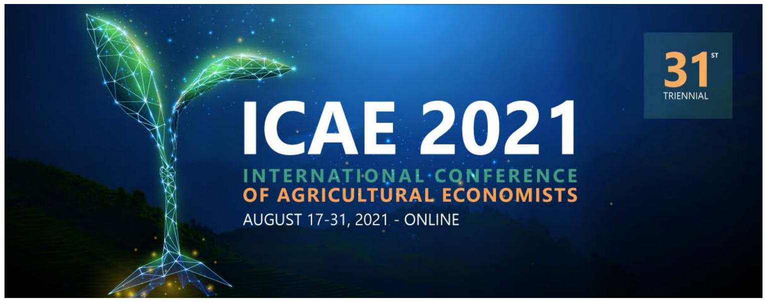

Labor displacement in agriculture: The case of oil palm in Indonesia

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1 Introduction

Empirical research has shown that growth in agricultural productivity substantially contributes to national GDP growth (McArthur & McCord 2017), poverty reduction (Christiaensen & Martin 2018) and reduced global pressure on forest land (Villoria 2019). Focusing on productivity in agriculture is also warranted since in many countries the share of agriculture in total value added remains well below the agricultural labor share (Emerick 2018). In high-income countries, technical change largely contributed to closing this gap, as the diffusion of labor-saving technologies led to a multifold increase in labor productivity. The diffusion and structural effects of labor-saving technologies are well documented for high-income countries (Sunding & Zilberman 2001; Gallardo & Sauer 2018). But evidence is scarce for developing countries, and economic conditions likely differ from the historical trajectories of high-income countries. Still, labor-saving technologies – such as mechanization or herbicide application – are often perceived as key technologies to increase agricultural labor productivity in developing countries (Haggblade et al. 2017; Sheahan & Barrett 2017; Adu-Baffour et al. 2019).

The argument that labor savings in agriculture can have heterogeneous effects on different strata of rural societies is widely recognized (Pingali 2007; Haggblade et al. 2017). Increasing labor productivity can directly boost profits at the farm level. At larger scales, such as village or district level, the effects are more ambiguous. Higher labor productivity can translate into higher incomes for agricultural laborers. Moreover, if sufficient income is generated in the agricultural sector, local demand effects can increase employment rates and wages across other sectors as well. Conversely, a labor-saving technology will reduce labor demand if wages and output stay constant. A lower labor demand in agriculture, or an oversupply of labor in the non-agricultural sector through farm households reallocating saved labor time, can displace individuals with limited access to production factors or lower labor productivity.[1]

While labor-saving technologies or land uses can increase income inequality, deepen poverty and eventually even foster civil unrest, detailed empirical evidence on the underlying mechanisms is surprisingly scarce in developing countries at larger scales. A few studies focused on direct productivity effects, income gains, cropland expansion and labor savings (Benin 2015; Fischer et al. 2018; Kirui 2019; Adu-Baffour et al. 2019). Yet, most studies do not empirically analyze the wider labor market effects. Different reasons might explain the scarcity of evidence. First, at larger scales, the spread of labor-saving technologies is often difficult to assess due to limited data availability. Second, the adoption of labor-saving technologies was in the past often restricted to large agricultural companies or relatively small groups of larger farms.

In this article, we contribute to the literature by analyzing the wider labor market effects of the labor savings introduced by the expansion of oil palm in Indonesia. Global production of palm oil rose by around 600 percent between 1990 and 2016 with Indonesia being the largest producer (US Department of Agriculture 2017; Byerlee et al. 2017). The differences in labor intensity and productivity between oil palm and alternative cash crops were recently found to increase the living standard of oil palm adopters and agricultural laborers (Euler et al. 2017; Kubitza & Gehrke 2018; Bou Dib et al. 2018). Following this literature, we argue that oil palm can be characterized as a

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[1] While the present article focuses on labor markets, higher agricultural productivity is also likely to decrease commodity prices and to increase the welfare of consumers.

labor-saving innovation in the sense that it requires less labor per unit of land than alternative crops. For labor-saving technologies, output is the same but the technology has changed such that less labor is required. This is, of course, not true for a labor-saving land use but primary data show that in comparison to competing land uses, one of the major effects of oil palm expansion is the significant decrease in labor intensity. We neither find convincing evidence that oil palm is skill-biased, nor that unobserved patterns in agricultural production significantly change due to oil palm expansion that in turn directly influence labor displacement. Migration flows and infrastructure development might change due to oil palm expansion but we control for these alternative explanations in the latter sections of the paper. Oil palm is also interesting because it is not only grown by large companies but to a substantial extent by smallholder farm households. In 2015, smallholder farm households cultivated more than 40 percent of the national oil palm area (Euler et al. 2016), and non-farm households in rural areas also derived substantial income from working on oil palm farms (Bou Dib et al. 2018). Yet, similar to the more general criticism of labor savings in agriculture, research also emphasizes the potentially adverse effects of oil palm expansion on the welfare of landless and other marginalized sections of society (Cramb & Curry 2012; Obidzinski et al. 2012; Li 2015).

A few studies already analyzed the economic effects of oil palm expansion in Indonesia to study long-term demographic changes (Kubitza & Gehrke 2018) and poverty reduction (Edwards 2019). Edwards (2019) examines the effect of oil palm expansion on poverty since the 2000s and finds a significant reduction in poverty as well as indirect effects on rural and social infrastructure. The paper applies a similar identification strategy as this paper. Yet, the paper does not focus on labor savings introduced by oil palm, nor on potential labor displacement. The study is also solely based on a regency-level panel from secondary data and not primary data. Kubitza & Gehrke (2018) focus on the effects of the oil palm expansion on changes in demographic patterns and find significant reductions in fertility. The study is also mostly based on a regency-level panel from secondary data and focuses on the theoretical and empirical determinants of long-term demographic changes. While both studies use similar identification strategies and contributed substantially to our knowledge on the economic effects of oil palm expansion, our study is unique due to its combination of new data at different scales as well as its focus on labor savings in agriculture and their effect on labor displacement. These aspects were not yet analyzed in depth in the literature to our knowledge.

The second contribution of our paper is the analysis of the employment effects of labor savings in agriculture with respect to crop land expansion. If the initial labor supply is limited, labor savings allow for cropland expansion and increases in output. Land expansion could mitigate the initial drop in demand for agricultural labor per unit area. If growth in agricultural output and income increases local demand, growth in other rural sectors is also likely to increase. Such aspects have rarely been considered in the existing empirical research on the effects of labor savings in agriculture. They may play an important role in the case of Indonesia, as oil palm cultivation is often linked to cropland expansion, deforestation and degradation of natural ecosystems (Butler & Laurance 2009; Koh et al. 2011; Carlson et al. 2018).

The rest of the paper is structured as follows. In section 2, we present our hyptheses on the effects of labor savings in agriculture on labor market outcomes at farm and aggregate scale. In section 3, we present the different data sources used. In section 4, we discuss our estimation strategies. Results are presented in section 5. A final discussion of the results and some conclusions are given in section 6.

2 Conceptual framework

In this section, we state the hypotheses to be tested. Based on considerations outlined in an appendix, we make the following predictions.

Prediction 1. When land is scarce:

1.1. Oil palm adoption increases total income of farm households through additional off-farm employment.

1.2. Oil palm adoption increases off-farm employment in farm households, in particular for women. Men and women shift out of agriculture.

Prediction 2. When land is abundant:

2.1. Oil palm adoption increases total income of farm households through cropland expansion.

2.2. Oil palm adoption has limited impact on off-farm employment in farm households. Sectoral shifts between men and women may occur.

At higher spatial scales, we expect more ambiguous labor market effects depending on the abundance of land.

Prediction 3. When land is scarce:

3.1. Employment in agriculture decreases, especially for women. If the non-agricultural sector does not absorb all freed labor, employment rates are likely to drop.

3.2. The effect on non-agricultural wages is ambiguous, but wages will fall if the labor supply effect dominates the local demand effect.

Prediction 4. When land is abundant:

4.1. Demand for agricultural labor will not decrease and may even increase, especially for men. Due to changes in relative labor productivity, women are likely to shift to the non-agricultural sector.

4.2. Agricultural and non-agricultural wages increase (based on 4.1).

3 Data

For our analysis we employ data from different analytical levels such as local household and national datasets, and from different sources such as surveys and remote sensing. The local household data provide details on agricultural input and output for rubber and oil palm at the plot level as well as employment data for oil palm adopters and non-adopters both at household and at individual level. These data were collected by the authors from a specific region (see details below), as the information is not readily available in national surveys. However, national surveys have larger sample sizes and provide regency-level panel data reaching several years back in time. Having panel data for the whole of Indonesia allows us to employ more sophisticated identification strategies and to detect the effects of oil palm expansion at larger scales. Table 1 lists the different datasets used for analysis.

Primary data were gathered as part of an interdisciplinary project located in Jambi Province, Sumatra. Jambi Province ranks sixth in national palm oil production in Indonesia (Kubitza et al. 2018b). Data were collected through several surveys. A farm-household survey was conducted in 2015 (*Survey I*). Sampling was based on a multi-stage framework and included 683 randomly selected farm households in 45 villages. Sampling details of Survey I are explained by (Kubitza et al. 2018b). In addition, 24 out of the 45 villages were randomly selected for a labor household survey (*Survey II*), which included 432 households. The sampling strategy for Survey II is detailed by (Bou Dib et al. 2018). Since Survey I and Survey II are partly overlapping in their definition of farm and labor households, we merged both datasets and drew a threshold at one hectare, referring to all households above this threshold as farm households. Additional data from agricultural traders (*Survey III*) were analyzed for robustness checks (Kopp & Brümmer 2017). For spatial data, land-cover maps for 2013 were derived from Landsat imagery with 30m spatial resolution (Melati et al. 2014). As an indicator for oil palm expansion at the village level, we use oil palm area per household. Geocoded data on the locations of palm oil mills in Jambi Province were obtained from the Global Forest Watch dataset.

National data were obtained from several sources. We included regencies (*kapubaten*) into our analysis and excluded cities (*kotas*), as oil palm expansion happens mainly in rural areas. The SAKERNAS, the national labor survey of Indonesia, provides annual data on the sectoral shares as well as wages in the agricultural and non-agricultural sector. Area under smallholder oil palm cultivation is available at an annual basis from the Tree Crops Statistics at the regency level. Based on these two data sources, we compiled a regency-level panel from 2000 to 2015. For additional robustness checks, we use PODES (Indonesian village survey) for infrastructure data and a subsample of the Indonesian census for migration data. The FAO's GAEZ (global agro-ecological zones) database provides spatial data on the maximum attainable yield of oil palm as well as other competing crops across the country at 10x10km resolution (Fischer et al. 2012). Yields are predicted based on agronomic modeling under pre-specified levels of fertilizer use and management conditions.[2] Model inputs include local soil and weather conditions. Spatial data on forest cover were available for 2000, 2005, 2010 and 2012 from Margono et al. (2014). The maps are based on the global forest cover change maps of Hansen et al. (2013), adjusted for the expansion of plantation crops in Indonesia. Data on large-scale oil palm plantations were sourced from Austin et al. (2017). Maps were created by visually interpreting LandSat satellite imagery. Maps were retrieved at a

[2] We specified low-level input use and rain-fed production.

250x250m resolution for the years 2000, 2005, 2010 and 2015. Only large oil palm estates were mapped due to the low resolution of the satellite imagery.[3]

4 Estimation strategy

4.1 Farm-scale models

We start by designing models to exam our predictions at the farm scale. To test if the additional income from oil palm adoption is either generated through land expansion or the allocation of freed labor to the off-farm sector, we regress total household income on the share of cropland planted with oil palm (*predictions 1.1 and 2.1*). We then stepwise add farm size and employment dummies as additional control variables. This household-level model is specified as follows:

$$TI_{kv} = \beta_0 + \beta_1 OP_k + \beta_2 A_k + \beta_3 OF_k + \beta_4 X_{kv} + \varepsilon_{kv} \quad (2)$$

where TI_{kv} is total income of a household k in village v (in log terms). OP_k is the share of cropland planted with oil palm. A_k is the total farm size, and OF_k includes dummies for off-farm employment. X_{kv} includes additional control variables such as age, education and migration background of the household head as well as village-level variables.

To test if farm-household members are more likely to work in general or to take up work in the off-farm sector (*predictions 1.2 and 2.2*), we regress several employment indicators on the share of

[3] Satellite data are only available for Kalimantan, Sumatra and Papua. Since the Tree Crop Statistics data report no significant oil palm expansion in Java, we set oil palm expansion to zero for all regencies in Java.

cropland planted with oil palm. We restrict the sample to working age individuals between 15-65 years. Our reduced-form model of labor supply is specified as follows:

$$OF_{ikv} = \beta_0 + \beta_1 OP_k + \beta_2 K_{ikv} + \varepsilon_{ikv} \quad (3)$$

where OF_{ikv} is a dummy for different types of work such as employment and self-employment dummies of individual i in household k in village v. K_{ikv} includes additional controls. We split the sample by gender.

To address the potential endogeneity bias of the oil palm area planted in equations (2) and (3), we employ an instrumental variable approach. We use the road distance of farm households' dwellings to the closest palm oil mill as an instrument for the share of farmers' cropland planted with oil palm. The distance to the closest palm oil mill is significantly correlated with oil palm adoption, since fresh fruit bunches have to be processed within two days to ensure high quality oil (Edwards 2019).[4] Having no palm oil mill in proximity substantially increases transaction costs. We assume that the decision to establish palm oil mills is not affected by individual characteristics of farmers or villages but by the location of large-scale oil palm plantations. The location of large-scale plantations is typically set by local or central government bodies. A wide array of literature documents that plantation projects were implemented regardless of the specific demands of local population groups (Zen et al. 2006; Cramb & McCarthy 2016; Gatto et al. 2017). Yet, if palm oil mills correlate with large oil palm plantations, the direct vicinity of such plantations could affect employment opportunities and income generation. Additionally, the presence of such plantations might spark land conflicts and decrease tenure security which in turn influences farmers' investment

[4] Pearson correlation coefficient for our dataset: -0.329***

decisions. We therefore control for village level variables such as bordering large-scale plantations, the number of land conflicts and the prevalence of secure land titles. Since farmers willing to plant oil palm could just migrate into the proximity of palm oil mills, we control for households' migration status in all regressions. Some regencies were more suitable for oil palm than others, and more central and economical active areas also did not lend themselves for oil palm plantations. We hence control for these and other regional characteristics in the later regression analysis through regency dummies, a village-level suitability index for oil palm cultivation and distance variables to the province capital, major educational facilities and road infrastructure.

To measure the road distance of palm oil mills to farm households, we use the GPS location of households' dwelling as well as GPS data from the Global Forest Watch, which registered palm oil mills for the whole of Indonesia. The road network data are obtained from OpenStreetMap. It is possible that the database did not register all palm oil mills in the region. To address this issue, we opted to correct the distance based on geocoded data through the survey-based data if the survey-based distance was smaller than the distance based on the geocoded data.

4.2 Aggregate-scale models

To test if oil palm expansion affected employment opportunities at wider scale, we regress the share of a regency's area planted with oil palm by smallholders on employment rates, sectoral shares (*predictions 3.1 and 4.1)* and wages (*predictions 3.2 and 4.2)*. We split our sample again by gender using a panel spanning from 2000 to 2015, which allows us to apply regency-level fixed effects. We opted for 5-year differences (2000-2005-2010-2015) since oil palm expansion and production processes are governed by lags and unlikely to be picked up by a year-on-year specification.

Since reverse causality and time-variant unobserved factors could still bias our results, we employ again an instrumental variable approach. Our instrument consists of two components. The cross-sectional geo-spatial component of our instrument is the maximum attainable yield of oil palm across the whole of Indonesia derived from the GAEZ database. We interact the cross-sectional variation in the maximum attainable yield of oil palm across regencies with the annual expansion of the national oil palm area. Such an instrument was already used by Edwards (2019) and Kubitza & Gehrke (2018). This interaction term provides a prediction of how much the oil palm area in a regency should have changed solely based on its suitability for oil palm cultivation. Our instrument correlates highly with the actual expansion. Concerning exogeneity, we see no reason why the necessary ecological and climatic conditions for oil palm cultivation should affect the development of sectoral shares and wages over time other than through oil palm expansion. We further assume that the national expansion of oil palm is driven by world market prices and the policies of the central government and not by idiosyncratic regional developments. Since the main islands are spatially segregated, which could lead to potentially different development paths, we additionally control for regional time trends. Other threats for identification could include differential trends in economic development between oil palm growing and non-growing regencies. To address this issue, we control for differential trends across regencies with different initial levels of important proxies for development such as population density, forest cover, share of households with access to electricity and share of villages with health infrastructure.

The first stage of our fixed effects IV model is as follows:

$$OP_{rt} = \beta_o + \beta_1 AY_r * OPA_t + \beta_2 OPA_t + \beta_3\, X_{rt} + \beta_4\, y_t * p_p + y_t + \mu_r + \varepsilon_{rt} \qquad (4)$$

where OP_{rt} is the share of smallholder oil palm area of total regency area. AY_r is the average max. attainable yield for oil palm in each regency r, and OPA_t is the national oil palm area in hectare in year *t*. X_{rt} includes additional controls such as average age. y_t are year fixed effects, p_p are region dummies and initial levels of development, and μ_r are regency fixed effects.

The second stage is as follows:

$$Y_{rt} = \beta_o + \beta_1 \widehat{OP}_{rt} + \beta_2 OPA_t + \beta_3 X_{rt} + \beta_4 \, y_t * p_p + y_t + \mu_r + \varepsilon_{rt} \qquad (5)$$

Y_{rt} represents sectoral shares and wage levels. The other variables are the same as in equation (4).

So far we designed models to test if changes in the labor market due to oil palm expansion indicate any labor displacement. As outlined in the conceptual framework these effects depend on the availability of land. It is challenging to define if a household, a village or a regency is land scarce or land abundant and our samples are not large enough to detect interaction effects between land scarcity proxies and oil palm expansion. While we can observe if the positive income effect of oil palm is related to land expansion, we do not know if farmers expanded agricultural land (*i.e.* via deforestation) or solely converted other crops. To address these challenges, we compiled data on regencies' forest cover over time based on satellite imagery. This allows us to test if the expansion of smallholder oil palm is decreasing forest cover, which would indicate an expansion of agricultural land. We use the same IV approach as described in equations (4) and (5).

5 Results

5.1 Descriptive statistics

Figure 1 shows employment rates and sectoral shares of men (Panel A) and women (Panel B) in 2000 and 2015. We compare between regencies with and without smallholder oil palm in 2015. As evident from Figure 1, the development of employment rates over time does not vary greatly between regencies with and without oil palm.

5.2 Regression results - farm scale

In Table 2, we present the effect of oil palm cultivation on farm households' total income (equation 2). Columns (1) to (3) show OLS (ordinary least square) estimates, while columns (4) to (6) show IV estimates. Additional control variables at household and village level are reported in Table A5 in the Appendix. The results show a consistently positive effect of oil palm cultivation on total income across all specifications. Effect sizes do not decrease strongly from column (1) to column (2) for the OLS estimates and from column (4) to column (5) for the IV estimates. We hence find no evidence that off-farm activities mediate the effect of oil palm cultivation on total income. However, controlling for total farm size seems to strongly mediate the effect of oil palm cultivation on total income in columns (3) and (6). These findings are consistent with studies that used propensity score matching and panel data models (Euler et al. 2017; Kubitza et al. 2018b). Overall, our results lend some supports for prediction 2.1 that under land abundance the observed positive income effect of oil palm cultivation is partly the result of cropland expansion.

In Table 3, we present the effects of oil palm adoption on employment indicators of individual farm household members using IV and probit models (equation 3). Additional control variables at individual, household and village level are reported in Tables A7and A8 in the Appendix. We find no evidence that employment rates of women or men decreased significantly (columns 1 and 2). But women are significantly less likely to work on their own farm (column 4) both in the IV and probit models. This result matches our plot-level results, which show a strong decrease of women's working hours comparing oil palm and rubber plots. While female labor supply in agriculture decreases, column (8) shows that women significantly increase their engagement in non-agricultural self-employment in both models. We find that oil palm significantly increases the likelihood of men working in the off-farm sector. However, these effects are not significant in our preferred IV model (column 5). Since we find no negative effects of oil palm adoption on men working in agriculture and general employment rates, our results are more consistent with prediction 2.2.

5.3 Regression results - aggregate scale

Tables 4-5 report estimates from a regency panel for the whole of Indonesia between 2000 and 2015 (equation 4-5) including also labor households. For robustness checks, we report IV alongside OLS estimates using regency-fixed effects in both specifications. Column (1) in Table 4 shows some evidence that women's employment rates decrease as a result of oil palm expansion. While the result is not consistent across all models, this still indicates that unlike at the farm-scale, labor displacement has taken place amongst women at larger scales. The extent of labor displacement was, however, limited by positive employment effects from the non-agricultural sector. Column (2) shows that women shift to the non-agricultural sector which partly offsets the large negative employment effect from the family agricultural sector (column 3). The coefficient shows that the expansion of smallholder oil palm area between 2000 and 2015 increased the share of women working in the non-agricultural sector by about 4%. The shift occurs primarily into non-agricultural employment (Table 4, column 6), although the OLS estimate implies that self-employment also played a role (Table 4, column 5). This differs from the farm-scale results. But the regency analysis might also capture the effect of migration from rural to urban areas. Laborers may potentially be leaving smaller villages in order to take up non-agricultural jobs in more urban areas.

For men, we observe a significant shift into agricultural wage labor (Table 5, column 4). We also find that men decrease their involvement in family agriculture (column 3) but the magnitude is smaller in comparison to the increase in agricultural wage labor and overall, we observe no significant shift from agricultural to non-agricultural activities for men (column 2). Taken together, these results indicate support for prediction 4.1 that under land abundance labor demand in agriculture does not decrease for men due to crop land expansion while women shift into the non-agricultural sector due to their lower relative labor productivity in oil palm.

Overall wages and wages in the non-agricultural sector do not significantly change for both women and men between 2000 and 2015. We note however that while most of the point estimates are positive, they are imprecisely measured which limits further interpretation. We only find some weak evidence that wages for men increased significantly in the agricultural sector (Table 6, column 6), which could be partly driven by the increasing labor productivity in oil palm cultivation. While these results neither support nor reject our predictions 3.2 and 4.2, we do not observe that wages are significantly falling.

One concern with our analysis is the robustness of our identification strategy. The suitability for oil palm cultivation should be unrelated with other geographic or agroecological characteristics that influence our outcome variables based on similar trends as the national oil palm expansion. We hence interact national oil palm expansion with spatial data on agroclimatic attainable yields from the GAEZ database for the most important crops in Indonesia – rice, maize, coconut and cocoa (FAOSTAT 2018). The estimates do not differ significantly from Tables 4-5. We also conduct a so-called falsification test of our instrumental variable (Table A15). We regress our instrument on sectoral employment shares of regencies with no oil palm cultivation, assuming that in this case our instrument should yield insignificant effects. We find only for one out twelve regressions a significant effect of our instrument. For this regression, we do not find that our IV estimates indicate other results compared to our OLS estimates (Table 5, column 5) and we can hence assume that our OLS estimates are still valid. Another concern could be that the effects of oil palm expansion only materialize with some time delay. To test if lagging the explanatory variable changes our results, we employ a two-year lag for oil palm expansion (Table A16). The results do not differ significantly to the main results in Table 4-5. Smallholder oil palm expansion is directly linked to large-scale oil palm plantations due to historical government policies such as the nucleus-estate schemes. Smallholders also depend on the infrastructure of large-scale plantations, in particular palm oil mills. Our variable might hence not only pick up the expansion of smallholder oil palm but also large-scale plantations. To address this concern, we merge our dataset with satellite data on the historical expansion of industrial-scale oil palm in Indonesia. Table A17 shows that our results on the effects of smallholder oil palm expansion are robust to controlling for industrial-scale oil palm.

5.4 Regression results – alternative explanations

We found consistent evidence that the expansion of oil palm did not lead to a significant displacement of male labor. Some evidence suggests that female labor might have been displaced but large parts of the female labor released from agriculture shifted into the non-agricultural sector. Our conceptual framework predicts such results if oil palm expansion is associated with a general expansion of agricultural land. Analysis from satellite imagery shows that half of Indonesia's forest loss between 2001 and 2016 is due to the expansion of large and small-scale plantations (Austin et al. 2019). While other agricultural land uses and grassland/shrubland are also converted to oil palm, forest conversion does play a major role in the expansion of oil palm (Krishna et al. 2017b). We hence expect that smallholder oil palm expansion is negatively related to forest cover in Indonesia. In Table 6, we estimate the effect of smallholder oil palm expansion on forest cover at the regency level, using data from 2000 to 2012. One-unit area increase in smallholder oil palm cultivation is associated with a loss of 0.65 units of forest cover. This confirms that smallholder oil palm expansion is not only associated with conversion of other crops but also with forest loss and a general expansion of agricultural land.

6 Conclusion

New labor-saving land uses and technologies are likely to spread in the rural areas of developing countries. However, the potential labor-displacing effects of such technical changes have received little attention in empirical work, in particular at larger scales. In this article, we have documented the labor market effects of a labor-saving land use – the expansion of oil palm among smallholder farmers in Indonesia – both at the farm as well as the national scale. Our results suggest that oil palm expansion has contributed to rising income levels for Indonesian smallholder farmers but significantly decreased the demand for agricultural labor per unit area, in particular female labor. At the same time, oil palm expansion led to new employment opportunities in the agricultural wage labor sector and the non-agricultural sector which buffered most of the adverse labor market effects for vulnerable groups such as women or rural laborer households.

Conceptually, if wages and output are fixed, a labor-saving land use change can decrease labor demand in the economy, affecting less productive population groups and groups with limited access to land and capital. But in Indonesia, output was not fixed and further cropland expansion was possible. At the farm scale, a considerable share of the positive income effect of oil palm cultivation is generated through cropland expansion. This was confirmed at national scale, where we found that oil palm expansion significantly increased deforestation.

The expansion of cropland compensated for some of the labor-displacing effects of oil palm and increased the demand for agricultural wage labor, especially for men. Indeed, we find clear evidence that men reallocated part of their time to agricultural wage labor. Besides direct labor demand effects, oil palm contributed to income growth, leading to local demand effects and a boost to the non-agricultural sector, which absorbed female labor that was freed from agriculture. At the farm scale, women increased their involvement in off-farm business activities, which we interpret as a measure to counteract the lower on-farm labor demand. At the national scale, we also find a significant shift of women from the agricultural to the non-agricultural sector. We find some evidence that female labor participation slightly decreased although the surge in non-agricultural employment counteracts the large drop in family agricultural employment. Taken together our results imply that local demand and productivity effects partly compensated the decrease in the demand for agricultural labor per unit area.

It should be stressed that these beneficial economic effects occurred largely at the expense of natural ecosystems, in particular forest land. Direct countermeasures to avoid deforestation could include increasing labor intensity per unit of land. Such measures would be however of limited scope since the marginal product of labor in oil palm cultivation will fall rapidly with increasing labor intensity. Alternatively, restricting further forest encroachment would force new oil palm adopters to reallocate some of their saved labor to the non-agricultural sector. Our results suggest that by incentivizing farm households to reallocate their labor to the off-farm sector rather than to expand agricultural land, rural laborers – and women in particular – might be displaced from the labor market. This presents a fundamental trade-off for policymakers. To manage labor savings in agriculture, we suggest that improvements in tenure security for agricultural and forest land might have to go hand-in-hand with employment initiatives focusing on marginalized rural population groups. Isolated interventions might entail undesirable social effects.

In general, we stress that combing detailed data from local surveys with nationally representative surveys was essential for our study. Without detailed primary data at the household, individual and plot level, we would not have been able to trace out the interlinkages between oil palm adoption, labor intensity and farm size expansion. At the same time, we would not have been able to show wider labor market effects on women and rural laborers without national data. Our results also underline that the economic, social and environmental effects of labor savings in agriculture have to be closely interpreted against the backdrop of land abundance and access to labor markets. While the Indonesian case, or also historical data from the agricultural expansion in the industrialized countries, show that labor-saving technologies can be economically beneficial, this may not be the case in settings with scarce land resources or limited access to the non-agricultural sector. Furthermore, if the economic benefits of labor-saving technologies are not widely distributed but accrue only to small sections of society such as owners of large-scale plantations, local demand effects could be substantially smaller and labor displacements more widespread. Besides these economic and social concerns, implementations of labor-saving technologies in settings with weak land regulation have to be conducted with caution in order to preserve remaining natural ecosystems.

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TABLES

Table 1: Datasets

Datasets	Year of survey/observation	Source
Local surveys		
Farm households (n = 683; Survey I)	2015	Primary data collected by authors
Labor households (n = 432; Survey II)	2015	
Trader households (n = 315; Survey III)	2012	
Spatial data		
Land cover in Jambi province	2013	Landsat data
Location of palm oil mills	2017	Global Forest Watch
Forest cover in Indonesia	2000, 2005, 2010, 2012	Margono et al. (2014)
Large-scale oil palm plantations	2000, 2005, 2010, 2015	Austin et al. (2017)
Max. attainable yield of different crops	1961-1990 (baseline data)	Global agro-ecological zones data
National surveys		
National labor force survey (SAKERNAS)	2000-2015	Badan Pusat Statistik (BPS)
Tree Crops Statistics	2000-2015	Ministry of Agriculture
National village survey (PODES)	2001, 2003, 2006, 2011, 2014	Badan Pusat Statistik (BPS)
Indonesian census	2000, 2010	IPUMS International database

Table 2: Effect of oil palm cultivation on annual farm household income (2015)

	OLS			IV		
	(1) Total income (log)	(2) Total income (log)	(3) Total income (log)	(4) Total income (log)	(5) Total income (log)	(6) Total income (log)
Share of oil palm (0-1)	0.268^{**}	0.273^{***}	0.094	1.018^{*}	1.045^{*}	0.490
	(0.106)	(0.101)	(0.089)	(0.537)	(0.534)	(0.514)
Employed household members (=1)		-0.386^{***}	-0.200^{***}		-0.428^{***}	-0.230^{***}
		(0.078)	(0.069)		(0.081)	(0.078)
Self-employed household members (=1)		0.225^{***}	0.210^{***}		0.173^{**}	0.185^{***}
		(0.071)	(0.061)		(0.080)	(0.067)
Total farm size (ha)			0.093^{***}			0.088^{***}
			(0.009)			(0.011)
F-Stat	17.639	20.997	26.104	18.404	20.833	28.026
Kleibergen Wald F-Stat				25.556	24.031	21.118
Observations	746	746	746	746	746	746

Notes: Data source is farm-household data (Survey I + II). Robust standard errors in parentheses. Instrument is the log distance to the closest palm oil mill. Dependent variable is log of total annual income ('000 IDR). We control for age and education of household head, female headed households, migrant households, number of women and adults, farm characteristics, distance to province capital, employed household members, self-employed household members and total farm size. Regency and survey dummies are included. At village level, we control for distance to the next all-season road, junior high school, a suitability index for oil palm cultivation in the village, the share of land with systematic or sporadic land titles, bordering large-scale plantations, transmigrant villages and the number of conflicts between farmers and companies in the last 10 years. Additional covariates included in estimation are reported in Table A5. Due to taking the log, 11 observations with zero or negative income were dropped from the analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of oil palm cultivation on employment status of individuals in farm households (2015)

	(1) Working (=1) (Men)	(2) Working (=1) (Women)	(3) Working on-farm (=1) (Men)	(4) Working on-farm (=1) (Women)	(5) Working off-farm (=1) (Men)	(6) Working off-farm (=1) (Women)	(7) Self employed off-farm (=1) (Men)	(8) Self employed off-farm (=1) (Women)
				IV				
Share of oil palm (0-1)	-0.154	-0.134	-0.202	-0.489*	0.400	0.155	0.004	0.353*
	(0.117)	(0.335)	(0.194)	(0.262)	(0.256)	(0.257)	(0.186)	(0.211)
F-Stat	115.774	24.817	180.262	48.978	61.859	24.135	5.209	5.375
Kleibergen Wald F-Stat	19.364	11.336	19.448	11.298	19.448	11.298	19.448	11.298
Observations	1114	1052	1114	1052	1114	1052	1114	1052
				Probit				
Share of oil palm (0-1)	0.006	-0.057	0.019	-0.126***	0.109***	0.039	0.040	0.053***
	(0.021)	(0.044)	(0.029)	(0.047)	(0.039)	(0.031)	(0.038)	(0.019)
Chi^2	513.975	888.620	1240.358	412.455	588.814	355.671	149.068	205.844
Observations	1114	1052	1114	1052	1114	1052	1114	1052

Notes: Data source is farm-household data (Survey I + II). Standard errors (clustered at household level) are shown in parentheses. Instrument is the log distance to the closest palm oil mill. We control for age, age squared, student, education level, migrant households, number of women and adults in household, farm characteristics, distance to province capital and total farm size. Regency and survey dummies are included. At village level, we control for distance to the next all-season road, junior high school, a suitability index for oil palm cultivation in the village, the share of land with systematic or sporadic land titles, bordering large-scale plantations, transmigrant villages and the number of conflicts between farmers and companies in the last 10 years. Additional covariates included in estimation are reported in Table A7 for IV models and Table A8 for probit models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Regency-level effects of oil palm expansion on sectoral shares of women (2000-2005-2010-2015)

	(1) Share of women working	(2) Share of women in non-agricultural sector	(3) Share of women in agricultural family labor	(4) Share of women in agricultural wage labor	(5) Share of women in non-agricultural self-employment	(6) Share of women in non-agricultural wage labor
			IV			
Share of smallholder oil palm area in regency (0-1)	-2.877**	4.244***	-7.245***	0.329	1.035	3.164***
	(1.348)	(1.378)	(2.093)	(0.733)	(0.884)	(1.068)
R2	0.157	0.303	0.011	0.104	0.093	0.402
Kleibergen Wald F-Stat	14.427	14.427	14.427	14.427	14.427	14.427
Observations	827	827	827	827	827	827
			OLS			
Share of smallholder oil palm area in regency (0-1)	-0.731	1.620***	-1.024***	-0.013	0.691***	0.785***
	(0.463)	(0.420)	(0.392)	(0.171)	(0.256)	(0.218)
R2	0.235	0.357	0.281	0.109	0.097	0.483
Observations	827	827	827	827	827	827

Notes: Data sources are SAKERNAS and Tree Crop Statistics. Dependent variables are shares, ranging between 0 and 1. IV and OLS estimates are reported with spatial HAC standard errors using a 150km cutoff. Instrument is the maximum attainable oil palm yield per regency times national oil palm expansion. We control for mean age of working-age women, national oil palm expansion, regency fixed-effects, year dummies, region trends and initial levels of population density, forest cover, hospital density and electrification multiplied by time trend. Initial levels are based on 2000 data. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Regency-level effects of oil palm expansion on sectoral shares of men (2000-2005-2010-2015)

	(1) Share of men working	(2) Share of men in non-agricultural sector	(3) Share of men in agricultural family labor	(4) Share of men in agricultural wage labor	(5) Share of men in non-agricultural self-employment	(6) Share of men in non-agricultural wage labor
			IV			
Share of smallholder oil palm area in regency (0-1)	-0.541	-0.774	-1.827**	2.795***	-1.078	0.634
	(0.660)	(1.112)	(0.813)	(0.776)	(0.925)	(0.836)
R2	0.137	0.384	0.053	0.087	0.098	0.564
Kleibergen Wald F-Stat	14.088	14.088	14.088	14.088	14.088	14.088
Observations	827	827	827	827	827	827
			OLS			
Share of smallholder oil palm area in regency (0-1)	-0.220*	0.150	-0.458**	0.808***	0.063	0.072
	(0.121)	(0.297)	(0.190)	(0.234)	(0.175)	(0.180)
R2	0.143	0.394	0.149	0.261	0.147	0.569
Observations	827	827	827	827	827	827

Notes: Data sources are SAKERNAS and Tree Crop Statistics. Dependent variables are shares, ranging between 0 and 1. IV and OLS estimates are reported with spatial HAC standard errors using a 150km cutoff. Instrument is the maximum attainable oil palm yield per regency times national oil palm expansion. We control for mean age of working-age men, national oil palm expansion, regency fixed-effects, year dummies, region trends and initial levels of population density, forest cover, hospital density and electrification multiplied by time trend. Initial levels are based on 2000 data. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Regency-level effects of oil palm expansion on forest cover (2000-2005-2010-2012)

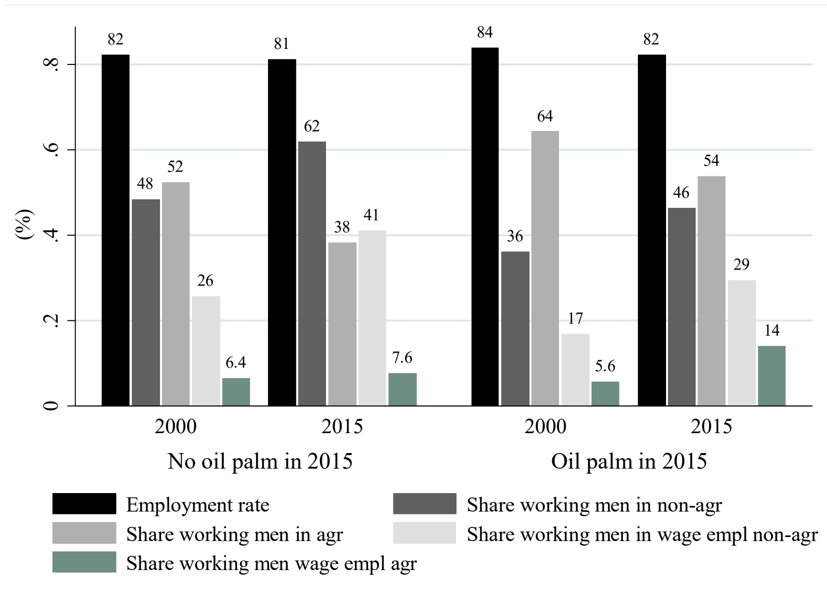
	(1) Share of forest cover	(2) Share of forest cover
	IV	**OLS**
Share of smallholder oil palm area in regency (0-1)	-0.645***	-0.591***
	(0.228)	(0.173)
R2	0.574	0.575
Kleibergen Wald F-Stat	11.375	
Observations	827	827

Notes: Data sources are Margono et al. (2014) and Tree Crop Statistics. Dependent variables are shares, ranging between 0 and 1. IV and OLS estimates are reported with spatial HAC standard errors using a 150km cutoff. Instrument is the maximum attainable oil palm yield per regency times national oil palm expansion. We control for national oil palm expansion, regency fixed-effects, year dummies, region trends and initial levels of population density, hospital density and electrification multiplied by time trend. Initial levels are based on 2000 data. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

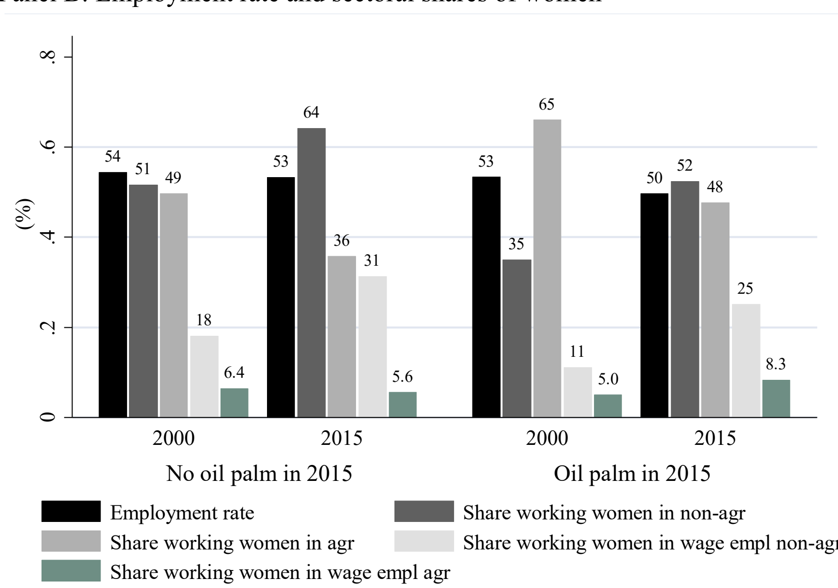
FIGURES

Figure 1: Gendered employment rates at the regency level in Indonesia

Panel A: Employment rate and sectoral shares of men



Panel B: Employment rate and sectoral shares of women



Notes: Data source is SAKERNAS. Analysis includes 208 regencies. In 2015, smallholders cultivated oil palm in 86 regencies (41%).