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ORIGINAL ARTICLE

Oil palm and structural transformation of agriculture in Indonesia

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Abstract

Structural transformation of agriculture typically involves a gradual increase of mean farm sizes and a reallocation of labor from agriculture to other sectors. Such structural transformation is often fostered through innovations in agriculture and newly emerging opportunities in manufacturing and services. Here, we use panel data from farm households in Indonesia to test and support the hypothesis that the recent oil palm boom contributes to structural transformation. Oil palm is capital-intensive but requires much less labor per hectare than traditional crops. Farmers who adopted oil palm increase their cropping area, meaning that some of the labor saved per hectare is used for expanding the farm. Average farm sizes increased in recent years. In addition, we observe a positive association between oil palm adoption and off-farm income, suggesting that some of the labor saved per hectare is also reallocated to non-agricultural activities. Oil palm adoption significantly increases the likelihood of households pursuing own non-farm businesses. However, oil palm adoption does not increase the likelihood of being employed in manufacturing or services, which is probably due to the limited non-farm labor demand in the local setting. Equitable and sustainable agricultural transformation requires new lucrative non-agricultural employment opportunities in rural areas.

KEYWORDS
farm size, off-farm employment, oil palm, rural development, structural transformation

JEL CLASSIFICATION
O13, O14, Q12, Q15, R14

1 | INTRODUCTION

The structural transformation of agriculture, or of economies more broadly, typically involves productivity growth in farming, an increase in mean farm sizes, and a gradual shift of agricultural labor to other sectors, including manufacturing and services (Bokusheva & Kimura, 2016; Jayne et al., 2016). During this structural transformation process, the share of labor working in agriculture and agriculture's relative contribution to the total economy decline, whereas the shares of the manufacturing and service industries increase (Duarte & Restuccia, 2010; Herrendorf et al., 2014). Productivity-enhancing and labor-saving innovations in agriculture are often important factors contributing to structural transformation (Alvarez-Cuadrado & Poschke, 2011; Bustos et al., 2016; Pingali, 2007). Labor that is saved in agriculture is reallocated to jobs in other sectors, which are often more productive (Berger & Frey, 2016).

All countries with significant economic growth over longer periods of time have seen such a structural transformation (Berger & Frey, 2016; Bokusheva & Kimura, 2016). This is also true in Indonesia, where agriculture's contribution to total gross domestic product (GDP) declined from 24% in 1998 to 13% in 2018, while the share of agricultural employment in total employment decreased from 45% to 31% (World Bank, 2020). One of the major agricultural crops in Indonesia is oil palm, which has gained significant importance during the last 20 years (Qaim et al., 2020). In 2018, oil palm was cultivated in Indonesia on more than 14 million hectares of land, even exceeding the area grown with rice, the country's main staple food (Indonesian Bureau of Statistics, 2019). Palm oil production contributes around 2.5% to Indonesia's total GDP and employs up to 8 million people in farming and processing (ILO, 2019; Ministry of Agriculture Indonesia, 2019a). Indonesia is the world's largest palm oil producer and exporter worldwide (Qaim et al., 2020). Apart from exports, palm oil is also heavily used domestically as cooking oil, biofuel, and as an important ingredient in processed foods, cosmetics, and pharmaceutical products (Corley & Tinker, 2016). The objective of this article is to analyze whether Indonesia' recent oil palm boom has contributed to structural transformation in local agriculture with rising farm sizes and a growing role of rural off-farm employment.

The massive expansion of oil palm in Indonesia has various types of effects, with both negative and positive sustainability outcomes. As some of the oil palm plantations were established on land previously covered with tropical rainforest, the crop's expansion is associated with deforestation, biodiversity loss, and climate change (Drescher et al., 2016; Obidzinski et al., 2012). Spatial overlaps of land concessions for palm oil companies and local community lands have also contributed to social conflicts in some situations (Abram et al., 2017). However, more than 40% of the total oil palm land in Indonesia is not cultivated by large palm oil companies but by small- and medium-sized family farms (Euler et al., 2016). Several studies show that smallholder farmers benefit from oil palm cultivation in terms of higher household living standards, as oil palm is more profitable than traditional crops such as rice or rubber (Euler et al., 2017; Krishna et al., 2017a; Kubitza et al., 2018). Oil palm is also a labor-saving innovation in the sense that it requires much less labor per hectare than most traditional crops (Feintrenie et al., 2010; Chrisendo et al., 2020).

The labor-saving nature of oil palm may contribute to increasing farm sizes and a growing role of off-farm employment over time, but such effects on structural change have hardly been analyzed up till now. Based on country-level statistics, agriculture in Indonesia is still dominated by very small farms without a visible trend towards consolidation (Winoto & Siregar, 2008). However, country-level statistics may mask certain trends that occur in regional oil palm hotspots. Euler et al. (2016) and Krishna et al. (2017a) used cross-sectional survey data from Jambi Province, Sumatra, where the expansion of oil palm was particularly strong during the last 20 years, to show that farms cultivating oil palm are somewhat larger than farms cultivating traditional crops. Yet, with cross-sectional data it is hardly possible to establish whether the adoption of oil palm actually contributed to increasing farm sizes. Chrisendo et al. (2020) also used data from Jambi showing that a switch from traditional crops to oil palm reduces the labor intensity per hectare of land, but the labor reallocation to other economic activities was not analyzed in more detail.

Here, we contribute to the existing literature by using panel data collected in three survey rounds from farm households in Jambi Province to analyze the effects of oil palm adoption on structural transformation. Based on a simple conceptual framework we develop concrete research hypotheses, namely that oil palm cultivation contributes to farm size expansion and increases households' involvement in off-farm employment. These hypotheses are tested empirically with descriptive statistics and econometric models. Panel data models with household fixed effects help to reduce self-selection problems and other issues of endogeneity.

The rest of this article is structured as follows. Section 2 provides some background on oil palm cultivation in Jambi. Section 3 explains the analytical framework, including the research hypotheses and the statistical methods used. The household panel survey and the definition and measurement of key variables are described in section 4. Section 5 presents and discusses the empirical results, while section 6 concludes.

2 | OIL PALM CULTIVATION IN JAMBI

Oil palm and rubber are nowadays the two main crops cultivated in Jambi Province (Qaim et al., 2020). Rubber has been cultivated since the early-twentieth century, mostly in traditional agroforestry systems and as a complement to rice, the main local food crop. Since the mid-twentieth century, traditional agroforestry systems lost in importance and were gradually replaced by rubber monoculture plantations (Feintrenie & Levang, 2009). The importance of local food crop cultivation declined, because farmers could make higher incomes with growing rubber. Rice and other foods could easily be accessed from the market, largely imported from other regions of Indonesia.

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The Journal of the International Association of Agricultural Economists
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Oil palm was sporadically grown in Jambi since the 1960s, but was promoted more strongly since the 1980s (Gatto et al., 2015). The Indonesian government's transmigration programs played an important role in promoting oil palm cultivation among smallholder farmers. In the transmigration programs of the 1980s and 1990s, households from Java and other densely populated islands were resettled to less-developed islands such as Sumatra, where they were supported in the cultivation of cash crops, especially oil palm (Bazzi et al., 2016; Feintrenie et al., 2010; Zen et al., 2006). The transmigrant households started their farming business with the 2–3 hectares of land allocated to them; initially they were poorer than typical autochthonous households in Jambi that had been involved in commercial rubber cultivation for long (Gatto et al., 2017).

To support the transmigrant families in the cultivation of oil palm, the government initiated the so-called Nucleus Estate and Smallholder (NES) schemes (Larson, 1996). These schemes were linked to large public or private companies that managed their own oil palm plantations and additionally procured produce from contracted smallholders. Under these contracts, the transmigrants received subsidized credits and technical support for plantation establishment. Furthermore, the government supported the development and upgrading of infrastructure in newly-created transmigrant communities. While most of the smallholders in the NES schemes were transmigrants, a few autochthonous farmers also participated (McCarthy et al., 2012; Zen et al., 2006). But in general, autochthonous households in Jambi benefited less from the government support and started to adopt oil palm significantly later than transmigrant households (Euler et al., 2016; Gatto et al., 2017).

From the early-2000s onward, the NES schemes and related contractual arrangements between palm oil companies and smallholder farmers lost in importance. While oil palm adoption rates in Jambi continue to rise, most smallholders now establish their plantations independently and supply the palm oil mills without a contractual arrangement (Qaim et al., 2020). Plantation establishment requires capital, so poorer households without access to credit are less able to adopt oil palm and benefit from this profitable crop (Euler et al., 2016; McCarthy et al., 2012; McCarthy & Zen, 2016). While oil palm has helped to lift many households in rural Jambi out of poverty, it also has the potential to contribute to rising inequality under the given institutional conditions (Abram et al., 2017; Bou Dib et al., 2018a, 2018b; Obidzinski et al., 2012).

Besides capital, access to land is also an important factor for establishing new oil palm plantations. Until recently, most of the new oil palm plantations in Jambi were established on forest land, bush land, or fallow areas, but—with increasing land scarcity—rubber plantations are also increasingly converted to oil palm land. The gradual switch from rubber to oil palm is further fueled by low rubber prices (IMF, 2020). Farmers unable to establish their own oil palm plantations sometimes sell some of their land to other farmers. Krishna et al. (2017b) showed that the frequency of land-market transactions in Jambi has increased recently.

In 2018, of the total 14 million hectares of oil palm in Indonesia, around one million hectares were cultivated in Jambi (Ministry of Agriculture Indonesia, 2019a). Of these one million hectares of oil palm land in Jambi, around 40% were managed by large companies, whereas the rest was cultivated by small- and medium-sized family farms. According to official statistics, around 285,000 farmers in Jambi cultivate oil palm. In addition, close to 200,000 rural laborers in Jambi are employed in the oil palm subsector (Ministry of Agriculture Indonesia, 2019a). For comparison, rubber was grown on 390,000 hectares in Jambi in 2018, so on a much smaller total area than oil palm. However, unlike oil palm, rubber is mostly grown by family farms with only little involvement of large companies. According to official statistics, there were still around 220,000 farmers in Jambi growing rubber in 2018 (Ministry of Agriculture Indonesia, 2019b). In addition, a large number of rural laborers are employed in rubber, often through sharecropping arrangements (Bou Dib et al., 2018b).

3 | ANALYTICAL FRAMEWORK

3.1 | Conceptual framework

We want to analyze whether the adoption of oil palm by family farms contributes to structural transformation of agriculture by looking at relevant mechanisms at the micro level over time. In general, farmers will only decide to adopt a new crop if it leads to higher profits than traditional crops. However, besides changes in profit, the adoption of the new crop can also lead to changes in capital requirements, input use, labor use, and agroecological conditions (e.g., water and nutrient cycles) (e.g., Krishna et al., 2017a; Mariyono, 2015; Mariyono et al., 2010; Merten et al., 2020). All these changes can lead to a reallocation of household resources with implications for farming structures and employment (Figure 1).

Oil palm adopters in Indonesia often use more chemical inputs—such as fertilizer and herbicides—than farmers growing rubber or other traditional crops (Darras et al., 2019). In contrast, oil palm requires much less labor than most traditional crops. Using survey data from Jambi, Chrisendo et al. (2020) showed that farmers who adopted oil palm use significantly less labor per hectare than

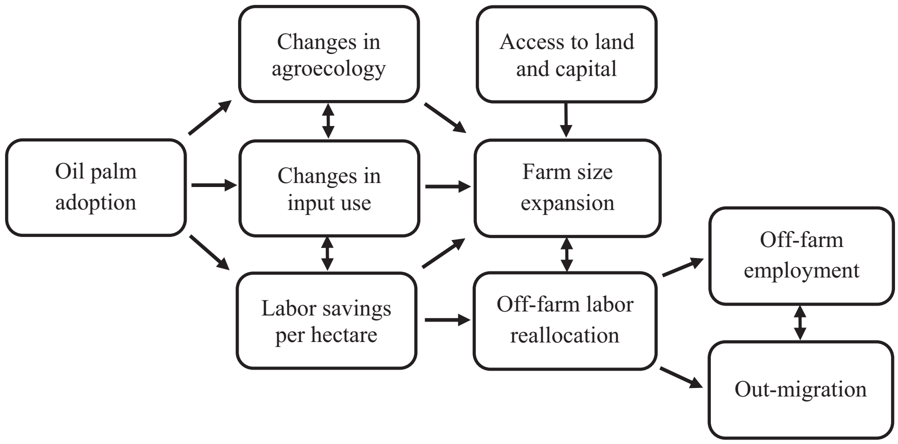

FIGURE 1 Oil palm adoption and structural transformation (possible mechanisms)

non-adopting farmers. In principle, the labor time saved per hectare of land can be used in different ways, either by expanding the fam size and cultivating additional land, or by pursuing off-farm activities. Both options can lead to further household income increases on top of the profit gains per hectare of land (Krishna et al., 2017a).

Which of the labor reallocation strategies an oil palm adopting household pursues will depend on the individual opportunities in the local setting. Expanding the farm size depends on access to additional land and capital. Capital can be saved or sometimes also obtained through credit markets. Additional land can be obtained through land market transactions. Alternatively, farmers in Jambi sometimes convert previous fallow land or forestland (Krishna et al., 2017b). If additional land and capital are not available or accessible, the labor saved per hectare will rather be reallocated to off-farm economic activities. Employment in manufacturing or the services sector is often more lucrative than agricultural work, but presupposes that related jobs are available and accessible in the local context. This also depends on educational levels. Other options are self-employment in own non-agricultural businesses or out-migration of family members to pursue more lucrative jobs in urban centers (de Brauw et al., 2014; Kreager, 2006). Obviously, the conditions can change over longer periods of time. For instance, oil palm adopters who benefit economically may invest more into the education of their children in order to improve access to lucrative non-farm jobs in the next generation.

We will use our panel data from farm households in Jambi Province to analyze these mechanisms, except for out-migration due to data limitations. Of course, we do not expect that all changes observed in farm sizes or off-farm employment are only driven by oil palm adoption. Many other economic and social reasons may also play a role (Li, 2009; Quetulio-Navarra et al., 2018; Thiede & Gray, 2017) and have to be controlled for in the econometric analysis to the extent possible.

3.2 | Research hypotheses

The first hypothesis that we want to test is that oil palm cultivation contributes to farm size expansion. We test this hypothesis by analyzing average farm sizes over time for the whole sample of farm households and also separately for oil palm adopters and non-adopters. In addition to the descriptive analysis, we run regression models of the following type:

$$FS_{i,t} = \alpha_1 + \beta_1 OP_{i,t} + \gamma_1 Z_{i,t} + \delta_1 T_t + \varepsilon_{i,t} \quad (1)$$

where $FS_{i,t}$ is the farm size measured in terms of hectares of land cultivated by farm household i in time period t, and $OP_{i,t}$ is a dummy variable that captures whether or not household i was involved in own oil palm cultivation in time period t.[1] $Z_{i,t}$ is a vector of control variables, which may include time-variant and time-invariant factors. We also include time fixed effects, T_t, to control for general trends. Finally, $\varepsilon_{i,t}$ is a random error term. We are particularly interested in the coefficient estimate β_1; a positive and significant estimate would support the first hypothesis that oil palm cultivation contributes to farm size expansion.

Our second hypothesis is that oil palm cultivation increases the households' involvement in off-farm employment. Again, we start the analysis with descriptive statistics by comparing off-farm employment participation between oil palm adopting and non-adopting households. In addition, we run regression models of the following type:

$$OFE_{i,t} = \alpha_2 + \beta_2 OP_{i,t} + \gamma_2 Z_{it} + \delta_2 T_t + \varepsilon_{i,t} \quad (2)$$

[1] It is also possible that farm size expansion happens with a certain time lag, for instance, when farmers first need to accumulate capital before they can access additional land and establish a new plantation. We therefore also run an alternative specification with $OP_{i,t-1}$ as explanatory variable.

where $OFE_{i,t}$ denotes participation in off-farm employment activities of household i in time period t. The other variables are defined as above. A positive and significant estimate for β_2 would support our second hypothesis that oil palm cultivation increases participation in off-farm employment.[2]

Off-farm employment of farm households is a very broad concept that can include low-paying agricultural work on farms or plantations owned by others, more lucrative jobs in different non-agricultural sectors, or self-employment in own non-farm businesses. We estimate separate models for different types of off-farm activities and expect positive effects of oil palm cultivation especially for the potentially more lucrative ones.

3.3 | Panel data estimators

The panel data models in Equations (1) and (2) include a time dimension, so that using ordinary least squares (OLS) for estimation would be inappropriate. In principle, the models can be estimated with a random effects (RE) panel estimator. The RE estimator leads to efficient estimates as it exploits the data variation within and between households. However, RE estimates may be biased when there is unobserved heterogeneity. In fact, unobserved heterogeneity is likely, because oil palm adoption, our main explanatory variable of interest, is not distributed randomly. Farmers decide themselves whether or not to adopt oil palm based on various observed and unobserved characteristics, which will likely lead to non-random selection bias. To reduce such bias, we use a fixed effects (FE) panel estimator, which only relies on the data variation within households over time, such that any unobserved factors that do not vary over time cancel out (Wooldridge, 2002).[3] While we estimate and show both RE and FE models, we rely on the FE estimates for interpretation, as these are more reliable in terms of reducing self-selection bias.

The model in Equation (1) has farm size as dependent variable, which is continuous. In contrast, the model in Equation (2) has off-farm participation as dependent variable, which is binary. For cross-section data models with binary dependent variables, probit or logit specifications are typically used. However, panel data logit or probit models are not straightforward to estimate with household FE, so that we estimate linear probability models, which is a common approach in panel data models with binary dependent variables (Wooldridge, 2002). In order to test whether the linear functional form leads to any bias, we use RE logit models as a robustness check. Moreover, as we look at households' involvement in different off-farm activities, we also use a multivariate probit (MVP) specification as another robustness check, as the MVP model controls for possible error term correlation (Greene, 2012).[4]

4 | DATA AND DEFINITION OF KEY VARIABLES

4.1 | Household panel survey

We conducted a survey of farm households in Jambi Province, Sumatra Island, Indonesia, in three rounds; in 2012, 2015, and 2018. As described above, Jambi is one of the hotspots of the recent oil palm boom in Indonesia. Farm households to be included in the survey were selected through a multi-stage sampling procedure. Five regencies in Jambi, which cover the largest part of the Province's lowland areas, were chosen purposively, namely Muaro Jambi, Batanghari, Sarolangun, Tebo, and Bungo. In each regency, we randomly selected four districts. In each district, we randomly selected two villages, resulting in a total of 40 villages. In addition, five villages were chosen purposively, in order to better align with some ongoing natural science research activities (Drescher et al., 2016; Grass et al., 2020). Depending on village size, 6–24 farm households were randomly selected in each of the 45 villages. In the regression models, we control for the non-randomly selected villages. Otherwise, the sample is representative of farm households in the lowland areas of Jambi Province (Euler et al., 2017).[5]

Details of the number of farms included in the sample are shown in Table 1. In the first survey round in 2012, we sampled a total of 684 farm households, of which 35% had adopted oil palm, while the others had not. In 2015 and 2018, we revisited the same households for the second and third survey rounds. Oil palm adoption rates increased to 46% in 2018. Some sample attrition occurred over time, but the attrition rates remained relatively small; 6% in 2015

[2] For the effect of oil palm adoption on off-farm employment we do not expect significant time lags, as starting off-farm employment does not require large amounts of capital. Some capital is required when starting self-employed business activities, but the local businesses typically start very small and then grow organically when being lucrative.

[3] When household fixed effects and dummy variables for the time periods are included, as we do in our estimations of Equations (1) and (2), the FE panel data estimator is essentially the same as the difference-in-difference estimator (Wing et al., 2018).

[4] Note that the MVP model is better suited than multinomial probit or logit models in our context, as households can be involved in different off-farm activities simultaneously.

[5] Note that we did not survey large company plantations, as these do not belong to local farm households. Large company plantations account for around 60% of the total oil palm area in Indonesia and around 40% in Jambi Province. Our sample is representative of local family farm households, but not of all agricultural production in the province.

TABLE 1 Number of farm households included in the panel survey

	2012	2015	2018	Total
Total number of farm households	684	687	689	2,060
Oil palm adopters	240	249	318	807
Non-adopters	444	438	371	1,253

and 4.5% in 2018. Attrition households were replaced by randomly sampling additional households in the same villages.

In all three survey rounds, face-to-face interviews were conducted with the household head using carefully designed and pre-tested structured questionnaires. The interviews were conducted in Bahasa Indonesia by a team of local enumerators who were selected, trained, and supervised by the researchers. The survey questions covered detailed information about general farm and household characteristics, agricultural and non-agricultural economic activities, and household consumption to measure living standards. In addition to information for the three survey years, we also included a few recall questions on land use in previous years, ranging back to the 1990s. Of course, answers to these longer-term recall questions may not be very precise and should be interpreted with some caution. For the regression models, we only use data from the three survey years (2012, 2015, and 2018), but for the descriptive analysis of farm size developments, the longer-term historical data can provide interesting additional insights.

4.2 | Measuring farm size

The first key outcome variable of our study is farm size. We measure farm size in terms of the number of hectares cultivated by the farm household in a particular year. The number of hectares cultivated may differ from the number of hectares owned, but land owned can be a somewhat ambiguous concept in the local setting, where many farmers do not have formal land titles and forest encroachment is common to obtain additional land for cultivation (Krishna et al., 2017b). For the regression models, we use the number of hectares cultivated in a particular year by an individual farm household as dependent variable. For the descriptive analysis, we look at average farm size developments in our sample over time.

We use three different measures of average farm size, namely the sample mean, the median, and the hectare-weighted median, which is also called the sample mid-point. The mean and the median are commonly used indicators in analyses of farm size structures (Eastwood et al., 2010; Lowder et al., 2016). They are particularly useful when the number of farms is distributed symmetrically across different farm sizes. However, when the farm-size distribution is skewed, using the mean or the median can create a downward bias in average farm size estimates (Lund & Price, 1998). Structural transformation is often characterized by the presence of numerous small farms, which operate small fractions of the total land and have low shares in total production, and a much smaller number of large farms, which cultivate much of the total land and produce much of the total agricultural output (Adamopoulos & Restuccia, 2014; Jayne et al., 2016).

The mid-point indicator can be used to overcome some of the limitations of the mean and the median in capturing the degree of land-use concentration (MacDonald et al., 2013). For n distinct ordered farm sizes $x_1, x_2, \dots, x_n$ with positive weights $w_1, w_2, \dots, w_n$ such that $\sum_{i=1}^{n} w_i = 1$, the weighted median, or the mid-point, is the farm size x_k satisfying:

$$\sum_{i=1}^{k-1} w_1 \leq \frac{1}{2} \quad \text{and} \quad \sum_{i=k+1}^{n} w_1 \leq \frac{1}{2} \tag{3}$$

In other words, the mid-point corresponds to a farm size that separates farmers into two parts, where 50% of the total farm area is operated by farms that are smaller and 50% by farms that are larger than the mid-point (Bokusheva & Kimura, 2016).

4.3 | Measuring off-farm employment

The second key outcome variable in our analysis is participation in off-farm employment. We measure whether or not a household or any of its members is involved in off-farm economic activities through different dummy variables. As quite different off-farm employment activities are possible, we differentiate between employed activities and self-employment in own non-farm businesses, such as transport, trade, and handicrafts. For employed activities, we further differentiate between sectors, including jobs in (i) agriculture and forestry, (ii) manufacturing, construction, and mining, and (iii) services, including transport, health, education, and government offices.

We include both formal and informal jobs, recognizing that some informal short-term employment may possibly not be perfectly recorded in the survey data (Schneider, 2014). The separation of employment by sector is an attempt to capture potential differences in returns to skill (Herrendorf et al., 2014). We expect that off-farm employment in agriculture and forestry is the least lucrative option, whereas employment in non-agricultural

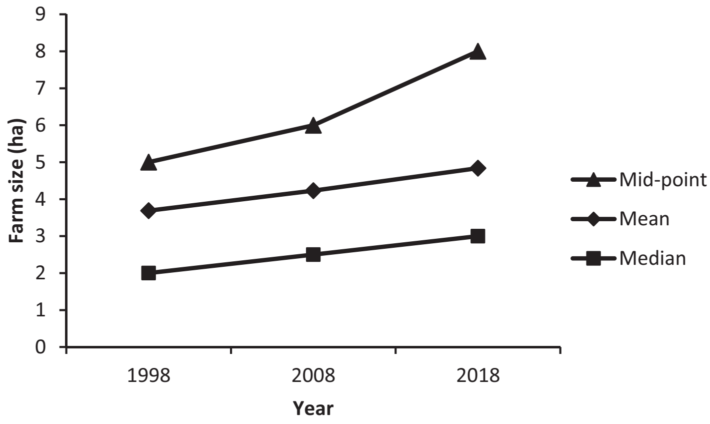

FIGURE 2 Development of average farm size in Jambi (1998-2018)

sectors and self-employment are activities with relatively higher payoffs. While this may not be perfectly true in all cases, this is a common general assumption made in the literature (Berger & Frey, 2016; Duarte & Restuccia, 2010).

5 | RESULTS AND DISCUSSION

5.1 | Oil palm and farm size

5.1.1 | Descriptive analysis

We now want to test the first hypothesis, namely that oil palm cultivation contributes to farm size expansion. Figure 2 shows the development of the average size of farms in our sample from Jambi between 1998 and 2018, measured in terms of the sample mean, median, and mid-point. All three indicators show that the average farm size increased over time. The median farm size increased by 50%, from about 2 ha in 1998 to 3 ha in 2018. The mean farm size is larger and increased from 3.7 ha to 4.8 ha during the same period. The mid-point is still larger and increased from 5 ha in 1998 to 8 ha in 2018, with an accelerated increase during the last 10 years.

The notable difference between the sample mid-point and mean is due to the fact that the distribution of farms across farm size categories is not symmetrical. In 1998, farms with less than 4 ha of land accounted for 70% of all farms. This share declined somewhat over time, but in 2018 more than 60% of all farms still had a size of less than 4 ha (Figure A1 in the Online Appendix). The share of large farms with more than 12 ha of land is low, but it doubled from 4% in 1998 to 8% in 2018. These farms above 12 ha now account for almost 40% of the total land cultivated by farm households in Jambi. Hence, there seems to be a profound structural transformation, which is not fully reflected by the development of mean farm sizes.

Further insights can be gained when analyzing the development of farm size distributions and land inequality with the Gini index. Based on our sample data, the Gini index for land was .46 in 1998 and increased to .52 in 2018. The rising inequality in the land distribution indicates a certain trend towards polarization of the farm structures. While larger farms further increase their scale of operation, many of the small farms continue to produce rather than leaving the sector. This is possible because forest and fallow land was still available in Jambi over the last 20 years, meaning that some farms could grow even without other farms exiting the sector. Figure A2 in the Online Appendix shows that the total land cultivated by sample farms increased significantly between 1998 and 2018. Only since 2012, the total area cultivated did not grow further, mainly because some of the rubber plantations were cut and partly converted to oil palm.

The analysis so far suggests that there is an ongoing structural transformation of agriculture in Jambi, but it is not yet clear to what extent this transformation is linked to oil palm cultivation. As mentioned, oil palm adoption rates in our sample increased over time. By 2018, 46% of the farm households were cultivating oil palm. Figure 3 shows the development of average farm sizes in terms of sample mid-points, separately for oil palm adopters and non-adopters. For non-adopters, who are primarily cultivating rubber, the average farm size slightly increased between 1998 and 2008, but remained more or less stagnant since then. In contrast, for oil palm adopters we see a much more rapid and continuous increase in average farm sizes over time. This is a clear indication that oil palm cultivation contributes to farm size expansion, as hypothesized.

5.1.2 | Econometric analysis

We now analyze the role of oil palm cultivation for farm size expansion more formally, by regressing farm size on oil palm adoption and other control variables and exploiting the panel structure of our data, as explained above in

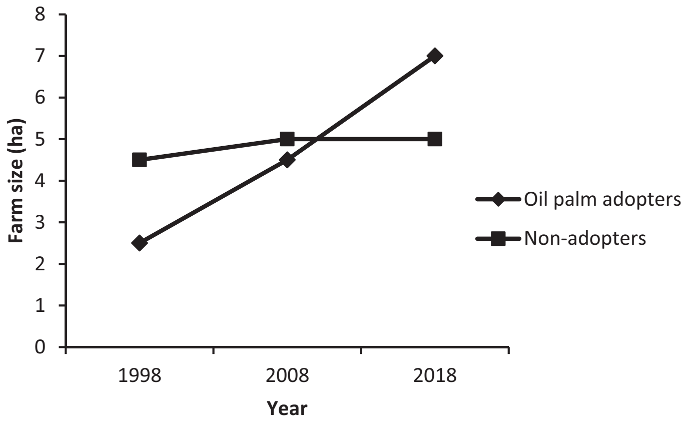

FIGURE 3 Development of mid-point farm sizes in Jambi for oil palm adopters and non-adopters (1998-2018)

TABLE 2 Determinants of farm size (panel data regression models)

Variable	(1) RE	(2) FE	(3) RE (lagged)[a]
Oil palm adoption (dummy)	.339***	.294***	.347***
	(.027)	(.031)	(.040)
Government land titles (dummy)	.007	−.014	.102**
	(.024)	(.025)	(.043)
Age of household head (years)	.006***	.003	.011***
	(.001)	(.002)	(.002)
Education of household head (years)	.009**	−.003	.030***
	(.004)	(.005)	(.005)
Female-headed household (dummy)	−.041	−.003	−.217***
	(.042)	(.046)	(.077)
Household size	.014**	.013*	.014
	(.007)	(.007)	(.012)
Migrant household (dummy)	−.089*		−.118***
	(.046)		(.040)
Access to credit (dummy)	.053***	.043**	.102**
	(.019)	(.019)	(.043)
Non-random village (dummy)	.299***		.328***
	(.066)		(.056)
Survey round 2015 (dummy)	−.015	−.007	−.053
	(.015)	(.016)	(.037)
Survey round 2018 (dummy)	−.084***	−.045*	
	(.023)	(.024)	
Constant	.933***	1.209***	.558***
	(.086)	(.095)	(.118)
Number of observations	2,060	2,060	1,301

Notes: Farm size as the dependent variable is measured in hectares and expressed in logarithmic terms. Coefficient estimates of panel data models are shown with standard errors in parentheses.

[a]The model in column (3) uses observations from only two survey rounds (2015 and 2018) and considers oil palm adoption in lagged form (t-1), meaning adoption in the previous survey round. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Equation (1). We express farm size in logarithmic terms for better empirical fit. Hence, the coefficient estimates can be interpreted in percentage terms. The estimation results are shown in Table 2.

Column (1) of Table 2 shows RE estimates. The oil palm adoption coefficient is positive, relatively large, and highly statistically significant. However, as discussed, the RE estimate may possibly suffer from selection bias. The FE

TABLE 3 Household characteristics of oil palm adopters and non-adopters

Variables	Oil palm adopters	Non-adopters
Household consumption expenditures (million IDR/AE/year)	15.260***	11.432
	(12.212)	(8.140)
Labor time spent on-farm (hours/ha/year)	278.313***	1143.799
	(449.138)	(1749.826)
Household off-farm income (million IDR/AE/year)	7.932***	5.124
	(16.487)	(10.910)
Participation in off-farm activities (dummy)	.669	.667
	(.471)	(.471)
Employed activities (dummy)	.494**	.545
	(.500)	(.498)
Agriculture/forestry (dummy)	.198**	.238
	(.399)	(.426)
Manufacturing/construction/mining (dummy)	.123	.140
	(.328)	(.347)
Services (dummy)	.173	.168
	(.379)	(.374)
Self-employed business activities (dummy)	.291***	.211
	(.455)	(.408)
Number of observations	807	1,253

Notes: Mean values are shown with standard deviations in parentheses. Observations from all three survey rounds were pooled. Monetary values were deflated using the consumer price index for Indonesia to allow comparison across survey rounds. In 2012, 1 US$ was equivalent to IDR 9,670. AE, adult equivalent. Mean differences between adopters and non-adopters were tested for statistical significance. **, *** significant at the 5% and 1% level, respectively.

estimator better controls for such bias, with results shown in column (2) of Table 2.[6] The FE estimates confirm the positive and significant effects oil palm adoption on farm size. After controlling for other relevant factors, oil palm adoption leads to an average increase in farm size by almost 30%. This is plausible and supports our first hypothesis. As oil palm requires less labor per hectare than relevant alternative crops, oil palm adopters can increase their farm size and cultivate more land. Farm size expansion would not be an easy option in settings where land availability is limited. However, as discussed, in Jambi many farms could access additional land without major constraints in the past.

Column (3) in Table 2 shows an alternative specification where oil palm adoption is included in lagged form. Lagged oil palm adoption also leads to a significantly positive effect on farm size. The effect size is even somewhat larger, suggesting that – beyond the labor savings – capital accumulation over time among the oil palm adopters may also be a relevant mechanism for farm size expansion. The important role of capital for expanding the farm size is also underlined by the positive and significant effect of access to credit and government land titles in column (3) of Table 2. Also beyond the oil palm context, access to credit is often positively associated with innovation adoption and farm size (Mariyono, 2019a, 2019b).

5.2 | Oil palm and off-farm employment

5.2.1 | Descriptive analysis

We now turn to our second hypothesis, namely that oil palm cultivation increases farm households' involvement in off-farm employment. Table 3 shows descriptive statistics for oil palm adopters and non-adopters in our sample. Oil palm adopters enjoy significantly higher living standards than non-adopters, as can be seen from the comparison of household consumption expenditures. Previous research showed that oil palm adoption contributes to significant gains in household living standards (Euler et al., 2017; Krishna et al., 2017a). As can also be seen in Table 3, oil palm farmers spend a much lower amount of time per hectare of farmland than non-adopters. Some of the labor saved per hectare is spent on cultivating additional land, as was shown above. But are oil palm adopters also reallocating saved labor time to off-farm activities? Significant differences in annual off-farm income between adopters and non-adopters suggest that they do (Figure 4). But the rates of participation in different off-farm activities show a somewhat mixed picture (Table 3).

[6] Note that time-invariant variables, such as household migration background or village fixed effects, cancel out in FE estimation.

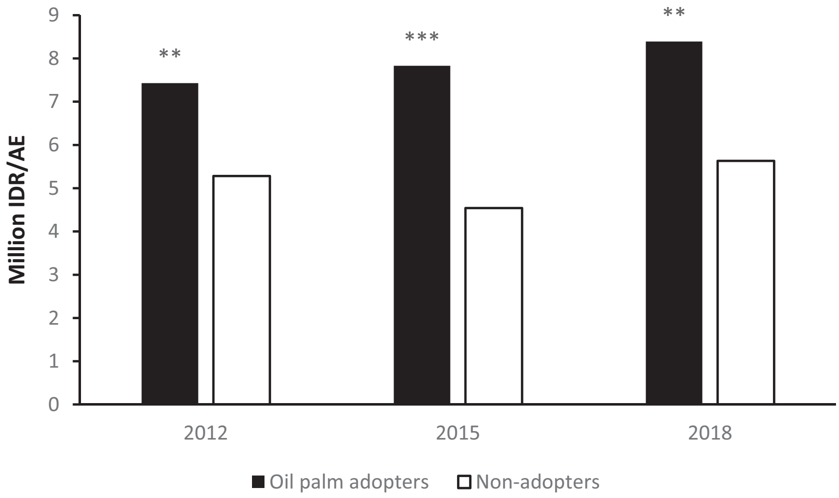

FIGURE 4 Annual off-farm income of oil palm adopters and non-adopters (2012-2018)
Notes: AE, adult equivalent. **, *** difference is statistically significant at the 5% and 1% level, respectively

Participation rates in all off-farm activities combined do not differ between oil palm adopters and non-adopters (Table 3). For employed activities, the rates are even somewhat lower among the oil palm adopters, which is driven by their lower participation in agricultural off-farm jobs. This is unsurprising, as agricultural employment is often not particularly lucrative and more common among poor and unskilled workers (Bou Dib et al., 2018b; Martinez et al., 2014; Schaner & Das, 2016). Participation in manufacturing and services jobs does not differ significantly between oil palm adopters and non-adopters. However, oil palm adopters participate significantly more in self-employed activities.

5.2.2 | Econometric analysis

We now run regression models to test our second hypothesis more formally. Table 4 shows results of linear probability models with household participation in different off-farm activities as dependent variable, as explained in equation (2). For brevity, we only show the FE specifications (RE results are shown in Table A1 in the Online Appendix with similar results). Oil palm adoption does not significantly affect household participation in any of the employed off-farm activities. However, it significantly increases participation in self-employed activities, including small businesses in transport, trading, and handicrafts, among others. The estimates in Table 4 imply that—after controlling for other factors—oil palm adoption increases the probability of pursuing self-employed business activities by 17.5 percentage points.[7] Insignificant effects of oil palm adoption on employed off-farm activities and significantly positive effects on self-employed activities are also found when using RE logit models and a multivariate probit as robustness checks (Tables A2 and A3 in the Online Appendix). Hence, the results do not seem to be driven by the choice of functional form.

That we see no significant effect of oil palm adoption on employed off-farm activities may surprise, given that oil palm requires considerably less labor per hectare of land. Possibly, our off-farm participation dummies are not sufficiently sensitive, as they do not capture the actual time that household members spent in off-farm activities. Unfortunately, we do not have more detailed time allocation data for off-farm activities. However, there is also a plausible reason why no effect on employed off-farm activities is observed, namely the lack of lucrative non-agricultural employment opportunities in the local setting. While Jambi City, the Province's Capital, is a vibrant place with many employment opportunities in manufacturing and services, it takes too long to reach the City for a daily commute from most of the Province's rural areas. In the rural areas themselves and in smaller towns nearby, the job opportunities are much more limited.

The limited employment opportunities in rural areas of Jambi have several implications that do not bode well for sustainable development. First, without lucrative non-agricultural employment options, marginal farms will continue to produce rather than exiting the sector. Second, oil palm adopters have a higher incentive for increasing their farm size in order to use the saved labor time productively. At least in the past, farm size expansion was often associated with additional deforestation and concomitant negative effects for biodiversity and climate change. Third, farmers with access to capital can resort to self-employed business activities, but this option is much less accessible

[7] In the models in Table 4, we control for farm size (land cultivated). As farm size is influenced by oil palm adoption, we ran the same models also without controlling for farm size as a robustness check. The effect of oil palm adoption remains very similar: insignificant for employed activities and a significant point estimate of .175 for self-employed activities.

TABLE 4 Determinants of participation in off-farm activities (FE panel data models)

Variables	Employed activities Agriculture	Manufacturing	Services	Self-employed
Oil palm adoption (dummy)	−.046	.009	.028	.175***
	(.041)	(.037)	(.037)	(.040)
Farm size (land cultivated in ha)	−.002	−.003	.002	-3.183e-4
	(.004)	(.003)	(.003)	(.003)
Female-headed household (dummy)	.025	.166***	.002	−.102*
	(.061)	(.055)	(.055)	(.059)
Household size	.022**	.019**	.040***	.024***
	(.009)	(.008)	(.008)	(.009)
Age of household head (years)	.001	.003	-2.551e-4	.002
	(.002)	(.002)	(.002)	(.002)
Education of household head (years)	.015**	.005	−.002	.003
	(.006)	(.006)	(.006)	(.006)
Access to credit (dummy)	.045*	−.015	−.008	.087***
	(.026)	(.023)	(.024)	(.025)
Distance to market (km)	.001	.002	.001	−.002
	(.002)	(.002)	(.002)	(.002)
Survey round 2015 (dummy)	.008	.083***	.010	.063***
	(.021)	(.019)	(.019)	(.020)
Survey round 2018 (dummy)	.003	−.048**	.133***	.034
	(.024)	(.022)	(.022)	(.023)
Constant	−.037	−.123	−.038	−.075
	(.129)	(.116)	(.117)	(.125)
R-squared	.012	.052	.062	.048
Number of observations	2,060	2,060	2,060	2,060

Notes: Coefficient estimates of linear probability models with fixed effects are shown with standard errors in parentheses. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

for poor and credit-constrained households. Improving off-farm employment options could therefore help to avoid rising inequality and environmental problems.

6 | CONCLUSION

With economic growth and development, countries typically experience a structural transformation where the agricultural sector shrinks in relative importance while the manufacturing and service sectors grow. Two important characteristics of this transformation within the agricultural sector are the expansion of average farm sizes and the reallocation of agricultural labor to other sectors. This process is often supported by the adoption of productivity-increasing and labor-saving agricultural innovations. In this article, we analyzed to what extent the adoption and cultivation of oil palm contributes to structural transformation in Indonesia. Indonesia has seen a rapid expansion of oil palm cultivation in recent decades. The country is now the biggest palm oil producer and exporter worldwide. The crop is partly grown on large company plantations, but over 40% of the oil palm area in Indonesia is also managed my small- and medium-sized family farms. We focused on these family farms to examine the effects of oil palm cultivation on farm size developments and participation in off-farm activities.

Our panel data from Jambi Province show that oil palm adoption and cultivation contribute to gains in household living standards and labor savings per hectare of land. Oil palm requires much less labor per hectare than alternative crops such as rubber. Our first research hypothesis was that oil palm cultivation increases average farm sizes over time, because some of the labor saved per hectare would be used to cultivate additional land. This hypothesis was confirmed. Average farm sizes increased significantly over the last 20 years, and especially so among the oil palm adopters. Panel data models with household fixed effects suggest that oil palm adoption increased farm sizes by 30% on average, after controlling for other factors that may also influence the scale of operation.

Our second hypothesis was that oil palm cultivation increases farm households' participation in off-farm employment, assuming that some of the labor saved would also be reallocated to non-agricultural activities. This hypothesis was confirmed only partly. Oil palm adopters have significantly higher off-farm incomes than non-adopters. However, when looking at participation rates in different types of off-farm activities we only found significant effects of oil palm adoption on self-employment in small family-run businesses, but not on external employment in manufacturing or services. The reason is probably that insufficient non-agricultural employment opportunities exist in the local rural setting.

Overall, we conclude that oil palm contributes to structural transformation of agriculture in Indonesia. Yet more policy attention may be needed to guide related developments in terms of sustainability and equity. The limited non-agricultural employment opportunities in rural areas may prevent marginal farms from exiting the sector. Moreover, oil palm farmers with limited options to reallocate their time to lucrative off-farm employment have a strong incentive for increasing their farm size instead. Especially when these farmers cannot purchase or rent land from exiting farms, they may further encroach forests with negative environmental effects. Self-employed business activities are an option for better-off households with access to capital and entrepreneurial skills, but are much less accessible for poor households with low educational levels. Hence improving off-farm employment opportunities as well as credit and vocational training options may be useful policies to avoid undesirable sustainability outcomes.

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DATA APPENDIX AVAILABLE ONLINE

A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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SUPPORTING INFORMATION

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

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