

Labor Displacement in Agriculture: Evidence from Oil Palm Expansion in Indonesia

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Abstract: *We analyze the labor market effects of oil palm cultivation among smallholder farmers in Indonesia. Oil palm requires less labor per unit of land than alternative crops, especially less female labor. Micro-level data and nationally-representative regency-level data show that oil palm adoption, on average, led to an expansion of total cropland at the expense of forestland, resulting in higher agricultural labor demand for men. At the same time, women's employment rates declined due to a substantial decrease in agricultural family labor, which was most evident in regions with high initial land scarcity and thus limited options for cropland expansion.*

JEL codes: O1, O13, Q1, Q15

1. Introduction

Empirical research has shown that growth in agricultural productivity substantially contributes to overall economic growth (McArthur and McCord, 2017), poverty reduction (Christiaensen and Martin, 2018), and reduced global pressure on forestland (Villoria, 2019). Productivity enhancements in agriculture are also necessary to keep labor in the sector, given that 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 in these countries (Gallardo and Sauer, 2018; Sunding and Zilberman, 2001). For developing countries, on the other hand, evidence is scarce and economic conditions are likely to differ from the historical trajectories of high-income countries. Still, labor-saving technologies – such as mechanization and herbicide application – are often perceived as key technologies to increase agricultural labor productivity in developing countries (Adu-Baffour, Daum, and Birner, 2019; Haggblade et al., 2017; Sheahan and Barrett, 2017).

It is widely recognized that labor savings in agriculture can have heterogeneous effects on different strata of rural societies and depend on the level of aggregation (Haggblade et al., 2017; Pingali, 2007). 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' rural areas at larger scales. A few studies focus on direct productivity effects, income gains, cropland expansion, and labor savings (Adu-Baffour, Daum, and Birner, 2019; Benin, 2015; Kirui, 2019). Yet, most studies do not empirically analyze the wider labor market effects (Bouwman, Andersson, and Giller, 2021; Caunedo and Kala, 2021). 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 in the past was often restricted to large agricultural companies or relatively small groups of larger farms.

This article contributes to the literature by analyzing the wider labor market effects of the labor savings introduced by the expansion of oil palm in Indonesia. The boom of the palm oil sector in Indonesia is related to targeted government interventions and large-scale acquisitions of concessions by transnational investors and also the widespread use of contract farming schemes around the world (Lay et al., 2021). In response, global production of palm oil rose by around 600 percent between 1990 and 2016 with Indonesia being the largest producer (Byerlee, Falcon, and Naylor, 2017; US Department of Agriculture, 2017). Due to differences in labor intensity and productivity between oil palm and alternative cash crops, oil palm expansion was found to increase the living standard of oil palm adopters and agricultural laborers (Bou Dib et al., 2018; Euler et al., 2017; Gehrke and Kubitzka, 2021).

To define a technology or practice as labor-saving, it is necessary to know which production system it may be replacing. Following the literature on oil palm cultivation and welfare, we argue

that oil palm can be characterized as labor saving in the sense that it requires less labor per unit of land than the dominant alternative crops in the regions such as rice and rubber. For labor-saving technologies, output is the same but the technology has changed such that less labor is required. Such new technologies can be also understood as a new way of allocating production factors to increase technical efficiency on the farm. A labor-saving land use goes certainly beyond only reorganizing production factors, however, 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 for oil palm being skill-biased, nor for unobserved patterns in agricultural production significantly changing 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 article. Oil palm is also interesting because it is not only grown by large companies but to a substantial extent by smallholder farm households. In 2019, smallholder farm households cultivated more than 40 percent of the national oil palm area in Indonesia (Chrisendo, Siregar, and Qaim, 2022), 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 strata of rural society (Cramb and Curry, 2012; Li, 2015; Obidzinski et al., 2012).

A few studies already analyzed the economic effects of oil palm expansion in Indonesia to study long-term demographic changes (Gehrke and Kubitzka, 2021) and poverty reduction (Edwards, 2019a). Examining the effect of oil palm expansion on poverty since the 2000s, Edwards (2019a) finds a significant reduction in poverty as well as indirect effects on rural and social infrastructure, applying a similar identification strategy as we do in this article. This study, however, does not focus

on labor savings introduced by oil palm, nor on potential labor displacement. Also, it is solely based on a regency-level panel from secondary data and not micro-level household data. Gehrke and Kubitzka (2021) focus on the effects of the oil palm expansion on changes in demographic patterns and find significant reductions in fertility. Their 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. Although we use similar identification strategies proposed by Edwards (2019a) and Gehrke and Kubitzka (2021), the current study is unique due to its combination of new data at different scales (household and regency level), as well as its focus on labor savings in agriculture and their effects on labor displacement. These aspects were not yet analyzed in depth in the existing literature to the best of our knowledge.

The second contribution of this article is the analysis of the employment effects of labor savings in agriculture with respect to crop land expansion. If the initial labor supply is the limiting factor, 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 occur. Such aspects have not been extensively considered in the existing empirical research on the effects of labor savings in agriculture, in particular when it comes to the role of smallholder farmers in oil palm cultivation. These factors 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 and Laurance, 2009; Carlson et al., 2018; Chrisendo, Siregar, and Qaim, 2021; Koh et al., 2011). For large-scale palm oil investments, recent studies already provide evidence on positive local spillovers such as increases in labor and total factor productivity of manufacturing plants not related to palm oil value chains (Kraus, Heilmayr, and Koch, 2021) and improved public infrastructure (Edwards, 2019b; Kraus, Heilmayr, and Koch, 2021).

The main research question addressed in this article is: how does a labor-saving innovation – such as the adoption of oil palm – affect welfare and employment in the rural labor market?² The widespread adoption of oil palm by smallholder farmers, constant returns to skill, and significant changes in labor intensity provide us with the unique opportunity to pin down the wider labor market effects of labor savings in agriculture. To guide our analysis, we focus on two major options for farm households to reallocate the labor time saved through oil palm adoption, which may have heterogeneous welfare and equity effects. First, the saved time may be reallocated to the off-farm sector. Second, more labor is employed to enable cultivation of additional cropland.³ In our empirical analysis, we employ different data sources such as local household data collected during several surveys as well as representative national survey data reaching from 2000 to 2015. In addition, we use land cover data derived from satellite imagery. Our identification strategy to tackle the potential endogeneity of oil palm adoption builds on fixed-effects models and an instrumental variable (IV) approach. For our local household data, we use a three-round panel dataset using village and household-level fixed effects. For the national panel with regency-level observations, we rely on regency-level fixed effects and an IV based on the variability in regencies' suitability for oil palm cultivation.

The remainder of this article is structured as follows. Section 2 presents our conceptual framework 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. Section 4 discusses 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

This section first outlines the effects of a labor-saving land use at the farm household scale before assessing wider labor market effects. We assume that once the necessary infrastructure such as palm

oil mills and roads are in place, the decision to adopt oil palm is mainly based on individual preferences and constraints of farm households. Recent research shows that the positive income effect of oil palm cultivation is partly driven by lowering the labor intensity compared to competing crops such as natural rubber and rice (Euler et al., 2017; Rist, Feintrenie, and Levang, 2010).⁴ Appendix Table A1 illustrates based on plot data the differences in intensity and productivity between oil palm and rubber from a survey in Jambi province in Sumatra (Gehrke and Kubitzka, 2021). Labor productivity is significantly higher in oil palm compared to rubber. Other studies confirm the relatively higher labor productivity in oil palm compared to rice cultivation (Rist, Feintrenie, and Levang, 2010). Male labor hours per hectare and per year are 72 percent lower for oil palm compared to rubber cultivation. For women, the labor hours decrease even more drastically by 92 percent since considerable additional physical strength is needed to harvest oil palm compared to rubber (Mehraban et al., 2022). Women are hence often restricted to maintenance work and collection of loose oil palm fruits (Koczberski, 2007; Li, 2015). We further observe that women receive lower wages in oil palm than men. Although we cannot calculate gender differences in agricultural productivity due to the joint management of plots, we interpret the changes in working hours and wages comparing oil palm and rubber as an indication of a relatively lower labor productivity of women in oil palm cultivation compared to men.

Estimates provided in Appendix Table A1 alongside findings of other studies suggest that oil palm has a lower land productivity compared to competing crops, especially rubber (Euler et al., 2017; Rist, Feintrenie, and Levang, 2010). However, if the opportunity costs of family labor, which are important for more labor-intensive cropping systems such as rubber, are included when calculating farm profits, oil palm is more profitable (Grass et al., 2020). Based on this evidence, we assume that at least some part of the positive income effect is derived from the reallocation of labor

to additional cropland or to the non-agricultural sector (Krishna et al., 2017a).⁵ Gehrke and Kubitzka (2021) provide further evidence on labor savings introduced by oil palm adoption.

Farm household scale

To derive testable hypothesis, we consider a typical agricultural household model, in which a household maximizes utility from the consumption of services and goods and leisure:

$$\max_{q,L} U(q, L; K) \quad [1]$$

where q is the vector of quantities of services and goods; L denotes the household's time allocated to leisure; and K represents the household characteristics. The time constraint faced by the household is given by:

$$T = T_F + T_A + T_{NA} + L \quad [2]$$

where T is the total time endowment.⁶ T_F denotes family labor hours deployed on the own farm. T_A represents labor hours deployed off-farm in agricultural employment. T_{NA} denotes labor hours in non-agricultural employment.

We assume a simplified budget constraint at the farm household level to illustrate the effects of a labor-saving land use change (Goodwin and Holt, 2002):

$$pq + r'X = A P_a f\{T_F, X\} + w_A T_A + w_{NA} T_{NA} \quad [3]$$

where p represents the price of services and goods. X is a vector of farm input quantities, the price vector of which is r . A refers to farm size, and the revenue is generated according to the production function f per land unit using family labor T_F and farm inputs X . P_a is the output price for agricultural good. w_A and w_{NA} are the wages for off-farm work in the agricultural and non-agricultural sector, respectively.⁷

To represent the reality on the ground, as captured by the descriptive statistics in Table A1 and findings in the existing literature, we make the following four assumptions with respect to our model. First, labor productivity increases compared to competing crops such as rubber or rice at low levels of labor input: $\frac{\partial f(OP)}{\partial T_F} > \frac{\partial f}{\partial T_F}$, where $f(OP)$ is production per unit of farmland A that is allocated to oil palm. Second, the amount of land per unit of labor in efficiency units is decreasing. Thus, the marginal product of labor in oil palm falls more rapidly with an increasing number of hours worked per unit area compared to competing crops (Bustos, Caprettini, and Ponticelli, 2016).⁸ Third, due to the additional physical strength needed in oil palm cultivation, the relative labor productivity of men increases compared to women: $\frac{\partial f(OP)}{\partial T_{F,M}} / \frac{\partial f}{\partial T_{F,M}} > \frac{\partial f(OP)}{\partial T_{F,W}} / \frac{\partial f}{\partial T_{F,W}}$. The subscript W denotes the labor allocation of women and M of men. Fourth, we also assume that wages in agriculture are a function of labor productivity and increase with oil palm expansion in the short run: $w_A(OP) > w_A$, where $w_A(OP)$ is the wage obtained in employment in oil palm cultivation. From this follows that agricultural wages for men increase more strongly due to their relatively higher labor productivity in oil palm compared to women: $w_{A,M}(OP)/w_{A,M} > w_{A,W}(OP)/w_{A,W}$.

In the following, we outline the expected effects of oil palm adoption at the farm household scale both for land scarce and land-abundant settings. If land is scarce (A is fixed), given that not all farm households have access to additional land (Krishna et al., 2017b), our first and third assumptions suggest that $T_{F,W}$ and $T_{F,M}$ decrease with oil palm adoption, with $T_{F,W}$ decreasing more drastically than $T_{F,M}$. Farm households can increase their incomes by allocating their freed labor time to the off-farm sector, thus increasing T_{NA} and T_A . Given free movement of labor between sectors and a competitive labor market, $w = \frac{\partial f P_a}{\partial T_F}$ in the long run. As the relative labor productivity of women in oil palm cultivation is declining with increasing land getting dedicated to oil palm growing, we expect that women in particular opt to work in the non-agricultural sector, hence $T_{NA,W}$ increases.

In a land-abundant setting, freed labor can be reallocated to new cropland, hence A increases, potentially offsetting the initial decrease in T_F . This will in particular be the case if $\frac{\partial f(OP)P_a}{\partial T_F} > w$ in the short run. This outcome is more likely for men as they have a relatively higher labor productivity in oil palm, although this may apply to female household members also.

The model further implies that with labor savings in agriculture, households might reallocate family labor hours deployed on farm T_F to leisure L , depending on the opportunity costs of each activity. We have argued that the positive income effects of oil palm adoption derive in part from the redistribution of labor to other productive uses. If saved labor is instead reallocated to leisure, income may not increase or, in the extreme case, even decrease. Yet, a shift of all the labor saved to leisure is unlikely in the Indonesian setting where many of the households are relatively poor. A reallocation of some of the labor to leisure would likely reduce the effects hypothesized here but not change the overall direction. Based on these considerations we state the following hypotheses.

Hypotheses set 1. If land is scarce:

- 1.1. Oil palm adoption increases total income of farm households through additional off-farm employment.
- 1.2. Oil palm adoption decreases the likelihood to work in agriculture, in particular for women in farm households. This can be offset by off-farm employment.

Hypotheses set 2. If 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.

Aggregate scale

At higher spatial scales, we expect more ambiguous labor market effects depending on the abundance of land. We follow the model by Gehrke & Kubitzka (2021) which considers each regency to behave like a small open economy with two sectors and integrate our reasonings on effect heterogeneity based on land scarcity.⁹ The model of Gehrke & Kubitzka (2021) is described in the following paragraph and the adjustments in this article's reasoning follow afterwards.

The model derives the general equilibrium effect of the oil palm expansion on wages as a combination of local economy and labor demand effects. First, with respect to the local economy, the model concludes that the higher labor productivity in oil palm increases wages in agriculture, $w_{A,M}$, in particular for men (*productivity effect*).¹⁰ Given that labor can move freely between sectors, all other wages would increase, too. Second, if oil palm adoption increases incomes due to higher labor productivity and land expansion, we expect an increasing demand for other local goods and services (Emerick, 2018; Klasen, Priebe, and Rudolf, 2013). This would increase wages in the non-agricultural w_{NA} (*local demand effect*). For labor demand effects, we expect that the demand for agricultural labor T_F decreases initially in particular for women due to their relatively lower labor productivity. In addition, lower labor demand in agriculture could decrease agricultural wages (*labor demand effect*). For land abundance, we consider however that cropland expansion could dominate over the labor demand effect, leading to higher demand in agricultural labor, in particular for male labor.

In a scenario with land scarcity, we expect that a major part of the freed labor in the farm sector is allocated to the non-agricultural sector, hence T_{NA} increases. Since the market clearing condition in the non-agricultural sector is $w_{AN} = p_{AN}MPL_{AN}$, with p_{AN} being the output price of the non-agricultural good and MPL_{AN} the marginal product of labor in that sector, we expect that the additional supply of labor to the non-agricultural sector decreases wage rates in that sector (*labor*

supply effect).¹¹ Which group of effects dominate, the labor demand and the labor supply effects or the productivity and the local demand effects depends ultimately on the newly generated consumption demand and thus on the magnitude of the income increase from adopting oil palm.¹² At an aggregated scale, an oversupply of non-agricultural labor and decreasing labor demand in agriculture would depress wages and reduce employment opportunities.

In a scenario with abundant land, we expect that the saved labor from oil palm adoption would be reallocated to additional cropland, *A*. If the additionally cultivated land absorbs freed labor (hence no labor supply and no labor demand effect), we expect that oil palm expansion is positively affecting agricultural employment and the non-agricultural sector through local demand linkages and increases in agricultural labor productivity. However, even under land abundance increases in the relative labor productivity of men could lead to a redistribution of labor activities between genders. Based on these considerations, the following impacts are possible in the case of land scarcity or land abundance.

Hypotheses set 3. If land is scarce:

- 3.1. Employment in agriculture decreases with oil palm adoption, especially for women. If the non-agricultural sector does not absorb all freed labor, total employment rates are likely to drop.
- 3.2. While the effect of oil palm on non-agricultural wages is ambiguous, it can be concluded that decreasing wages are an indicator of the labor demand and supply effects dominating over the local demand and productivity effect.

Hypotheses set 4. If land is abundant:

- 4.1. Demand for agricultural labor will likely 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

The empirical analysis employs 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 the household and the 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 back to the early 2000s. Using panel data for all of Indonesia enables us to apply a more refined identification strategy and to observe the effects of oil palm expansion at broader scales. Table 1 lists the different datasets used for the analysis.

[Insert Table 1 here]

Primary data were gathered as part of an interdisciplinary project located in Jambi Province, Sumatra (Kopp and Brümmer, 2017). Jambi Province ranks sixth in national palm oil production in Indonesia (Kubitza et al., 2018). To establish a panel dataset, a household survey was conducted in 2012, 2015, and 2018. Sampling was based on a multi-stage framework and included 683 randomly selected farm households in 45 villages. Sampling details are explained by Kubitza et al. (2018). Since the survey partly also included household relying to a lesser extent on farming, we drew a threshold at one hectare, referring to all households above this threshold as farm households reducing sample size across all three waves from 2051 to 1874. Geocoded data on the locations of palm oil mills in Jambi Province for each particular year were obtained from Benedict et al. (2023).

National data were obtained from several sources. We included regencies (*kapupaten*) into our analysis and excluded cities (*kotas*), as oil palm expansion happens mainly in rural areas.¹³ 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 with annual frequency. 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 (FAO, 2023; Fischer et al., 2012). Yields are predicted based on agronomic modeling under pre-specified levels of fertilizer use and management conditions.¹⁴ 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 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.¹⁵

4. Estimation strategy

Farm household-scale models

We start by designing models to evaluate our hypotheses at the farm household 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 proxied by expenditures on the share of cropland planted with oil palm (*hypotheses 1.1 and 2.1*). We then stepwise add farm size and employment dummies as additional control variables. Clusters of

smallholders growing oil palm could correlate with the locations of large oil palm plantations and palm oil mills (Cramb and McCarthy, 2016; Gatto et al., 2017). These large-scale plantations and palm oil mills could affect employment opportunities and income generation in adjacent villages. Additionally, the presence of such plantations might spark land conflicts and decrease tenure security which in turn influences farmers' investment decisions. Some regencies were also more suitable for oil palm than others, and more central and economical active areas also did not lend themselves for oil palm plantations. To address these potential endogeneity bias as much as possible with our dataset, we employ either village-level or household-level fixed effects in all our models. The model with village-level fixed effects is specified as follows:

$$T_{kvt} = \beta_0 + \beta_1 OP_{kt} + \beta_2 A_{kt} + \beta_3 OF_{kt} + \beta_4 X_{kvt} + \mu_v + \gamma_t + \varepsilon_{kvt} \quad [4]$$

where T_{kvt} is total expenditure of a household k in village v in year t (in log terms). OP_{kt} is the share of cropland planted with oil palm. A_{kt} is the total farm size, and OF_{kt} includes dummies for off-farm employment. X_{kvt} includes additional control variables such as age, education and migration background of the household head. γ_t represent year fixed effects. μ_v represents village-level fixed effects. We also employ household-level fixed effects models as robustness check throughout the analysis.

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

$$OF_{ikvt} = \beta_0 + \beta_1 OP_{kt} + \beta_2 K_{ikvt} + \mu_v + \gamma_t + \varepsilon_{ikvt} \quad [5]$$

where OF_{ikvt} is a dummy for different types of work such as employment and self-employment dummies of individual i in household k in village v in year t . K_{ikvt} includes additional controls. We split the sample by gender. We again employ household-level fixed effects models as robustness check throughout the analysis.

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 (*hypotheses 3.1 and 4.1*), and wages (*hypotheses 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 an IV approach. This is particularly important because, unlike our farm-household data collected within a single province, our regency-level data encompass regions with significant differences in political and societal dynamics. These differences could potentially be linked to both agricultural development and labor market outcomes. 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.¹⁶ 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 (2019a) and Gehrke and Kubitzka (2021). 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.¹⁷ 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.¹⁸ 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:

$$OP_{rt} = \beta_0 + \beta_1 AY_r * OPA_t + \beta_2 OPA_t + \beta_3 X_{rt} + \beta_4 y_t * p_p + y_t + \mu_r + \varepsilon_{rt} \quad [6]$$

where OP_{rt} is the share of smallholder oil palm area of total regency area. In the Appendix, we conduct robustness checks using the expansion of large-scale oil palm estates as additional control. 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:

$$Y_{rt} = \beta_0 + \beta_1 \widehat{OP}_{rt} + \beta_2 OPA_t + \beta_3 X_{rt} + \beta_4 y_t * p_p + y_t + \mu_r + \varepsilon_{rt} \quad [7]$$

Y_{rt} represents sectoral shares and wage levels. The other variables are the same as in equation (6). In addition, we test if infrastructure development and migration could be confounding transmission mechanisms.¹⁹ We use the same IV approach as described in equations (6) and (7).²⁰

So far, our models 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. To test for this hypothesized effect heterogeneity, we compile 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. In addition, we interact smallholder oil palm expansion OP_{rt} with the forest share of each regency in 2000 which serves as a proxy for regencies where the oil palm expansion took place in a relatively land-scarce versus land-abundant setting. Due the lack of multiple instruments, we use OLS models with regency-level fixed effects.

5. Results

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 decrease in employment rates over time is slightly more pronounced in regions with oil palm. We also observe a shift into agricultural wage employment in regencies with oil palm, in particular for men. In addition, the drop of women working in agriculture and the shift of women into the non-agricultural sector seems to be more pronounced in regencies with palm oil production. This provides us some indication that women and men shifted sectors due to the oil palm expansion. However, aggregate data may mask the large heterogeneity between regions in their transition pathways towards an oil palm dominated agriculture. Studies from areas formerly dominated by rubber plantations in Sumatra underline that, for farmers independently switching from rubber to oil palm, only men increased off-farm labor and only on the extensive and not on the intensive margin (Chrisendo et al., 2020; Mehraban et al., 2022). In contrast, a study from Kalimantan highlighted significant differences between villages dominated by swidden agriculture

compared to oil palm villages, with significantly higher off-farm labor in the latter, for both women and men (Rowland et al., 2022).

[Insert Figure 1 here]

Appendix Figure A1 illustrates Indonesia's oil palm expansion disaggregated by producer type. We find an increasing importance of smallholders over time. In 2017, smallholder farmers cultivated around 40 percent of the total oil palm area. Appendix Table A2 provides a detailed description of all variables. Appendix Table A3 reports descriptive statistics for all variables of interest based on the local household surveys. Appendix Table A4 reports descriptive statistics for all variables of interest based on the national data.

Regression results – farm household scale

In Table 2, we present the effect of oil palm cultivation on farm households' total expenditures (equation 4). Columns (1) to (3) show estimates of models with village-level fixed effects, while columns (4) to (6) show models with household-level fixed effects. Additional control variables at the household and village level are reported in Appendix Table A5. The results show a consistently positive effect of oil palm cultivation on total expenditure across all specifications.²¹ Effect sizes only slightly decrease from column (1) to column (2) and from column (4) to column (5). We hence find some evidence that off-farm activities mediate the effect of oil palm cultivation on total expenditures. However, controlling for total farm size seems to strongly mediate the effect of oil palm cultivation on total expenditures in columns (3) and (6). The findings are consistent with studies that used propensity score matching or panel data models without fixed effects (Euler et al., 2017; Kubitzka et al., 2018). Overall, our results support hypothesis 2.1 that under land abundance the observed positive expenditure effect of oil palm cultivation is partly the result of cropland expansion. However, our results also suggest that off-farm self-employment could mediate the effect of oil palm cultivation to some degree (hypothesis 1.1). In general, due to the increasing land scarcity

in Indonesia, it is likely that the labor time saved through the adoption of oil palm will be increasingly redirected towards off-farm self-employment rather than expanding cropland. This could be also true for our research region in Sumatra, which has witnessed extensive deforestation of lowland forests in the past few decades and a rise in land scarcity. This transition is evident in land transactions, as indicated by recall data collected from the surveyed farm households: prior to 2010, the majority of new plots originated from forested or bush areas, whereas by 2015, new oil palm plots were predominantly situated on land previously utilized for agriculture (Appendix Figure A2).²²

[Insert Table 2 here]

In Table 3, we present the effects of oil palm adoption on employment indicators of individual farm household members using again village and household-level fixed effects models (equation 5). Additional control variables at individual and household level are reported in Appendix Tables A6 and A7. While we find a weak but significant positive effect of the share of land under oil palm cultivation on employment rates of men, employment rates for women are negatively affected in both models, although the effect is only significant in the village-level model (columns 1 and 2). This is because women are significantly less likely to work on their own farm (column 4), although the effect is again only significant in the village-level fixed effects model. It is plausible that the effect of increasing oil palm acreage within a household is decreasing working hours in agriculture for women rather than pushing them completely out of agriculture. Overall, the result matches our plot-level results, which show a strong decrease of women's working hours comparing oil palm and rubber plots (see Appendix Table A1). We do not find that women increase working off-farm in general or engage in non-agricultural self-employment (columns 6 and 8). We find, however, that oil palm significantly increases the likelihood of men working in the off-farm sector and engaging in non-agricultural self-employment (columns 5 and 7). Since we find negative effects of oil palm

adoption on women working in agriculture and their employment rates, our results imply to some extent land scarcity (hypothesis 1.2) and the replacement of cropping systems with higher labor intensities. The result could be also driven by preferences for leisure, we show, however, in our aggregate-scale models that these dynamics differ between regions with land scarcity versus land abundance and are hence likely driven by land access and not preferences for leisure. Our second finding is that while men do not leave agriculture completely which is reasonable as our sample consists of farm households where men usually conduct some agricultural work on their farm, they take up additional off-farm work, probably because they spend less time in agriculture (Appendix Table A1). Again, our results reflect the transition in Jambi where land resources over time are becoming scarcer (Appendix Table A2).

[Insert Table 3 here]

Regression results - aggregate scale

Tables 4-5 report estimates from a regency panel for the whole of Indonesia between 2000 and 2015 (equation 6-7) including also labor households.²³ For robustness checks, we report IV alongside OLS estimates using regency-level fixed effects in both specifications.²⁴ Column (1) in Table 4 shows evidence that women's employment rates decrease as a result of oil palm expansion which is similar to the farm-scale models. The observed decrease in employment was mainly driven by the large negative employment effect from the family agricultural sector which is also in line with our plot-level data and the estimates from the farm-level models (column 3). These effects are consistent across a large diversity of specifications (see Appendix Tables A10-A18). To some extent, the labor displacement could also have been limited by positive employment effects from the non-agricultural sector. However, only the OLS estimate in column (2) suggests that the expansion of smallholder oil palm area increased the share of women working in the non-agricultural sector.

[Insert Table 4 here]

For men, we observe a significant shift into agricultural wage labor (Table 5, column 4). The differences to farm-level models could result from using different samples. At the aggregate scale, we also include labor households and cities within regencies and thus also partly control for regional migration. This effect is again stable across a large diversity of specifications (see Appendix Tables A10-A18). 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. Overall, in contrast to women, we observe no significant and consistent shift out of agricultural activities for men across all models, but rather the opposite. Similar to farm-scale results, these findings are mixed concerning our hypotheses outlined in Section 2. Considering the decreasing labor intensities per hectare for men in oil palm cultivation compared to competing cropping systems, the growing share of men in the agricultural workforce supports hypothesis 4.1. This implies that, within the timeframe of our data, Indonesia had still sufficient land resources, which allowed the demand for male labor in agriculture to remain stable or even grow due to cropland expansion. Nonetheless, we also observe a decline in female participation in the agricultural sector, resulting in reduced employment rates. While higher reservation wages could potentially account for this change, the decline in female employment may also suggest that not only did cropland expand, but cropping systems with higher labor intensities for women were replaced by oil palm (hypothesis 3.1). We analyze and explain these ambiguous results in more detail in Section 5.4.

[Insert Table 5 here]

Appendix Table A9 reports the results for wages. Overall wages and wages in the non-agricultural sector do not significantly change for both women and men between 2000 and 2015.²⁵ We note, however, that while most of the point estimates are positive for the IV models, they are imprecisely measured which limits further interpretation. We only find some weak evidence in the OLS models that wages for men increased significantly in the agricultural sector, which could be

partly driven by the increasing labor productivity in oil palm cultivation. While these results neither support nor reject our hypotheses 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).²⁶ Results are reported in Appendix Tables A10. The estimates support our main conclusions from Tables 4-5. 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 re-estimated our model using SAKERNAS data from 2002, 2006, 2011 and 2015 and a two-year lag for oil palm expansion (Table A11). Again, the results are not significantly different from the main results in Table 4-5.²⁷ Smallholder oil palm expansion is directly linked to large-scale oil palm plantations due to historical government policies such as the nucleus estate and smallholder (NES) scheme. 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 A12 shows that our results on the effects of smallholder oil palm expansion are robust to controlling for industrial-scale oil palm.²⁸

Effect heterogeneity and robustness checks

Our conceptual framework predicts effect heterogeneity in settings of land scarcity versus land abundance which could also explain the mixed results in both our models in Section 5.3. To assess the potential heterogeneity, we interact the regency-level forest share in 2000 with our smallholder oil palm expansion variable. The results in Table 6 show that in contexts of greater land scarcity,

there is a significant negative effect on agricultural family labor for both men and women, presumably because more labor-intensive cropping systems have been replaced by oil palm (column 3). In column 5, we find that men move from agricultural family labor to non-agricultural self-employment and agricultural wage labor, although the effect is not significant at conventional levels of statistical significance. For women, however, the decline in employment in family agriculture leads to a significant decline in workforce participation. This confirms our hypothesis 3.1 that in land-scarce settings, employment in agriculture decreases, especially for women, and that if the non-agricultural sector does not absorb all the labor that becomes available, employment rates decline, too. In contrast, family labor in agriculture does not decrease in land-abundant settings. Neither do women drop out of the labor market nor do men shift into non-agricultural self-employment. This is in line with hypothesis 4.1 that in land-abundant settings, demand for agricultural labor will not decrease and may even increase, especially for men.

[Insert Table 6 here]

Overall, we found robust and consistent evidence that the expansion of oil palm did on average not lead to a significant displacement of male labor from the labor market in general. We find, however, that the smallholder oil palm expansion led to male labor reallocating towards agricultural wage labor away from agricultural family labor and 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 Appendix Table A19, 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 0.72 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.

Possible confounding mechanisms are discussed in the following. In an additional robustness check, we control for several infrastructure variables, such as roads, schools, and electricity at the regency level, using PODES data.²⁹ To assess the effect of potentially confounding variables, we have to use a fixed effects specification without an IV as in the OLS section of Table 4. Appendix Table A15 shows the results for the time period adjusted to data availability without controlling for infrastructure. Table A16 includes the infrastructure variables as additional controls. The results are qualitatively similar to the estimates in Table A15, which supports our argument that the results are not primarily due to infrastructure development.³⁰

As discussed previously, one concern with the validity of our estimates stems from the fact that oil palm expansion correlates with migration flows. We control for migration status in all household and individual-level regressions. Moreover, controlling for the share of migrants at the regency level does not alter the effect of oil palm expansion on sectoral shares, as additional robustness checks indicate (see Appendix Tables A17 and A18).³¹ These tables give some support to the observation that only some population groups enter the non-agricultural sector. Men enter agricultural wage labor but women switch also into the non-agricultural sector, which is in line with the gendered productivity differentials between oil palm and alternative crops.

6. Conclusion

While several new labor-saving land uses and technologies are introduced and promoted in the rural areas of developing countries, their potential labor-displacing effects have received little attention in empirical research. This article documents the labor market effects of a labor-saving land use –

the expansion of oil palm among smallholder farmers in Indonesia – both at the farm household as well as the national scale. Our results suggest that oil palm expansion has contributed to rising income levels for Indonesian smallholder farmers but has significantly decreased the demand for agricultural labor per unit area. At the same time, oil palm expansion, in particular into forestlands, led to new employment opportunities in the agricultural wage labor sector which buffered most of the adverse labor market effects for vulnerable groups such as rural, landless labor households. For women, the results are less positive from a labor market perspective, and we observe decreasing labor force participation among women due to a large drop in agricultural family work.

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 the results indicate 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, the literature suggests that oil palm contributed to income growth and increased investments, leading to local demand effects and a boost to the non-agricultural sector (Edwards, 2019b; Gehrke and Kubitzka, 2021; Kraus, Heilmayr, and Koch, 2021). For women that are generally less likely to work in the oil palm sector compared to other crops, local demand effects and a growing non-agricultural sector could have absorbed female labor that was freed from agriculture. We find, however, neither at the farm scale nor at the national scale robust evidence that women increased their involvement in the non-agricultural sector. Due to the drop in family agricultural employment

for women, female labor participation hence decreased substantially. This trend is worrying, and its implications should be the focus of further research.

Our results also suggest that these effects are highly heterogeneous between regions with scarce land resources compared to regions with abundant land resources. In settings with abundant land resources for agricultural expansion, as proxied by forestland, we find that women face neither a decline in employment in family agriculture nor a decline in general employment rates. In contrast, the decline in female agricultural employment is quite strong in regions with scarce land resources. This effect heterogeneity may also explain heterogeneity between different case studies in different regions but also differences across time, as the substantial positive income effects of the oil palm expansion, in particular for smallholder farmers, are likely to be more muted in the face of population growth and reduced availability of land for agricultural expansion.

In this context, it should be stressed that these beneficial economic effects for rural laborers occurred largely at the expense of natural ecosystems, in particular forestland. Direct countermeasures to prevent deforestation could include increasing the labor intensity per unit of land. However, measures in this direction would be limited in scope since the marginal product of labor in oil palm cultivation will fall rapidly with increasing labor intensity. Alternatively, restricting further forest encroachment and improving the rural labor market opportunities in general would force new oil palm adopters to reallocate more of their saved labor to the non-agricultural sector. Our results suggest that without land expansion by farm households, rural laborers without significant own land – and women in particular – find little working opportunities in smallholder agriculture and would face increasing competition in the non-agricultural 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 lands might have to go hand-

in-hand with non-agricultural employment initiatives focusing on marginalized rural population groups. Isolated interventions might entail undesirable social effects.

Our results 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 (and also historical data from the agricultural expansion in industrialized countries) shows 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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References

- Adu-Baffour, F., T. Daum, and R. Birner. 2019. Can small farms benefit from big companies' initiatives to promote mechanization in Africa? A case study from Zambia. *Food Policy*, 84: 133–145. <https://doi.org/10.1016/j.foodpol.2019.03.007>
- Austin, K. G., A. Mosnier, J. Pirker, I. McCallum, S. Fritz, and P. S. Kasibhatla. 2017. Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments. *Land Use Policy*, 69: 41–48. <https://doi.org/10.1016/j.landusepol.2017.08.036>
- Austin, K. G., A. Schwantes, Y. Gu, and P. S. Kasibhatla. 2019. What causes deforestation in Indonesia? *Environmental Research Letters*, 14(024007). <https://doi.org/10.1088/1748-9326/aaf6db>
- Benedict, J. J., K. M. Carlson, R. Febrian, and R. Heilmayr. 2023. *Characteristics of Indonesian palm oil mills*. <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SMPITC&widet=dataverse@harvard>
- Benin, S. 2015. Impact of Ghana's agricultural mechanization services center program. *Agricultural Economics*, 46(S1): 103–117. <https://doi.org/10.1111/agec.12201>
- Bou Dib, J., V. V. Krishna, Z. Alamsyah, and M. Qaim. 2018. Land-use change and livelihoods of non-farm households: The role of income from employment in oil palm and rubber in rural Indonesia. *Land Use Policy*, 76: 828–838. <https://doi.org/10.1016/j.landusepol.2018.03.020>

- Bouwman, T. I., J. A. Andersson, and K. E. Giller. 2021. Herbicide Induced Hunger? Conservation Agriculture, Ganyu Labour and Rural Poverty in Central Malawi. *The Journal of Development Studies*, 57(2): 244–263. <https://doi.org/10.1080/00220388.2020.1786062>
- Bustos, P., B. Caprettini, and J. Ponticelli. 2016. Agricultural productivity and structural transformation: Evidence from Brazil. *American Economic Review*, 106(6): 1320–1365. <https://doi.org/10.1257/aer.20131061>
- Butler, R. A., and W. F. Laurance. 2009. Is oil palm the next emerging threat to the Amazon? *Tropical Conservation Science*, 2(1): 1–10.
- Byerlee, D., W. P. Falcon, and R. Naylor. (2017). *The tropical oil crop revolution: Food, feed, fuel, and forests*. Oxford University Press.
- Carlson, K. M., R. Heilmayr, H. K. Gibbs, P. Noojipady, D. N. Burns, D. C. Morton, N. F. Walker, G. D. Paoli, and C. Kremen. 2018. Effect of oil palm sustainability certification on deforestation and fire in Indonesia. *Proceedings of the National Academy of Sciences*, 115(1): 121–126. <https://doi.org/10.1073/pnas.1704728114>
- Caunedo, J., and Kala, N. 2021. *Mechanizing Agriculture*. Cambridge, MA. <https://www.nber.org/papers/w29061> <https://doi.org/10.3386/w29061>
- Chrisendo, D., V. V. Krishna, H. Siregar, and M. Qaim. 2020. Land-use change, nutrition, and gender roles in Indonesian farm households. *Forest Policy and Economics*, 118: 102245. <https://doi.org/10.1016/j.forpol.2020.102245>
- Chrisendo, D., H. Siregar, and M. Qaim. 2021. Oil palm and structural transformation of agriculture in Indonesia. *Agricultural Economics*, 52(5): 849–862. <https://doi.org/10.1111/agec.12658>

- Chrisendo, D., H. Siregar, and M. Qaim. 2022. Oil palm cultivation improves living standards and human capital formation in smallholder farm households. *World Development*, 159: 106034. <https://doi.org/10.1016/j.worlddev.2022.106034>
- Christiaensen, L., and W. Martin. 2018. Agriculture, structural transformation and poverty reduction: Eight new insights. *World Development*, 109: 413–416. <https://doi.org/10.1016/j.worlddev.2018.05.027>
- Clark, C. (1940). *The conditions of economic progress*. Macmillan.
- Colella, F., R. Lalive, S. O. Sakalli, and M. Thoenig. 2019. *Inference with Arbitrary Clustering* (Discussion Paper Series No. 12584). Bonn. IZA Institute for Labor Economics.
- Collier, P., and S. Dercon. 2014. African agriculture in 50 years: Smallholders in a rapidly changing world? *World Development*, 63: 92–101. <https://doi.org/10.1016/j.worlddev.2013.10.001>
- Cramb, R., and G. N. Curry. 2012. Oil palm and rural livelihoods in the Asia-Pacific region: An overview. *Asia Pacific Viewpoint*, 53(3): 223–239. <https://doi.org/10.1111/j.1467-8373.2012.01495.x>
- Cramb, R., & McCarthy, J. F. (Eds.). (2016). *The oil palm complex: Smallholders, agribusiness, and the state in Indonesia and Malaysia*. NUS Press.
- Edwards, R. B. 2019a. *Export agriculture and rural poverty: Evidence from Indonesian palm oil*. https://static1.squarespace.com/static/57d5edcf197aea51693538dc/t/5c6cbb1aa4222f75067de956/1550629671736/eard_v9_1901-merged.pdf
- Edwards, R. B. 2019b. *Spillovers from agricultural processing*. <https://farmlabor.ucdavis.edu/sites/g/files/dgvnsk5936/files/inline-files/Ryan%20Edwards%3B%20Ag%20Spillovers.pdf>

- Emerick, K. 2018. Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics*, 135: 488–503. <https://doi.org/10.1016/j.jdeveco.2018.08.013>
- Euler, M., V. V. Krishna, S. Schwarze, H. Siregar, and M. Qaim. 2017. Oil palm adoption, household welfare, and nutrition among smallholder farmers in Indonesia. *World Development*, 93: 219–235. <https://doi.org/10.1016/j.worlddev.2016.12.019>
- FAO. 2023. *Global Agro Ecological Zones*. <http://www.fao.org/gaez/>
- FAOSTAT. (2018). *Production - Harvested area*. Food and Agricultural Organization. <http://faostat3.fao.org>
- Fischer, G., F. O. Nachtergaele, S. Prieler, E. Teixeira, G. Tóth, H. van Velthuisen, L. Verelst, and D. Wiberg. 2012. *Global Agro-Ecological Zones (GAEZ v3.0): Model Documentation*. Laxenburg, Austria and Rome, Italy. IIASA and FAO. http://pure.iiasa.ac.at/id/eprint/13290/1/GAEZ_Model_Documentation.pdf
- Gallardo, R. K., and J. Sauer. 2018. Adoption of labor-saving technologies in agriculture. *Annual Review of Resource Economics*, 10(1): 185–206. <https://doi.org/10.1146/annurev-resource-100517-023018>
- Gatto, M., M. Wollni, R. Asnawi, and M. Qaim. 2017. Oil palm boom, contract farming, and rural economic development: Village-level evidence from Indonesia. *World Development*, 95: 127–140. <https://doi.org/10.1016/j.worlddev.2017.02.013>
- Gehrke, E., and C. Kubitza. 2021. Agricultural Productivity and Fertility Rates: Evidence from the Oil Palm Boom in Indonesia. *Journal of Human Resources*: 0520-10905R1. <https://doi.org/10.3368/jhr.0520-10905R1>

- Goodwin, B. K., and M. T. Holt. 2002. Parametric and semiparametric modeling of the off-farm labor supply of agrarian households in transition Bulgaria. *American Journal of Agricultural Economics*, 84(1): 184–209. <https://doi.org/10.1111/1467-8276.00252>
- Grass, I., C. Kubitzka, V. V. Krishna, M. D. Corre, O. Mußhoff, P. Pütz, J. Drescher, K. Rembold, E. S. Ariyanti, A. D. Barnes, N. Brinkmann, U. Brose, B. Brümmer, D. Buchori, R. Daniel, K. F. A. Darras, H. Faust, L. Fehrmann, J. Hein, . . . M. Wollni. 2020. Trade-offs between multifunctionality and profit in tropical smallholder landscapes. *Nature Communications*, 11(1): 1–13. <https://doi.org/10.1038/s41467-020-15013-5>
- Haggblade, S., B. Minten, C. Pray, T. Reardon, and D. Zilberman. 2017. The herbicide revolution in developing countries: Patterns, causes, and implications. *The European Journal of Development Research*, 29(3): 533–559. <https://doi.org/10.1057/s41287-017-0090-7>
- Hansen, M. C [M. C.], P. V. Potapov [P. V.], R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. High-resolution global maps of 21st-century forest cover change. *Science (New York, N.Y.)*, 342(6160): 850–853. <https://doi.org/10.1126/science.1244693>
- Kirui, O. K. 2019. *The Agricultural mechanization in Africa: micro-level analysis of state drivers and effects* (ZEF – Discussion Papers on Development Policy No. 272). Bonn. Center for Development Research.
- Klasen, S. K., J. Priebe, and R. Rudolf. 2013. Cash crop choice and income dynamics in rural areas: Evidence for post-crisis Indonesia. *Agricultural Economics*, 44: 349–364. <https://doi.org/10.1111/agec.12015>

- Koczberski, G. 2007. Loose Fruit Mamas: Creating Incentives for Smallholder Women in Oil Palm Production in Papua New Guinea. *World Development*, 35(7): 1172–1185. <https://doi.org/10.1016/j.worlddev.2006.10.010>
- Koh, L. P., J. Miettinen, S. C. Liew, and J. Ghazoul. 2011. Remotely sensed evidence of tropical peatland conversion to oil palm. *Proceedings of the National Academy of Sciences*, 108(12): 5127–5132. <https://doi.org/10.1073/pnas.1018776108>
- Kopp, T., and B. Brümmer. 2017. Traders' market power along Indonesian rubber value chains. *China Agricultural Economic Review*, 9(2): 169–187. <https://doi.org/10.1108/CAER-07-2015-0080>
- Kraus, S., R. Heilmayr, and N. Koch. 2021. *Spillovers to manufacturing plants from multi-million dollar plantations: evidence from the Indonesian palm oil boom*. Berlin. Mercator Research Institute on Global Commons and Climate Change. https://smkraus.github.io/files/KHK_palm_oil_spillovers_manufacturing.pdf
- Krishna, V. V., M. Euler, H. Siregar, and M. Qaim. 2017a. Differential livelihood impacts of oil palm expansion in Indonesia. *Agricultural Economics*, 48(5): 639–653. <https://doi.org/10.1111/agec.12363>
- Krishna, V. V., C. Kubitzka, U. Pascual, and M. Qaim. 2017b. Land markets, property rights, and deforestation: Insights from Indonesia. *World Development*, 99: 335–349. <https://doi.org/10.1016/j.worlddev.2017.05.018>
- Kubitzka, C., V. V. Krishna, Z. Alamsyah, and M. Qaim. 2018. The economics behind an ecological crisis: Livelihood effects of oil palm expansion in Sumatra, Indonesia. *Human Ecology*, 46(1): 107–116. <https://doi.org/10.1007/s10745-017-9965-7>

- Lagakos, D., and M. E. Waugh. 2013. Selection, agriculture, and cross-country productivity differences. *American Economic Review*, 103(2): 948–980.
<https://doi.org/10.1257/aer.103.2.948>
- Lay, J., W. Anseeuw, S. Eckert, I. Flachsbarth, C. Kubitzka, K. Nolte, and M. Giger. (2021). *Taking stock of the global land rush: Few development benefits, many human and environmental risks. Analytical Report III*. Centre for Development and Environment, University of Bern; Centre de coopération internationale en recherche agronomique pour le développement; German Institute of Global and Area Studies; University of Pretoria; Bern Open Publishing.
<https://boris.unibe.ch/156861/>
- Lewis, W. A. 1954. Economic development with unlimited supplies of labour. *The Manchester School*, 22(2): 139–191. <https://doi.org/10.1111/j.1467-9957.1954.tb00021.x>
- Li, T. M. 2015. *Social impacts of oil palm in Indonesia: A gendered perspective from West Kalimantan* (Occasional Paper No. 124). Bogor, Indonesia. Center for International Forestry Research (CIFOR). <https://doi.org/10.17528/cifor/005579>
- Margono, B. A., P. V. Potapov [Peter V.], S. Turubanova, F. Stolle, and M. C. Hansen [Matthew C.]. 2014. Primary forest cover loss in Indonesia over 2000–2012. *Nature Climate Change*, 4(8): 730–735. <https://doi.org/10.1038/NCLIMATE2277>
- McArthur, J. W., and G. C. McCord. 2017. Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, 127: 133–152.
<https://doi.org/10.1016/j.jdeveco.2017.02.007>
- Mehraban, N., B. L. Debela, U. Kalsum, and M. Qaim. 2022. What about her? Oil palm cultivation and intra-household gender roles. *Food Policy*, 110: 102276.
<https://doi.org/10.1016/j.foodpol.2022.102276>

- Obidzinski, K., R. Andriani, H. Komarudin, and A. Andrianto. 2012. Environmental and social impacts of oil palm plantations and their implications for biofuel production in Indonesia. *Ecology and Society*, 17(1). <https://doi.org/10.5751/ES-04775-170125>
- Pingali, P. (2007). Chapter 54 Agricultural mechanization: Adoption patterns and economic impact. In R. Evenson & P. Pingali (Eds.), *Handbooks in economics: Vol. 18. Handbook of agricultural economics: Agricultural development: Farmers, farm production and farm markets* (Vol. 3, pp. 2779–2805). Elsevier. [https://doi.org/10.1016/S1574-0072\(06\)03054-4](https://doi.org/10.1016/S1574-0072(06)03054-4)
- Pirker, J., A. Mosnier, F. Kraxner, P. Havlík, and M. Obersteiner. 2016. What are the limits to oil palm expansion? *Global Environmental Change*, 40: 73–81. <https://doi.org/10.1016/j.gloenvcha.2016.06.007>
- Rist, L., L. Feintrenie, and P. Levang. 2010. The livelihood impacts of oil palm: Smallholders in Indonesia. *Biodiversity and Conservation*, 19(4): 1009–1024. <https://doi.org/10.1007/s10531-010-9815-z>
- Rowland, D., G. Zanello, E. Waliyo, and A. Ickowitz. 2022. Oil palm and gendered time use: A mixed-methods case study from West Kalimantan, Indonesia. *Forest Policy and Economics*, 137: 102682. <https://doi.org/10.1016/j.forpol.2021.102682>
- Sheahan, M., and C. B. Barrett. 2017. Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy*, 67: 12–25. <https://doi.org/10.1016/j.foodpol.2016.09.010>
- Sunding, D., and D. Zilberman. (2001). Chapter 4 The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In B. L. Gardner & G. C. Rausser (Eds.), *Handbooks in economics: Vol. 18. Handbook of agricultural economics* (Vol. 1, pp. 207–261). Elsevier. [https://doi.org/10.1016/S1574-0072\(01\)10007-1](https://doi.org/10.1016/S1574-0072(01)10007-1)

US Department of Agriculture. 2017. *Oil crops yearbook*. <https://www.ers.usda.gov/data-products/oil-crops-yearbook.aspx>

Villoria, N. B. 2019. Technology spillovers and land use change: Empirical evidence from global agriculture. *American Journal of Agricultural Economics*, 101(3): 870–893. <https://doi.org/10.1093/ajae/aay088>

TABLES

Table 1: Datasets

Datasets	Year of survey/observation	Source
Local surveys		
Farm households (n = 683 per survey round)	2012, 2015, 2018	Primary data collected by authors
Spatial data		
Location of palm oil mills	1922-2022	Benedict et al. (2023)
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 (2012-2015-2018)

	Village-level FE			Household-level FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total HH expenditure (log)	Total HH expenditure (log)	Total HH expenditure (log)	Total HH expenditure (log)	Total HH expenditure (log)	Total HH expenditure (log)
Share of oil palm (0-1)	0.294*** (0.060)	0.268*** (0.057)	0.173*** (0.051)	0.232** (0.115)	0.202* (0.113)	0.152 (0.109)
Employed HH members (=1)		-0.605 (1.034)	-0.608 (0.916)		-0.011 (0.033)	-0.008 (0.033)
Self-employed HH members (=1)		0.256*** (0.034)	0.240*** (0.032)		0.148*** (0.040)	0.148*** (0.040)
Total farm size (ha)			0.049*** (0.005)			0.038*** (0.010)
F-Stat	10.853	14.294	21.162	4.533	5.275	6.063
Observations	1854	1854	1854	1761	1761	1761

Notes: Data source is farm-household data. Clustered standard errors at household level in parentheses. Dependent variable is log of total annual household expenditure ('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, distance to next palm oil mill, employed household members, self-employed household members, total farm size, and year dummies. Additional covariates included in estimation are reported in Table A5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of oil palm cultivation on employment status of individuals in farm households (2012-2015-2018)

	(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)
Village-level FE								
Share of oil palm (0-1)	0.017 (0.020)	-0.159*** (0.043)	0.041 (0.027)	-0.146*** (0.034)	0.151*** (0.043)	0.002 (0.040)	0.070** (0.032)	0.029 (0.033)
F-Stat	494.760	89.602	399.988	61.836	66.373	21.417	10.062	8.658
Observations	2759	2610	2759	2610	2759	2610	2759	2610
Household-level FE								
Share of oil palm (0-1)	0.076* (0.043)	-0.078 (0.094)	0.079 (0.069)	-0.046 (0.085)	0.163 (0.110)	0.000 (0.080)	0.165** (0.069)	-0.048 (0.062)
F-Stat	538.625	58.762	387.982	37.355	40.157	16.408	7.176	6.762
Observations	2693	2548	2693	2548	2693	2548	2693	2548

Notes: Data source is farm-household data. Standard errors (clustered at household level) are shown in parentheses. We control for age, age squared, student, education level, migrant households, number of women and adults in household, farm characteristics, distance to province capital, distance to next palm oil mill, total farm size and year dummies. Additional covariates included in estimation are reported in Table A6 for village-level fixed effects models and Table A7 for household-level fixed effects 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)	(2)	(3)	(4)	(5)	(6)
	Share of women working	Share of women in non-agricultural sector	Share of women in agricultural family labor	Share of women in agricultural wage labor	Share of women in non-agricultural self-employment	Share of women in non-agricultural wage labor
IV						
Share of smallholder oil palm area in regency (0-1)	-2.910** (1.184)	-0.162 (0.630)	-3.188** (1.284)	0.942 (0.626)	-0.639 (0.454)	0.438 (0.286)
R2	0.155	0.402	0.106	0.072	0.115	0.558
Kleibergen Wald F-Stat	23.532	23.532	23.532	23.532	23.532	23.532
Observations	827	827	827	827	827	827
OLS						
Share of smallholder oil palm area in regency (0-1)	-0.731** (0.348)	0.339*** (0.129)	-0.613** (0.301)	-0.011 (0.190)	0.186** (0.093)	0.114 (0.075)
R2	0.235	0.409	0.216	0.116	0.185	0.564
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 100km 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 data from 2000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of men working	Share of men in non-agricultural sector	Share of men in agricultural family labor	Share of men in agricultural wage labor	Share of men in non-agricultural self-employment	Share of men in non-agricultural wage labor
IV						
Share of smallholder oil palm area in regency (0-1)	-0.372 (0.523)	-1.771** (0.886)	-1.053* (0.627)	2.686*** (0.604)	-1.695** (0.670)	0.112 (0.571)
R2	0.143	0.345	0.120	-0.009	-0.000	0.567
Kleibergen Wald F-Stat	23.312	23.312	23.312	23.312	23.312	23.312
Observations	827	827	827	827	827	827
OLS						
Share of smallholder oil palm area in regency (0-1)	-0.222* (0.122)	0.007 (0.203)	-0.401*** (0.135)	0.672*** (0.160)	-0.012 (0.133)	0.012 (0.126)
R2	0.144	0.401	0.150	0.251	0.158	0.567
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 100km 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 data from 2000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Regency-level effects of oil palm expansion in land-scare and land-abundant settings (2000-2005-2010-2015)

	(1) Share working	(2) Share in non- agricultural sector	(3) Share in agricultural family labor	(4) Share in agricultural wage labor	(5) Share in non- agricultural self- employment	(6) Share in non- agricultural wage labor
Men						
Share of smallholder oil palm area in regency (0-1)	-0.296 (0.305)	0.589 (0.379)	-1.027*** (0.291)	0.674 (0.428)	0.592** (0.232)	0.018 (0.261)
Share of smallholder oil palm area in regency (0-1) # Share of forest cover in 2000 (0-1)	0.218 (0.680)	-1.713* (0.988)	1.841*** (0.706)	-0.005 (1.027)	-1.777*** (0.631)	-0.020 (0.673)
R2	0.144	0.402	0.159	0.251	0.165	0.567
Observations	827	827	827	827	827	827
Women						
Share of smallholder oil palm area in regency (0-1)	-1.777*** (0.675)	0.108 (0.262)	-1.516** (0.683)	-0.452 (0.567)	0.276 (0.229)	-0.061 (0.182)
Share of smallholder oil palm area in regency (0-1) # Share of forest cover in 2000 (0-1)	3.067* (1.606)	0.678 (0.599)	2.649* (1.524)	1.292 (1.307)	-0.264 (0.495)	0.512 (0.437)
R2	0.241	0.409	0.220	0.119	0.185	0.564
Observations	827	827	827	827	827	827

Notes: Data sources are SAKERNAS, Margono et al. (2014), and Tree Crop Statistics. Dependent variables are shares, ranging between 0 and 1. OLS estimates are reported with spatial HAC standard errors using a 100km cutoff. 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 data from 2000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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%).

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.

² Unlike the body of literature that exists on the long-run structural effects of labor savings in agriculture (Bustos, Caprettini, and Ponticelli, 2016; Clark, 1940; Lagakos and Waugh, 2013; Lewis, 1954; McArthur and McCord, 2017), we focus on short- and medium-term impacts, namely those related to the displacement of labor.

³ Increasing labor intensity per unit area is hardly an option, since labor requirements in oil palm cultivation are relatively fixed with the given production technology. In addition, oil palm is a cash crop that is traded internationally, so that increases in output do not lead to falling prices locally. For non-tradable commodities, higher productivity would lower output prices leading to different effects (Collier and Dercon, 2014).

⁴ PODES (Indonesian village survey) data show that rubber and rice are the main competing crops of oil palm at the village level in Indonesia.

⁵ Palm oil is a highly demanded export product. We assume hence a high elasticity of the final demand.

⁶ Note that T is constrained by the available family labor.

⁷ We define off-farm work as including agricultural employment, non-agricultural employment and self-employment. Note that we use the terms off-farm and on-farm in the case of land-use change at farm scale. In the case of interpreting the effects at higher scales, we differentiate between the agricultural and non-agricultural sector.

⁸ A technical change which increases labor productivity is labor saving as long as the elasticity of substitution between land and labor is smaller than the land share of output (Bustos, Caprettini, and Ponticelli, 2016). A condition that is likely to be satisfied in the context of agriculture.

⁹ In the model, the agricultural sector produces goods that can be traded, while in the non-agricultural sector production factors and the non-agricultural good are immobile.

¹⁰ Recent studies on large-scale palm oil investments found increases in labor and total factor productivity of manufacturing plants not related to palm oil value chains (Kraus, Heilmayr, and Koch, 2021) and improved public infrastructure (Edwards, 2019b; Kraus, Heilmayr, and Koch, 2021). This suggests that if smallholder oil palm expansion correlates with the expansion of large-scale estates, we would also expect increases in non-agricultural wages w_{AN} . We conduct a robustness check in the empirical part to test the relation between both production models.

¹¹ As long as the non-agricultural good is a non-tradable.

¹² This effect partly also depends on the share of the additional consumption demand which is satisfied by either local or foreign markets. We assume, however, that this ratio remains constant.

¹³ In Indonesia, provinces are the highest level of local governance. They are further divided into regencies (*kabupaten*) and city-districts (*kotas*). Regencies in Aceh, Papua, and the Maluku islands were excluded from the analysis since data are not available for several years. We included in total 209 regencies.

¹⁴ We specified low-level input use and rain-fed production.

¹⁵ 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.

¹⁶ Maximum attainable yield of oil palm is mostly affected by differences in climatic conditions such as the level and variation in temperature, radiation, and rainfall (Pirker et al., 2016). These conditions are captured by the GAEZ at pixel level.

¹⁷ Pearson correlation coefficient: +0.305***

¹⁸ We define five regions including the main islands Sumatra, Kalimantan, Java, Sulawesi with their adjacent smaller islands and a fifth category including all other islands.

¹⁹ The Indonesian government supported migration movements from the densely populated main island (Java) to the outer islands to obtain laborers for large-scale plantations. These migration movements altered the cultural and socio-demographic composition of the labor force. It is not unreasonable to assume that migrants are more open to innovation and hence more likely to adopt oil palm and also to take up non-agricultural employment.

²⁰ Our analysis rests on spatial data. In these data, unobserved shocks can be correlated across neighboring regencies. To account for both, cross-sectional spatial correlation and location-specific autocorrelation, we use heteroskedasticity and autocorrelation-consistent (HAC) standard errors that are also robust to spatial autocorrelation (Colella et al., 2019). We use a time lag cutoff of 10 years and a distance cutoff of 100km. Spatial distance is based on the location of regencies' capitals.

²¹ Effect sizes are larger in the IV than in the OLS models. Since the Kleibergen-Paap Wald statistic is sufficiently high (>10) we tend to reject the notion that this is due to a weak instrument. Other reasons could include estimating a local average treatment effect and endogeneity bias in the OLS models. In general, the output prices for rubber, the

main competing crop, were extremely low in 2015, which may have contributed to the large effect sizes (Kubitza et al., 2018).

²² We note however that cropland expansion for individual farms could still take place even in land-scarce settings in the case that some farmers are willing to sell their land.

²³ First-stage results are reported in Appendix Table A8.

²⁴ Effect sizes are larger in the IV than in the OLS models. Since the Kleibergen-Paap Wald statistic is sufficiently high (>10) we tend to reject again the notion that this is due to a weak instrument. Other reasons could include estimating a local average treatment effect, endogeneity bias in the OLS models and correcting for measurement error.

²⁵ In contrast, Gehrke & Kubitza (2021) found a weakly significant effect of oil palm expansion on women's wages in the non-agricultural sector. However, the study uses a different sample, examining only women aged 15-49.

²⁶ The ranking is based on harvested area. We did not include rubber since no GAEZ data on attainable yields are available.

²⁷ We also tested the effect of oil palm expansion on working hours (see Appendix Tables A13 and A14). The effects seem to be concentrated at the extensive margin rather than the intensive margin of labor supply.

²⁸ Given that palm oil production technologies are similar in smallholder systems and large-scale plantations, male labor productivity is also higher in large-scale plantations. Male laborers switching into agriculture is hence reasonable (Table A12, OLS model, column 10). Clear evidence of case studies exists that large-scale plantations replaced labor-intensive smallholder systems (Cramb and McCarthy, 2016). Yet, it is unlikely that large-scale oil palm plantations were replacing labor-intensive smallholder systems to the same extent as smallholder oil palm expansion replaced other agricultural land uses of smallholders. This could explain why we find no evidence that women are displaced from agriculture due to the expansion of large-scale oil palm plantations.

²⁹ To merge the different datasets, we had to restrict the timespan to 2001-2014 with 3-year differences. The results hardly differ from the earlier ones shown in Tables 4 and 5 for the 5-year differences.

³⁰ We observe in line with our expectations that men are more likely to work in agricultural wage employment and that women are less likely to work in agricultural family labor with smallholder oil palm expansion. The results, however, also show an increase for women working in agricultural wage employment which we have not observed in any other regressions. However, these are OLS results, and the effect is no longer significant in our preferred IV

models. In addition, 2- or 3-year differences are not ideal as oil palm expansion and production processes (oil palm becomes productive after approximately three years) are governed by lags and unlikely to be picked up by this specification. We hence opted for 5-year differences in our main models (2000-2005-2010-2015).

³¹ We use a census subsample to obtain data on migration. We use census data for 2000 and 2010. The baseline results confirm our findings reported in Tables 4 and 5.



