the relatively higher altitude regencies (e.g., Tebo), and hence a negative association of altitude and oil palm adoption was observed.

[2] The migrants generally adopt the crop that is prevalent in the village to where they migrated. Before 1990s, rural migration was mainly to the rubber-dominant autochthonous villages. After 1990, many transmigrant villages with oil palm were established in the province, which attracted a large share of migrants.

[3] Farmer participation in transmigrant programs for oil palm adoption is often associated with government provision of land titles in Indonesia (McCarthy and Cramb, 2009). Oil palm transmigrants would be mostly with land titles, questioning whether the association between oil palm adoption and possession of land titles is spurious. Further examination, however, reveals that even independent adopters from autochthonous villages tend to have land titles more frequently than the non-adopters.

The effect of variables presented in Table 2 on outcome variable might not be homogeneous across the group of adopters. One example in which a variable has heterogeneous impacts on PACE is the migration background of the household (as illustrated in Figure 1). Accordingly, the difference in PACE across adoption groups is only significant for non-migrants (+30.8% for adopters, compared to non-adopters) but not for migrants. That is, while among non-adopters, migration has a significant positive effect on PACE, this difference vanishes in case of adopters – both migrant and non-migrant adopters are found to have comparable PACE. There could be a multitude of similar factors that generate differential impacts across adoption groups and a single mean function would be less meaningful. An extensive analysis of these factors is necessary for which regression models need to be employed, which take care of potential self-selection bias related to the adoption decision. The empirical framework to carry out the impact estimation is detailed in the next section.

Figure 1: Illustration of differential impacts of oil palm with respect to migration status



Note: PACE stands for per capita consumption expenditure and AE for adult equivalent. Error bars denote standard errors. 1 US$ = 9,387 IDR in 2012 (World Bank, 2015).

3. ANALYTICAL FRAMEWORK

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 household characteristics $(\boldsymbol{z}_i)$, including those defining access to factors of production. The adoption decision can be formulated as a binary choice model. The simplest approach to examine the impact of oil palm adoption on PACE would be to include a dummy variable that indicates whether a household has adopted oil palm (A_i) in the set of explanatory variables, and estimate its marginal effect using ordinary least squares (OLS). This method, however, might lead to biased estimates as it assumes that adoption is exogenously determined, while the decision to adopt or not is voluntary. Unobservable farm and household characteristics could affect both the adoption decision and PACE simultaneously, resulting in selection bias and inconsistent estimates for the oil palm adoption. In the current paper, we rely on a set of standard treatment-effect models to estimate the mean impacts and endogenous switching regression to estimate the heterogeneous impacts of oil palm adoption on PACE.

3.1 Estimating the mean impact of oil palm adoption

Treatment-effect framework employs a linear model for the outcome variable and a constrained normal distribution to estimate the deviation from the conditional independence assumption (Cameron and Trivedi, 2005; Guo and Fraser, 2014). The endogenous treatment-effect model is composed of an equation for the consumption expenditure ($PACE_i$) and an equation for the adoption decision (A_i). In the first stage, a selection model is used, which includes a binary function modelling cultivation of oil palm. The observed realization A_i of the dichotomous latent variable A_i^* captures the expected benefits from oil palm adoption, and has the following form:

Selection equation: $A_i^* = \boldsymbol{z}_i\alpha + \eta_i \quad \text{with } A_i = \begin{cases} 1 \ if\ A_i^* > 0 \\ 0\ otherwise \end{cases}$ ... (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 covariates used to model A_i and $PACE_i$ respectively, and include farm-household and village characteristics, α and β are parameter vectors, 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-effect 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 $PACE_i$. Thus, the instrumental variables only determine the adoption decision, but not the outcome variable. In this study, we use the altitude of the household residence (meters above the mean sea level), and the number of years a household was engaged in farming while a village level contract was signed (0 for farmers from villages with no contract), as the instruments. We verify admissibility of these instruments by performing a simple falsification test, following Di Falco et al. (2011).

There are a number of studies that have used standard treatment-effect models to model the impacts of adoption (e.g., Chang et al., 2008; Chen et al., 2005). The major limitation of these models is the underlying assumption that the impact of adoption variable is homogeneous and can be represented as a simple intercept shift on the outcome variable. On the contrary, many of the farm-household conditions systematically could influence the intervention, as shown in Figure 1, leading to heterogeneous impacts.

3.2 Estimating the heterogeneous impacts of oil palm adoption

The heterogeneity in consumption impacts of oil palm can be accounted for through an ESR framework, which consists of two stages. Similar to the standard treatment-effect model, the first stage is a selection equation, based on a dichotomous choice selection function, as already shown in equation (1a). In the second stage, two regime equations are specified explaining the outcome of interest, 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 in 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 the selection equation (eq. 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 the outcome functions (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} are not defined (Maddala, 1983). 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 output functions (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 & Bosch, 1995). If the estimated covariance of $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to adopt and the PACE are correlated, providing evidence for endogenous switching. In the ESR model, oil palm adoption is treated as a regime shifter. The model accounts for observed systematic differences between farmers in the two adoption regimes. When there are unobserved factors that matter, there will be a correlation between the error terms of the regime equations (2a and 2b) and the selection equation. 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 & Sajaia, 2004).

An efficient method to estimate ESR models is full information maximum likelihood.[4] Similar to the treatment-effect model, for the ESR model to be correctly specified, $\boldsymbol{z}$ should contain at least one instrumental variable in addition to $\boldsymbol{x}$ that is correlated with oil palm adoption, but uncorrelated directly with PACE.

There exist a number of studies that captured the heterogeneous impact of technology adoption in agriculture using ESR models. Some of the examples are Abdulai and Huffman (2014), Noltze et al (2013), Di Falco et al (2011), Rao and Qaim (2011), and Alene and Manyong (2007). In the present study, the ESR model can be used to compare the expected PACE of oil palm adopters to non-adopters, and to investigate the expected consumption expenditure in the counterfactual hypothetical cases that adopter households had not adopted, and that non-adopter households had adopted oil palm. The conditional expectations in the four cases are defined as follows:

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

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

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

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

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

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

This equation returns the effect of oil palm adoption on PACE for those households that actually adopted oil palm, while controlling for all other possible causes of income differences. The procedure implies that the unobserved factors have different effects

[4] The alternative two-step procedure, in which IMR values are included in equations (2a) and (2b) to correct for selection bias (Wooldridge, 2002). This procedure often results in heteroskedastic residuals that cannot be used to derive consistent standard errors (Maddala, 1983), and it performs poorly in cases of high multicollinearity between the covariates in the selection equation (1a) and that in the PACE equations i.e., equation (2a) and (2b) (Lokshin & Sajaia, 2004; Hartman, 1991).

depending on which regime applies. By holding λ_{1i} constant and taking the differences in effects $(\sigma_{1\eta} - \sigma_{2\eta})$, we eliminate the effects of unobserved factors, and the estimated income difference would be purely due to oil palm adoption. The ATT is due to the 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, 1983). If that is the case, simple comparison of mean income of farmers in the two adoption profiles (a) and (b) would lead to an upward bias of the treatment-effect, which is controlled for in equation (5).

Similarly, we calculate the average treatment-effect on the untreated (ATU) for the households that actually 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 outcome described in equations (4a)-(4d) to calculate the heterogeneity effects. Following Carter and Milon (2005) and Di Falco et al (2011), the difference between (4a) and (4d) can be indicated as the 'base heterogeneity' (BH) effect for adopters and the difference between (4c) and (4d) for non-adopters.

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

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

4. ESTIMATION RESULTS AND DISCUSSION

4.1 Mean consumption impacts of oil palm

The estimates of mean impact of oil palm adoption on the natural logarithm of PACE are presented in Table 3. The log-transformation is carried out to obtain a more symmetric distribution for PACE as there is substantial skewness for the variable. The transformation also helps improve the interpretability of coefficients. The first two columns show OLS estimates for a set of household and farm characteristics with a dummy variable representing oil palm adoption. In the treatment-effect framework, outcome equations are estimated jointly with selection functions. The selection functions are provided in the third and fifth columns of the table. The falsification test as suggested by Di Falco et al. (2011) proved the validity of the instrumental variables included: statistically significant in the adoption model, while not in the outcome model among non-adopters (Appendix III). Model specifications are altered either by excluding or including variables representing opportunity cost of family labour, viz. farm size, number of adults in the household and dummy variables representing off-farm income generation activities. However, irrespective of the presence of these variables, the correlation of error terms (σ) is not statistically different from zero in the standard treatment-effect model. Although we could not have known it *a priori*, this implies that the null hypothesis of absence of farmer self-selection bias cannot be rejected. Further, the magnitude of the impact of oil palm adoption is comparable between OLS and treatment-effect models. Hence, to delineate the mean effect of oil palm adoption, the OLS estimates are resorted.

In the OLS models, the percentage effect of the oil palm adoption dummy on PACE is obtained following the transformation suggested by Halvorsen and Palmquist (1980).[5] The OLS model (column 1), which is estimated without the factor endowment variables, shows that oil palm adoption increases PACE by 20.8%. This is very close to what the descriptive statistics showed earlier (Table 2). However, once the variables that stand proxy for family labour scarcity are included in the model estimation, the effect of oil palm adoption drops to +7.5% (column 2). The level of statistical significance also diminishes. The reduction in the magnitude of the impact is highly relevant as it presents clear evidence for the possible pathways through which oil palm increases farmer welfare: farm size expansion and diversification of income sources. As seen already, the two competing perennial crops of Jambi, rubber and oil palm, provide financial outlays of comparable magnitude from a given unit of land. However, since rubber is highly labour intensive, and in scenarios where human labour is the most limiting factor of production, households cannot expand their farm income resorting only to rubber. Due to the low labour requirement, oil palm is preferred by farmers and the surplus labour could be used for farm expansion and income diversification.

With respect to additional covariates, we find consistent and positive impacts on PACE for household participation in group activities (+12.3%), area of cultivated land (+0.2% for 1% increase in farm size), average education level of household adults (+2.7% for additional year of schooling), and involvement in business activities (+28.7% for participants). The possession of formal land titles is found to increase PACE by 8.2%, possibly by increasing the household access to formal credit markets that require hypothecation of collateral. [6] On the other hand, the number of adults in the household is found to have a strong negative impact (-7.8% with additional adult equivalent), possibly because of shared consumption and the associated reduction in consumption expenditure.

[5] Halvorsen and Palmquist (1980) showed that when a dummy variable enters a semi-logarithmic equation as explanatory variable, as in our outcome equations, its coefficient measures the discontinuous effect on the outcome variable of the factor represented by the dummy variable. The percentage effect can be obtained only by transforming the coefficient, as $100.\{\exp(coef) - 1\}$, and this will be indicated as 'Halvorsen-Palmquist transformation' in the rest of the paper.

[6] The percentage effects for group participation, involvement in business enterprises and participation in the formal credit markets are calculated using Halvorsen-Palmquist transformation.

Table 3. Mean impact of oil palm on PACE: Ordinary least squares and standard treatment-effect model estimates

	Ordinary least squares on PACE [000 IDR/AE]		Standard treatment effect models			
	Model 1	Model 2	Model 1		Model 2	
			Selection eq.	*ln*PACE [000 IDR/AE] eq.	Selection eq.	*ln*PACE [000 IDR/AE] eq.
	(1)	(2)	(3)	(4)	(5)	(6)
Oil palm adoption [dummy]	0.189***	0.072*		0.177		0.065
	(0.045)	(0.044)		(0.124)		(0.130)
Ethnicity: Malayu [dummy]	-0.065	-0.005	0.059	-0.064	0.131	-0.005
	(0.058)	(0.054)	(0.168)	(0.058)	(0.176)	(0.055)
Migrant [dummy]	0.022	0.082	0.742***	0.025	0.878***	0.084
	(0.083)	(0.078)	(0.237)	(0.088)	(0.247)	(0.084)
Years since migration [year]	0.001	-3.E-04	-0.026***	0.001	-0.033***	-4.E-04
	(0.003)	(3.E-03)	(0.009)	(0.003)	(0.009)	(3.E-03)
Distance to the market [km]	-0.005*	-0.005*	-0.014*	-0.005*	-0.013	-0.005*
	(0.003)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)
Group membership [dummy]	0.105**	0.116***	0.496***	0.107**	0.504***	0.117**
	(0.048)	(0.045)	(0.134)	(0.053)	(0.139)	(0.049)
Log of cultivated land [ha]		0.169***			0.410***	0.170***
		(0.020)			(0.070)	(0.025)
Number of adults in the household		-0.078***			-0.053	-0.079***
		(0.015)			(0.050)	(0.015)
Employed or hiring out labour [dummy]		0.036			0.098	0.036
		(0.039)			(0.128)	(0.038)
Own business [dummy]		0.252***			0.156	0.252***
		(0.045)			(0.146)	(0.045)
Average age of adult members[years]	0.005**	0.001	-0.003	0.005**	-0.010	0.001
	(0.002)	(0.002)	(0.008)	(0.002)	(0.008)	(0.002)
Average education of adult members [years of schooling]	0.040***	0.027***	0.017	0.040***	-0.012	0.027***
	(0.008)	(0.007)	(0.023)	(0.008)	(0.024)	(0.007)
Share of female adult members [0-1]	-0.127	-0.125	-0.626	-0.128	-0.483	-0.125
	(0.139)	(0.130)	(0.429)	(0.138)	(0.452)	(0.128)
Titled land [share]	0.085*	0.079*	0.182	0.085	0.132	0.079*
	(0.046)	(0.043)	(0.134)	(0.046)	(0.140)	(0.042)
Credit taken from formal sources [dummy]	0.066	0.012	0.234*	0.068	0.162	0.012
	(0.048)	(0.045)	(0.138)	(0.049)	(0.143)	(0.045)
Random villages [dummy]	-0.009	0.055	-0.343*	-0.012	-0.225	0.053
	(0.069)	(0.065)	(0.195)	(0.073)	(0.201)	(0.066)
Transmigrant villages [dummy]	-0.110*	-0.062	0.442***	-0.107	0.612***	-0.060
	(0.060)	(0.056)	(0.174)	(0.065)	(0.181)	(0.064)
Years of farming till contract signing			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)	
Adj. R^2	0.14	0.27				
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	

Notes: PACE stands for per capita consumption expenditure and AE for adult equivalent. Dependent variable in OLS and output equation of treatment effect models are log transformed. Figures in parentheses show std. errors. ***, **, *: Statistically significant at 0.01, 0.05 and 0.10 levels respectively. Regency dummies are included in the estimation.
1 US$ = 9,387 IDR in 2012 (World Bank, 2015).

4.2 Heterogeneous impacts of oil palm

We now turn to the heterogeneous implications of oil palm adoption. Results of endogenous switching regression models, which are estimated by full information maximum likelihood and differentiating between oil palm adopters and non-adopters, are shown in Table 4. The first column presents the selection equation, while the second and third columns show the outcome equations (log of PACE) for smallholders who did not adopt oil palm and for those who did adopt, respectively. Similar to the standard treatment-effect model, the correlation coefficients of error terms (σ) are not statistically significant, showing that self-selection would not be an issue. The positive sign for σ for adopters indicates a negative selection bias, suggesting that farmers with below-average PACE are more likely to adopt oil palm, which is in contrast to many previous studies employing ESR (Abdulai and Huffman, 2014; Rao and Qaim, 2011; Di Falco et al., 2011) that showed more progressive and productive farmers adopting technical innovations faster. However, the statistical insignificance of the variable, as also in the case of covariance estimate for non-adopters, prevents further inference. However, many observed variables have differential impacts across the ESR models, possibly leading to significant difference in average treatment effect for adopters (ATT) and for non-adopters (ATU).

Migrant status, time of migration, group affiliation, size of cultivated land, transmigrant village dummy and years of farmer involvement in farming at the time of enactment of village-level contracts with oil palm company are found statistically significant in the selection equation. Across the two outcome equations (regimes), there are structural differences that illustrate the presence of heterogeneity in the sample (cf. Table 4; columns 2 and 3). For instance, the negative PACE impact of distance to market variable and the positive impact of group participation are stronger in case of adopters than non-adopters. The PACE increase associated farm size expansion is also larger for adopters. Education has no effect on PACE of adopters, but it is strong and positive among non-adopters. Negative impact of share of female adults and positive impact of land titles are present only in case of adopters. Although the differences in many coefficients are marginal across the regimes, they could lead to a strong aggregate effect. The estimation of mean effects through OLS or standard treatment-effect models would not have facilitated a clear understanding of potential structural differences between the PACE function of adopters and that of non-adopters.

Table 4. Heterogeneous impacts of oil palm on PACE: Endogenous switching regression estimates

	Selection eq.	*ln*PACE [000 IDR/AE] eq.	
		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 [dummy]	0.096	0.009	0.081
	(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 [year of schooling]	-0.012	0.045***	-0.010
	(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)
Titled land [share]	0.133	0.052	0.131*
	(0.140)	(0.053)	(0.075)
Credit taken from formal sources [dummy]	0.160	-0.044	0.107
	(0.144)	(0.061)	(0.068)
Random villages [dummy]	-0.219	0.050	0.087
	(0.202)	(0.083)	(0.121)
Transmigrant villages [dummy]	0.612***	0.013	-0.138
	(0.181)	(0.083)	(0.135)
Years of farming till contract signing	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	

Notes: # PACE stands for per capita consumption expenditure (000 IDR per adult equivalent). Figures in parentheses are std. errors. ***, **, *: Statistically significant at 0.01, 0.05 and 0.10 levels respectively. Regency dummies are included in the estimation. 1 US$ = 9,387 IDR in 2012 (World Bank, 2015).

Table 5 presents the expected consumption expenditure per adult equivalent under actual and counterfactual conditions. The expected PACE by adopters is about 16.2 million IDR, while it is about 12.4 million IDR for non-adopters. This comparison, nevertheless, could be misleading and prompt the researcher to conclude that on an average, adopters spend 3.8 million IDR (+30.0%) more than non-adopters. However, a comparison with the counterfactual case denotes that adopters spend only about 1.4 million IDR more than what they would spend had they not adopted oil palm, indicating that the actual ATT would be +9.2%. On the other hand, non-adopters would have spent about 0.9 million IDR less (ATU; -6.9%) had they adopted oil palm. Further, there is evidence for strong heterogeneity effects, as shown in the last row of Table 5. Oil palm adoption generates significant gains in PACE among adopters compared to non-adopter counterfactual. An examination of density function of ATT (Figure 2) shows that 26.9% adopters would have better-off by non-adoption (that is, negative ATT), while 34.4% non-adopters would have benefitted with oil palm (positive ATU). These results imply that the impact of oil palm adoption might not be universally positive across different groups of smallholders in Jambi.

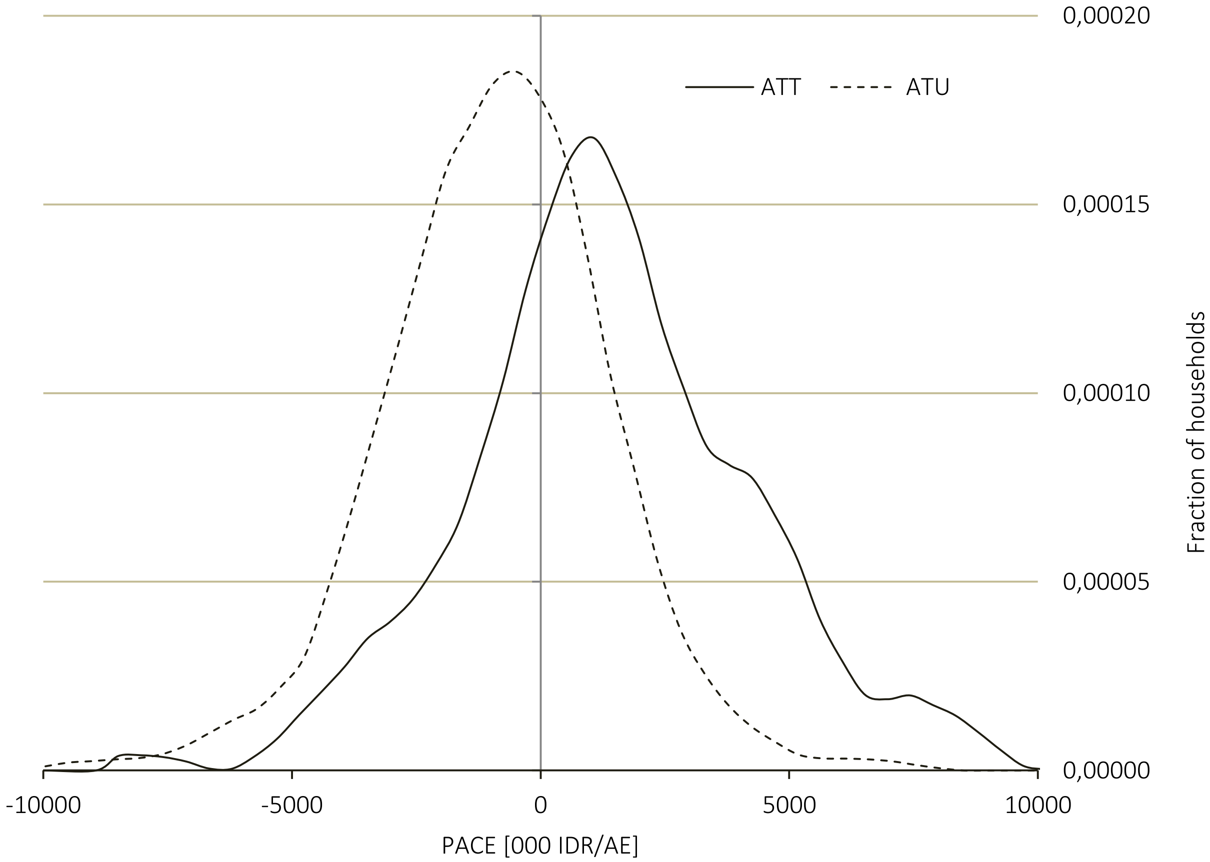
The differential impact of oil palm adoption could not only be present between the group of adopters and non-adopters, but also within the group of adopters, depending on the relative factor endowment. Differences in ATT with respect to input constraints are demonstrated by Kabunga et al. (2012), with respect to poverty status and landholding by Rao and Qaim (2011), and with respect to farm size and education status by Asfaw et al. (2012). In the current study, the ATT is consistently positive and ATU negative across the quartiles of landholdings per adult equivalent, and the magnitude of effect is found more or less uniform (Table 6). An examination of ATT values with respect to household's involvement in business activities indicates that the magnitude of ATU is pronounced among those possess a family business. No significant variation was observed for ATT.

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

Subsamples	Estimated PACE [000 IDR/AE]		Average treatment effect	
	Adoption	Non-adoption	Value [000 IDR/AE]	% over non-adoption
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	4626.3***	2418.99***		
	(283.49)	(253.40)		

Note: Estimated from Table 4. PACE stands for per-capita consumption expenditure, AE for adult equivalent, ATT for average treatment effect for the treated, and ATU for average treatment effect for the untreated. Figures in parentheses are standard errors. ***: Statistically significant at 0.01 level. 1 US$ = 9387 IDR in 2012 (World Bank, 2015).

Figure 2: Density functions of ATT and ATU



Notes: Estimated from Table 4. Functions are estimated non-parametrically using Epanechnikov kernel. PACE stands for per-capita consumption expenditure, AE for adult equivalent, ATT for average treatment effect for the treated, and ATU for average treatment effect for the untreated.

Table 6: Differential ATT and ATU with respect to cultivated land-person ratio and household's involvement in business activities

	Number of		ATT		ATU	
	Adopters	Non-adopters	Value [000 IDR/AE]	% over non-adoption	Value [000 IDR/AE]	% over non-adoption
Cultivated land per adult [ha] quartiles						
Lowest 25% [≤ 0.5]	32	168	756.65	6.8	-644.02	-6.2
			(345.70)		(151.95)	
Q2 [0.51-1.00]	77	136	1327.93	10.0	-946.93	-7.8
			(261.15)		(172.30)	
Q3 [1.01-1.67]	43	71	1284.11	8.7	-834.41	-6.1
			(435.95)		(317.93)	
Highest 25% [>1.67]	81	75	1659.26	9.4	-1154.87	-7.2
			(414.95)		(368.60)	
Involvement in business						
Not involved	177	367	1314.99	9.6	-695.18	-5.9
			(204.86)		(115.54)	
Involved	56	83	1487.99	8.1	-1538.63###	-10.1
			(472.35)		(302.64)	

Note: Estimated from Table 4. Figures in parentheses are std. errors. ATT stands for average treatment effect for the treated and ATU for average treatment effect for the untreated. ###: Difference from the previous category value is significant at 0.01 level. 1 US$ = 9,387 IDR in 2012 (World Bank, 2015).

5. CONCLUSION

The expansion of oil palm and associated changes in factor markets potentially has significant social and livelihood implications in rural Indonesia. The associated land transformations have given rise to a number of socioeconomic concerns, including whether the crop can contribute to sustainable rural livelihoods, while ensuring social equality (Cramb and Curry, 2012; McCarthy, 2010). The financial outlay obtained from unit area under oil palm is found to be similar to that of its competing crop, rubber, and the mean consumption functions show an insignificant impact of oil palm adoption. Nevertheless, a stratum of households – namely those with easy access to working capital and high opportunity cost of family labour – are found deriving disproportionately higher benefits from oil palm adoption. This is because oil palm is more capital-intensive and has relatively low labour requirements. We find that smallholders having access to formal credit, possessing larger farms, and engaged in off-farm entrepreneurial activities are expected to benefit more than households with lower access to markets and resources. As observed by Kathage et al. (2015), non-adoption of some technologies could be explained by low potential returns and not due to lack of awareness of the farmers. Due to the comparative disadvantage of adoption, public awareness campaigns to promote oil palm would be imprudent in many parts of Jambi.

Based on these results, we identify two crucial aspects of smallholder agriculture that require greater research focus. First is with regard to the co-evolution of factor markets and associated institutions related to oil palm diffusion. The study suggests a close association of factor market endowments with the smallholder land-use. Labour scarcity and rising labour costs increase the attractiveness of cultivating oil palm, while efficient labour markets, ensuring labour availabiliy throughout the year might facilitate rubber cultivation. Sharecropping is found commonly practiced among rubber farmers in Jambi as an institutional arrangement to address labour scarcity. Since farmers' participation in sharecropping arrangements as well as oil palm adoption are potentially influenced by the possession of land titles, these micro-level institutions might also contribute to oil palm adoption and its heterogeneous impacts among the rural households. However, there is not much empirical evidence on the exact impact pathways, which may be possible to identify only with panel datasets and dynamic models.

Second, spillover effects of oil palm adoption on non-farming households warrant greater research focus. We found that the prevalence and impact of oil palm depends largely on labour availability in the location concerned, suggesting that oil palm adoption could have significant livelihood effects for non-farm households, especially through labour markets. Farmers switching to oil palm have reduced employment opportunities for agricultural labourers and thereby might have increased the wage income variability of these households. If this holds true, oil palm diffusion could have a negative social effect. However, the magnitude of the livelihood impact of oil palm adoption on labour households depends on a number of factors, including the prevalence of sharecropping arrangements in the locality, the patterns of hiring labour, existing wage rate etc. There is only limited evidence for spillover effects of land-use changes in developing countries, and to the best of our knowledge, the concrete impacts of oil palm adoption on labour-providing households are hardly examined.

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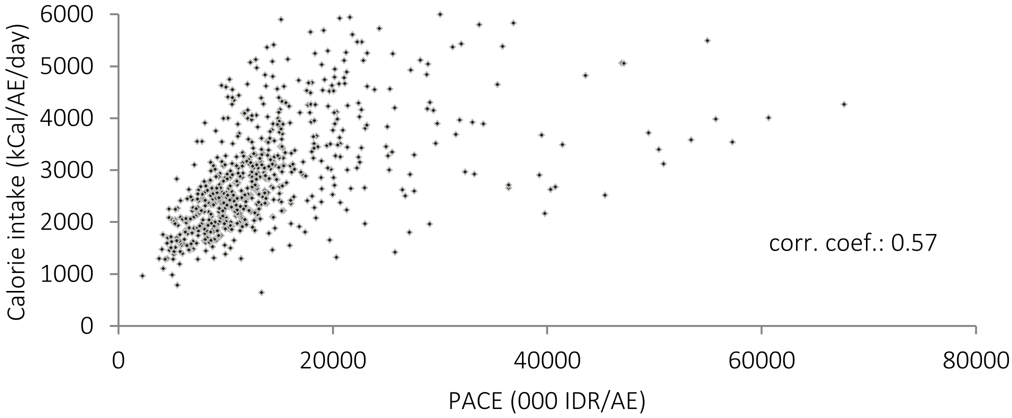
Appendix I: Description of variables

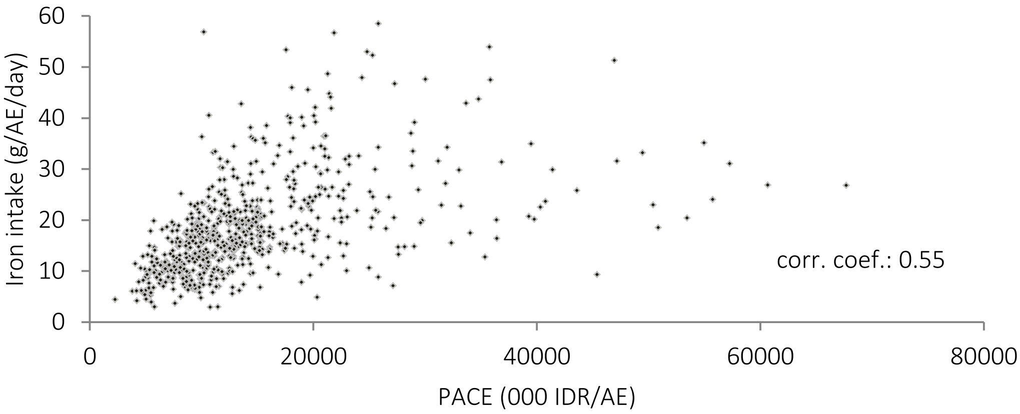
Variables	Description [unit of measurement]
PACE	Per-capita annual consumption expenditure of the household [thousand IDR per AE or adult equivalent]
Oil palm adoption	1 if household adopted oil palm; 0 otherwise [dummy]
Ethnicity: Melayu	1 if household belongs to Melayu ethnicity; 0 otherwise [dummy]
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]
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 villages	1 if the household is from a randomly selected village; 0 otherwise [dummy]
Transmigrant villages	1 if the household is from a transmigrant village; 0 otherwise [dummy]
Years of farming till contract signing	Duration [number of years] for which a particular household was involved in farming before the village level contract was enacted; 0 for farmers residing in villages with no contract and farmers migrated after enacting contract.
Altitude of place of residence	Altitude [meters above the mean sea level] of place of residence

Appendix II. Correlation between per capita annual consumption expenditure and nutrient intake

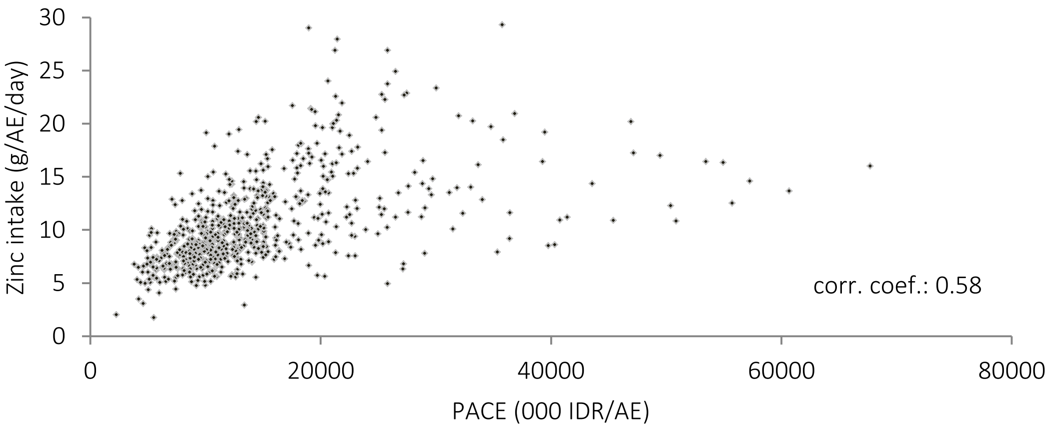
(a) Calorie



(b) Iron



(c) Zinc



PACE stands for per-capita consumption expenditure, AE for adult equivalent.
Source: Household survey (2012).

Appendix III: Verification of instrumental variables

	Dependent variable	
	Oil palm adoption [dummy, OLS]	PACE among non-adopters [000 IDR/AE, OLS]
Difference in starting of farm and village contract [years]	0.032***	-215.378
	(0.003)	(247.772)
Altitude of place of residence [m]	-0.002***	-17.539
	(6.E-04)	(36.161)
Model intercept	0.324***	15879.850***
	(0.038)	(2303.857)
Adj. R^2	0.17	0.00

Note: Figures in parentheses show standard errors. ***: Statistically significant at 0.01 level. PACE stands for per-capita consumption expenditure, AE for adult equivalent, OLS for ordinary least squares.
1 US$ = 9387 IDR in 2012 (World Bank, 2015).