Tropical Oil Crops and Rural Poverty

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Abstract

The tripling of area planted with tropical oil crops since the 1990s represents the most significant global agricultural transformation since the green revolution. I study the poverty impacts of the largest modern plantation-based agricultural expansion, Indonesian palm oil over the 2000s. Causal effects are identified by instrumenting the decadal expansion in the area planted with oil palm in each district with its agro-climatically attainable yield. Of the more than 10 million Indonesians lifted from poverty over the 2000s, my most conservative estimate suggests at least 1.3 million rural people have escaped poverty due to growth in the palm oil sector. The areal expansion increased expenditure for low income households and expanded rural public services related to agricultural manufacturing, specifically road networks and households' access to electricity.

Keywords: agriculture, cash crops, plantation, palm oil, poverty, Indonesia
JEL codes: C23, C26, I32, Q15, Q18

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1 Introduction

The largest agricultural transformation since the green revolution has been unfolding over the past two decades in tropical oil crops. From 1990 to 2010 global soybean production grew by 220% and palm oil over 300%, more than rice during the green revolution and also almost exclusively in the developing world. The tropical oil crops revolution is a stark contrast to the green revolution that engaged tens of millions of small-scale food producers across the developing world and arose from rapid technology-driven yield improvements (intensification). Oil crop production often involves giant agro-industrial plantations and has increased principally through area expansion (extensification). The area planted for oil crops since the 1970s has expanded by over 150 million hectares, three times that of *all* cereal crops in the same period (Byerlee et al., 2016). Most major agricultural and food policy debates involve tropical oil crops: genetically modified organisms, food versus biofuels, small farmers versus agribusiness, mono- versus inter-cropping, "land-grabbing", and environmental footprint of the food we consume. The most prominent debate concerns clearing forests across the tropics to plant oil crops and impacts on wildlife and communities inhabiting these areas.

Palm oil is the world's most consumed vegetable oil. Crude palm oil is derived from the reddish pulp of the fruit of the oil palm, a plantation-based, labor-intensive cash crop originating from Africa (*Elaeis guineensis*) and the Americas (*Elaeis oleifera*), mostly grown in developing countries today.[1] Global palm oil demand grew from less than 5 million metric tonnes per year in 1970 to over 70 million in 2015, and is expected to further double over the next decade (USDA, 2016). Millions of people across Asia, South America, and Africa earn income from oil palms, yielding more oil per hectare than any other crop (4–10 times that of other oilseeds) from relatively little inputs. While oil palm is one of the most economically attractive uses for land in humid lowland tropics (Butler

[1] A cash crop is typically grown to sell rather than consume, usually to global export markets. See Corley and Tinker (2015) for further details on history and physiology of the oil palm.

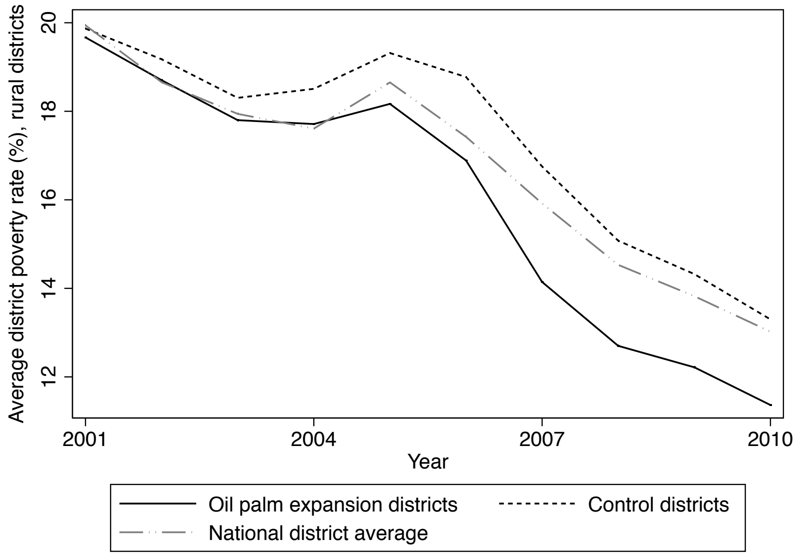
et al., 2009), it is one of the world's most socially contested industries, particularly in its largest producer: Indonesia.[2] The most important questions surrounding the tropical oil crops revolution involve understanding and aligning complex environmental–economic trade-offs, yet there is surprisingly little systematic evidence on how the global palm oil boom has affected welfare in the low-income communities where it is grown.

In this article I ask whether the world's largest modern plantation-based agricultural expansion has been pro-poor. I estimate the impacts of the remarkable expansion in palm oil production in Indonesia on poverty over the 2000s using rich new longitudinal data. Blending administrative information on local oil palm acreage at the district (*kabupaten*) level with survey-based estimates of district poverty, I relate decadal changes in oil palm plantation area to changes in district poverty over the same period to compare the poverty elasticity of oil palm land against alternative uses for land (e.g., rice and forestry). Causal effects are identified through an instrumental variable (IV) strategy exploiting detailed geo-spatial data on agro-climatic suitability for oil palm and other key crops for every field in Indonesia. By controlling for potential yields of other crops that could share agro-climatic suitability characteristics with oil palm, I ensure the identifying variation relates only to oil palm and not other types of agriculture.

The key finding is that districts with larger oil palm expansion have achieved more poverty reduction than otherwise similar rural districts without oil palm expansion. The magnitude of the estimated poverty reduction from increasing the district share of oil palm land by ten percentage points from my preferred IV estimator is around 40% of the poverty rate. Figure 1 shows my main result in the raw data. I compare the average poverty rate of rural districts with oil palm expansion against those without and the national district average. Rural districts had similar poverty levels in the early 2000s, but as the decade progressed districts engaged in the oil palm boom diverged strongly from other

[2] Dennis et al. (2005), Koh and Wilcove (2007), and Busch et al. (2015) highlight the environmental impacts of the palm oil sector. McCarthy (2010), Rist et al. (2010), McCarthy et al. (2011), and Cramb (2013) describe local social impacts.

Figure 1: Average District Poverty Rates, 2001–2010



Notes: Constructed from World Bank (2015). All cities (*kotas*), and districts in Java, the Lesser Sunda Islands, Maluku, and Papua are excluded, to only compare rural districts in major oil palm producing regions of Sumatra, Kalimantan, and Sulawesi. The national district average is for all districts nationwide, including cities and regions not producing much palm oil.

rural districts and the national average. A simple policy simulation based on my most conservative estimate suggests at least 1.3 million out of the approximately 10 million people lifted from poverty over the 2000s have escaped poverty due to growth in the oil palm sector. Poverty gaps significantly narrow, suggesting not only those near the poverty line are being lifted up. I assess short-term effects with panel estimation and distributed lags to find dynamics reflecting the perennial crop's life cycle, and I find no evidence of any major effect heterogeneity when I disaggregate oil palm land by large industrial plantations and smallholders. Similar effects are also observed across Indonesia's major palm oil producing regions and at the province level. The observed district poverty reductions can be explained by more rapid increases in household expenditures for people in the bottom quintile and agriculture, and through greater provision of public goods most related to agricultural manufacturing, specifically roads and electricity. Oil palm expansion tends to coincide with a sustained boost to primary, industry, and total district outputs, and no discernible impact on services.

This article offers three contributions. First, evidence that Indonesia's palm oil boom delivered strong rural poverty reduction is provided against a salient policy debate on palm oil across the developing world. The welfare impacts of tropical oil crops are typically neglected in debates that, for good reason, tend to focus on environmental issues. Coalitions of activists are mobilized around the world arguing in popular fora that oil palm production is environmental and socially damaging and should be limited through government policy or consumer boycotts. My findings are a stark contrast to the large set of claims about the immiserizing effects of plantation crops, and in particular oil palm. Using the world's largest modern plantation sector expansion as a case study, I show how plantation-based cash crop systems actively including smallholders can deliver geographically disbursed poverty reduction in remote parts of the tropics. Although environmental concerns are likely to remain the first order issue in global policy debates about palm oil, income effects may well be the first order issue in rural communities it comes from, and a critical consideration in understanding the sector's voracious growth and environmental challenges to date. I focus on Indonesia—and Indonesia's palm oil sector is unique in many respects—but my findings should be useful to inform some of the most prominent global agriculture, environment, and food policy debates, and other developing countries looking towards oil palm for poverty reduction.

Second, I shed new light on the role of plantation-based cash crops and agricultural manufacturing in economic development and poverty reduction. While the role agriculture has been widely studied, little attention has been paid to plantation agriculture or cash crops despite their ubiquity.[3] Agricultural growth tends to be pro-poor, but plantation-based cash crops have starkly different characteristics to other forms of agriculture and large-scale agricultural development remains highly contested.[4] Unlike

[3]Dercon (2009), Gollin (2010), and Dercon and Gollin (2014) review of the role of agriculture in economic development and poverty reduction. Pryor (1982), Barbier (1989), Maxwell and Fernando (1989), and Tiffen and Mortimore (1990) study plantation agriculture.

[4]See, e.g., Quizon and Binswanger (1986), Ravallion and Chen (2003), Kraay (2006), Anriquez and Lopez

subsistence food crops, cash crops seldom feed those employed in modern sectors (c.f., Lewis, 1954; Schultz, 1964). The potential for agricultural demand-led industrialization is also ambiguous. Consumption linkages may be greater than other agriculture due to higher yields and profits, while low technology, skill, and processing requirements suggest limited production linkages (c.f., Johnston and Mellor, 1961; Ranis and Fei, 1961; and Adelman, 1984). But plantation-based cash crops are different. The plantation system arises from the need for closer coordination between farm production and large-scale processing, and the need to process crops shortly after harvest.[5] While the agricultural technology and infrastructure mechanisms responsible for past agriculture-led poverty reduction are generally less applicable for cash crops, these are central features of the plantation system and important in explaining the strong poverty elasticities documented in this article (Gollin et al., 2002; Ravallion and Datt, 2002; Hayami, 2010). A third contribution is my use of a parsimonious new IV approach to study the causal effects of agricultural growth at the sub-national level.

The next section provides a brief background on Indonesia's oil palm expansion and the conceptual framework guiding my empirical analysis. Section 3 explains the data and Section 4 estimation and identification. Section 5 presents the main results. Section 6 examines a migration-based explanation for the observed fall in district poverty rates, and Section 7 explores causal channels foreshadowed in Section 2. Section 8 concludes with a simple policy simulation to calculate the contribution of the oil palm boom to national poverty reduction, and some final remarks.

(2007), Ravallion and Chen (2007), Maertens and Swinnen (2009), and Christiaensen et al. (2012).

[5]Examples include black tea, sisal, and palm oil, which must be milled within 24 hours of harvest; c.f., green tea, cocoa, coconuts, and copra do not require much further processing or marketing, so are more suitable to independent smallholders and family farms.

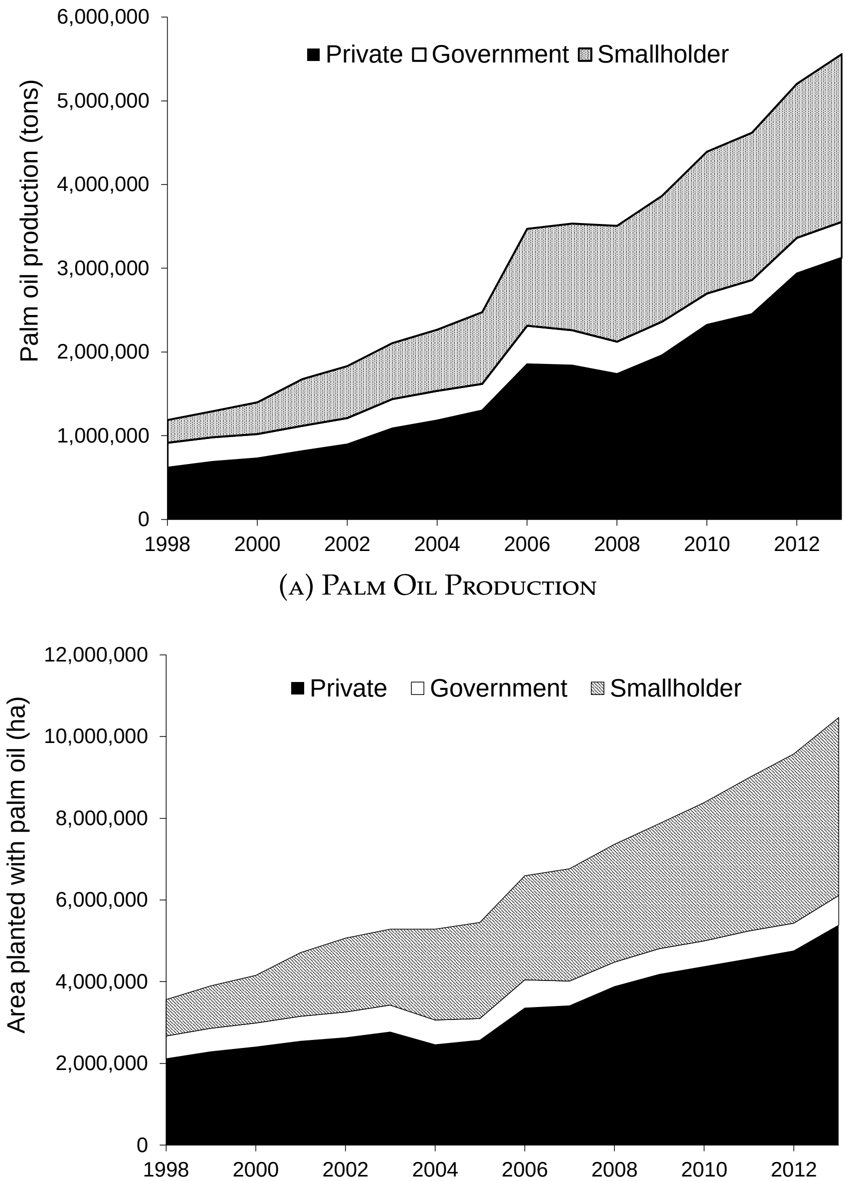
2 Context and conceptual framework

2.1 Indonesia's oil palm boom: the macro picture

Indonesia is currently experiencing the world's largest modern plantation-based agricultural expansion, the ideal setting to study the links between oil crops and rural poverty in the developing tropics. The third most populous developing country after China and India, Indonesia supplied more than 40 per cent of the 60.54 million metric tons of palm oil produced in 2014–15. Global palm oil production has doubled every decade since the 1960s, surpassing soy bean oil in 2007 to become the dominant vegetable oil (USDA, 2015). With a comparative advantage in unskilled labor-intensive goods and proximity to India and China (the largest purchasers), Indonesia was well-placed to capitalize on the growing demand. Palm oil has been Indonesia's largest agricultural export for the last two decades, with its rapid increase in production coming almost exclusively through land area expansion (92 per cent) rather than intensification and higher yields (Gaskell, 2015; Gatto et al., 2015). The area of Indonesian land planted with oil palm increased from under four million hectares at the turn of the century to around 12 million today (Directorate General of Estate Crops, 2014).

Figures 2a and 2b present national palm oil production and area planted by private, government, and smallholder sectors from 1998 to 2012. Private sector plantation area doubled and state-owned plantation area remained static. Together they represent large industrial plantations, while smallholders typically manage around two hectares each in partnership with large plantations or as independent farmers. The area managed by smallholders, by contrast, has roughly tripled over this period. Today smallholders manage around five million hectares of oil palm, almost half of the area planted. Indonesia's atypical smallholder involvement in plantation industries stems from past rural development policies, where industrial plantations allocated a portion of all new developments to company-supported smallholders, known as "plasma" or

Figure 2: Indonesia's palm oil expansion



(a) Palm Oil Production

(b) Area Planted with Palm Oil

"scheme" smallholders (Pramudya et al., 2016). The role of smallholders has further increased since the fall of President Suharto in 1998, with the decentralized governance it ushered in allowing farmers to more easily plant existing farm or other land with oil palms. Indonesia's oil palm expansion embodies "Jevon's paradox", where increasing the efficiency at which a resource—in this case, land—drives greater demand for that resource (Alcott, 2005). The environmental impacts of Indonesia's plantation sectors are well documented, for example clearing primary forest, draining peat lands, forest fires, and biodiversity and wildlife loss (Fargione et al., 2008; Gibbs et al., 2010; Hunt, 2010; Koh et al., 2011; Carlson et al., 2013; Vijay et al., 2016). Land use is the central policy issue but there is a paucity of systematic evidence on the welfare impacts of existing land use change.

Three decades of economic growth and structural change since the 1970s saw broad-based benefits and poverty reduction across Indonesia (Hill, 1996). Rural poverty reduction was mostly driven by agricultural growth, including through the green revolution (Suryahadi et al., 2009; de Silva and Sumarto, 2014).[6] Since the Asian Financial Crisis and the fall of Suharto in 1998, economic growth and poverty reduction slowed. The steadily rising manufacturing share of gross domestic product (GDP) ground to a halt with the contemporaneous palm oil and mining booms of the 2000s. The poverty headcount continues to fall, but it is unclear how much progress can be attributed to oil palm (Burke and Resosudarmo, 2012). Resosudarmo and Bhattacharya (2015) show mining made little contribution. Almost 100 million Indonesians remained vulnerable to poverty in 2014, and 28 million (11.4% of the population) lived below the poverty line.

[6] Booth (1988), Fuglie (2010), and Rada et al. (2011) provide further background on Indonesian agricultural development, and Falcon (2014) provides an enlightening first-hand account.

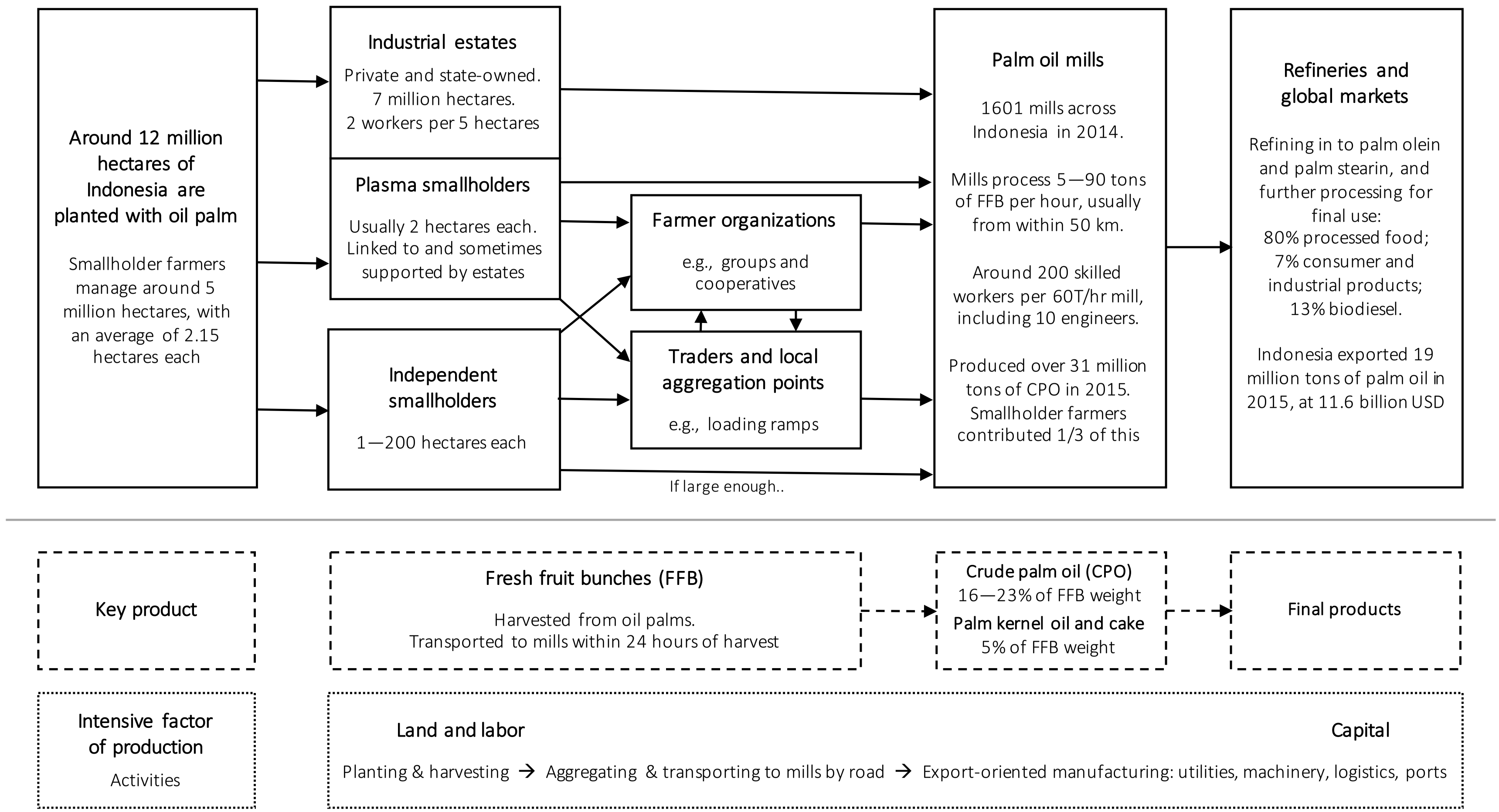
2.2 Estates, smallholders, and poverty: a conceptual framework

The poverty elasticity of economic growth in different sectors depends on sectors' relative importance to the economy and poor people (Thorbecke and Jung, 1996; Loayza and Raddatz, 2010). Economic expansion in the oil palm sector is likely to be pro-poor if poor people (a) are employed, (b) have access to land to become smallholders, or (c) benefit from related economic development. A simplified overview of the Indonesian palm oil sector is presented in Figure 3. Lower quintiles of the income distribution are more likely to be directly engaged in the earlier labor-intensive stages of production, although aggregation and milling provide ample scope for indirect effects.

Any poverty benefits from oil palm expansion could be a purely labor income story for smallholders or plantation and other workers: a direct labor income effect. Oil palm is a labor-intensive cash crop requiring little skill or capital to grow and harvest (c.f., costs mostly relate to land acquisition, transport, and capital-intensive mills). Harvesting involves pulling fresh fruit bunches from trees with a long sickle and oil palms bear a relatively consistent amount of fruit around every ten days with limited seasonality. Yield maximizing practices related to pest management, fertilizer application, pruning, and harvesting at the optimal time, and workers are often employed to take care of the trees. The key on-farm technology is seed quality, determined at the planting stage. Plantation laborers and cultivators are paid local agricultural wages, although overall returns to labor in large oil palm plantations (c.f., actual paid wages) have been estimated to be 2–7 times this (Budidarsono et al., 2012). Roughly two laborers are needed for every five hectares of Indonesia's current 7 million hectares of industrial plantations.

Smallholder farmers manage almost half of the area planted with oil palm (5 million hectares), with an average planting of 2.15 hectares each (Badan Pusat Statistik (BPS), 2013). Smallholder oil palm accounts for significantly more direct livelihoods per hectare than industrial plantations. Economies of scale have long characterized plantation economies: returns disproportionately accrue to land and capital owners (Hayami, 2010).

Figure 3: Indonesia's palm oil sector



Notes: Author's own depiction. Figures are for Indonesia, from no earlier than 2013, and sourced from Badan Pusat Statistik (2013), the Directorate General of Estate Crops (2014), and site visits in 2015 and 2016.

Large capital outlays typically see domestic and international companies own palm oil mills, which prefer to the own (or at least manage) the planted area feeding the mill, to ensure a steady supply of high quality fruit. But so do smallholders, who can earn considerably more farming cash crops and selling their fruit to the mills than as laborers on someone else's plantation. Accordingly smallholders often report improved yields, profits, nutrition, and incomes after entering the sector (Budidarsono et al., 2012; Cahyadi and Waibel, 2013). People living below the poverty line are more likely to be landless and unable to *legally* become smallholders, but legality hardly prevents people from occupying and planting new land under such decentralized and porous governance arrangements. Independent smallholders typically lack formal land title and do not apply best management practices, with yields well below industrial plantations and company-supported smallholders. To the extent that income as a low yield smallholder is greater than that from alternative rural land uses—or not having any land at all—we might still expect to see poverty reduction from informal areal expansion by independent smallholders. People with limited or no land also gain employment on large industrial plantations and assisting smallholders, whose largest production related expenditure is hired labor (BPS, 2013).

Oil palm combines high returns to labor with the need for immediate, proximate agricultural manufacturing infrastructure. Processing for key food crops, like rice, typically takes place within the village where it is grown, and many cash crops do not require immediate processing (e.g., cocoa and coffee). A typical 60 ton per hour palm oil mill comprises heavy industrial machinery and a few hundred skilled workers, including ten engineers. Indonesia's over 1600 palm oil mills each buy fresh fruit bunches from dozens of villages, often through a complex network of traders providing important aggregation and logistical functions for independent smallholders and farmer groups needing to get their fruit to the mill within 24 hours of harvesting (Directorate General of Estate Crops, 2014). Urgent processing requirements mean the area feeding each mill is roughly a 50 kilometer radius. Impacts at the early stages of the supply chain are thus likely to be spatially concentrated and realized within districts. The transport networks (i.e., roads) and local industrial capacity (utilities) required to run export-oriented agricultural manufacturing plants could alleviate constraints to rural development and deliver indirect benefits to local communities.

Potentially positive impacts contrast against a burgeoning critical literature arguing that, in addition to its environmental impacts, the palm oil sector acts as an economic enclave and brings little benefits to local communities (Cramb, 2011; Obidzinski et al., 2014).[7] While some people may gain employment on plantations or be incorporated into plantation activities as smallholders, critics argue these gains are dwarfed by environmental and social costs, particularly displacement, loss of traditional forest-based livelihoods, and social disruption.[8] Of particular significance is the haze from fires lit to clear land for oil palm, with public health impacts likely to stymie poverty reduction efforts (Frankenburg et al., 2005; Miriam et al., 2015; Koplitz et al, 2016).

At the macro level, a booming natural resource sector—even for a diffuse natural resource like oil palm—could negatively affect poverty reduction and economic development through "resource curse" mechanisms. That Indonesia's forestry sector is home to significant rent-seeking is well documented (Burgess et al., 2012). Any institutional deteriorations likely have important implications for the effectiveness of decentralized service delivery, poverty reduction programs, and the distributional impacts of local economic growth. A booming low-skilled primary export sector also provides weaker incentives for human capital development and could retard the structural change that underpinned Indonesian economic growth and poverty reduction in the

[7]In their study of local village capacity and development, Bebbington et al. (2006) select villages to cover the context of "a rural economy based both on household agriculture and other livelihood activities within the context of a frontier economy dominated by capital intensive natural resource extraction activities, such as logging, oil palm plantations, oil and gas." Framing plantation-based agriculture as an extractive industry like oil and gas rather than a cash crop or agricultural manufacturing is common in academic and popular media writing.

[8]See, e.g., Cooke (2002), Li (2011), White and White (2012).

preceding decades (Hill, 1996; Edwards, 2016). Coxhead and Shrestha (2016) emphasize such a structural story, showing that informal sector employment—where earnings are often lower than the formal sector—has increased more in districts that produced more palm oil at the start of the 2000s.[9] There is likely to remain a lively debate over the palm oil sector's broad social impacts, but the question of whether this unprecedented agricultural transformation has been good for the rural communities where palm oil is grown is ultimately an empirical one.

3 Data

3.1 Oil palm

My main explanatory variable is official district oil palm acreage, measured in hectares and digitized from the Tree Crop Statistics of Indonesia for Oil Palm yearbooks. Produced by the Department of Agriculture for each district annually since 1996, data cover land of varying condition (damaged, immature, and mature) and ownership (private, state, and smallholder).[10] While data on official oil palm land are likely imperfect, focusing on planted area declared by the Indonesian Government has greatest tractability.[11]

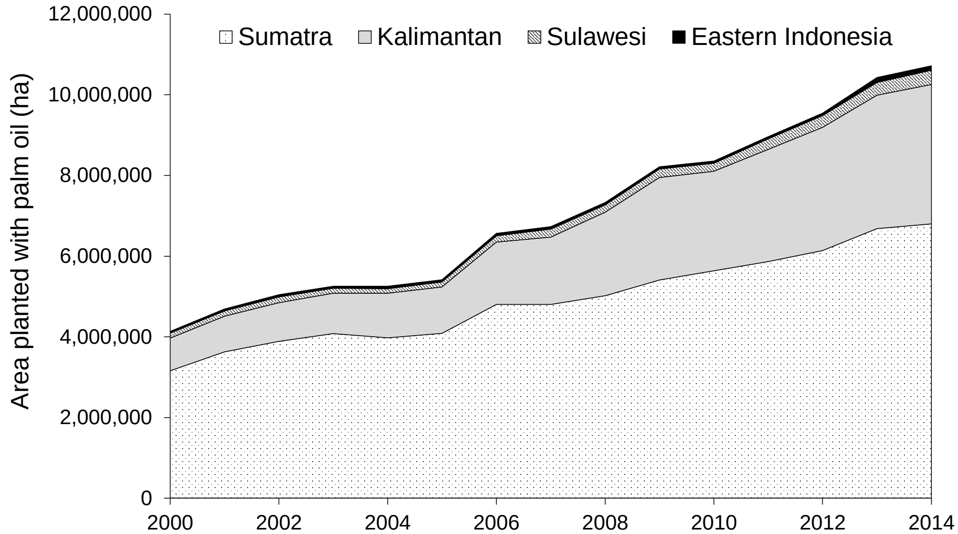
[9]Coxhead and Shrestha's (2016) identifying variation is the cross section of palm oil production in tons in 2000 as a share of district GDP, so not directly comparable to my study. By contrast, I exploit district areal expansion over the period that followed, including many places that produced little or no palm oil in 2000. While the urban informal services sector typically acts as a sink for the unemployed and corresponds to very low earnings, whether this is the case for informal smallholders and other workers around plantation sectors is unclear.

[10]Districts with no oil palm land are missing values in the original data, so I recode them as zeros to retain the baseline and control districts. Before recoding as zeros, I cross-checked data against other sources for official plantation figures and gained strong anecdotal evidence from public officials confirming data are more or less nationally exhaustive. There are no large jumps from the imputed zero values. All increase gradually. Similar results are obtained if I drop all districts with no oil palm, focusing only on changes in districts with oil palm land. See appendix.

[11]Alternative remotely-sensed satellite data are ill-suited for this study. Tree cover data cannot distinguish between mature oil palm plantations and natural or other forests, and land cover data on plantations, which can be combined with tree cover data to more accurately measure deforestation around plantations, is only available for a recent cross-section and still exposed to measurement error. Anecdotal evidence from non-government organizations focused on land issues suggests small unofficial, informal, and illegal oil palm developments tend to locate alongside and proportionally to officially declared plantations, as they require the same supply chain infrastructure and have generally grown together.

Figure 4: Oil Palm Land as a Share of District Area, 2009

Figure 5: Area Planted with Palm Oil, By Region



I convert oil palm land area to a share of total district area to focus on changing compositions: comparing oil palm land to other land uses. As oil palm expansion has been predominantly in rural districts, the comparison tends to be against other types of agriculture and rural livelihoods (e.g., rice, rubber, coffee, and forestry). Shares also capture population and labor exposure in agrarian districts where land is a primary factor of production. Oil palm land as a share of total district in 2009 is shown in Figure 4. Expansion has been most pronounced in the north-western islands of Sumatra, Kalimantan, and to a lesser extent Sulawesi. Figure 5 illustrates the contribution of each region to the increase in planted area since 2000.

3.2 Poverty

My primary outcome variable is the district poverty rate from 2002 to 2010, taken from Indonesia's central statistics agency, *Badan Pusat Statistik* (BPS). The poverty rate is the principal social policy target for Indonesian governments and a reasonable proxy for broader welfare outcomes in rural agrarian regions. The poverty rate is defined as the share of total district population living below an expenditure-based poverty line varying

Figure 6: District Poverty Rates, 2010

by district and period and linked by a universal consumption requirement, mostly caloric. The Indonesian poverty line marks an extremely low standard of living at around $25 USD per person per month. Poverty figures are derived from the consumption module of BPS' district-representative national socio-economic survey (SUSENAS), implemented at least annually and covering almost two million people across all provinces in 2010. SUSENAS is agnostic to whether consumption goods are purchased in formal or informal markets and a consistent method has been used to calculate poverty rates for the period under study (i.e., the method changed in 1998 and 2011). The distribution of household expenditure can be steep around the poverty line, so I also estimate impacts on the depth of poverty measured by the poverty gap index: the average gap between the expenditure of poor people and the poverty line. This allows me to assess whether only people near the poverty line are affected or those further below.[12] District poverty rates in 2010 are presented in Figure 6. Most of the poor live in populous Java and poverty rates remain highest in the eastern periphery, away from the north-western islands most engaged in the palm oil boom.

3.3 Pemekaran

Indonesian districts (*kabupaten* and *kota*) are clearly defined legal and geographical units with district-level administrations reflecting local economies. A district panel provides temporal and spatial variation suitable to identifying aggregate district-level impacts. Indonesia underwent one of the world's largest reconfigurations of a modern state with the fall of President Suharto in 1997, democratizing and decentralizing power to around 300 district governments. New political and fiscal powers drove the number of districts to proliferate from 292 in 1998 to 514 in 2014, a process known as *pemekaran*. Fitriani, Hofman, and Kaiser (2005) provide a detailed account of *pemekaran*, highlighting how district splits followed sub-district (*kecamatan*) boundaries and did not

[12]More detailed distributional analyses using individual-level data are beyond the scope of this article.

affect neighboring districts' borders. I combine the pseudo-panel of district poverty variables with official district oil palm statistics and apply year-2001 district boundaries to obtain a nationally-exhaustive balanced panel of 341 constant geographic units.[13]

4 Empirical approach

I relate changes in shares of district area used for oil palms to poverty with the long-difference equation:

$$ln(y_{d,2010}) - ln(y_{d,2002}) = \beta(P_{d,2009} - P_{d,2001}) + \delta_i + \gamma X_{d,2000} + \varepsilon_d \quad (1)$$

$ln(y_{d,2010}) - ln(y_{d,2002})$ denotes the change in the log poverty rate over the period of rapid oil palm expansion, 2002–2010, in district d. I log poverty to better compare relative changes in prevalence between districts with high and low poverty rates.[14]

$P_{d,2009} - P_{d,2001}$ is the 2001–2009 change in the share of district area used for oil palm plantations, lagged by one year because poverty is measured in the middle of the year and oil palm at the end. Palm oil land shares are not logged to retain zero values. Differencing removes any district-specific, time-invariant level sources of bias jointly affecting land use and poverty (e.g., local geography, climate, history, institutions, and culture), and exploits the different trends in oil palm expansion and poverty reduction across districts. β is the effect of an additional percentage point of oil palm land as a share of total district land on the district poverty rate (i.e., a semi-elasticity). Using the oil palm share of district area allows me to compare the effect of using additional oil palm land relative to the average

[13] In most Indonesian data, districts retain the original names and codes after splitting and reducing in size. Care is needed to avoid applying district fixed effects to such units. In international data, this equates to letting the USSR series continue without its former members instead of creating a new series for Russia. Alternative district definitions yield similar results, but constant land area units allow an uninterrupted panel dataset better suited to my research question. Summary statistics are reported in the appendix.

[14] The logged dependent variable ensures districts with relatively low levels of poverty making similar proportional gains to districts with higher relative levels of poverty are accounted for similarly. Results are similar using alternative functional forms (e.g., linear–linear, linear–log, log–log; see appendix), suggesting districts with relatively low levels of poverty are not driving my results.

of all other possible uses for land.

δ_i are island fixed effects, capturing region-specific factors and allowing different regional trends (e.g., related to different patterns of economic development or large regional infrastructure investments). Island groups are defined as Java, Sumatra, Kalimantan, and Sulawesi, with remaining eastern islands grouped together. $\gamma X_{d,2000}$ includes initial log poverty and per capita regional (i.e., district) GDP (RGDP), capturing convergence across regions with higher poverty rates and allowing variable trends by initial conditions. Standard errors are adjusted for heteroskedasticity.

I opt for long differences because any poverty impacts arising from additional oil palm land are not likely to be fully realized immediately. Plantation companies must establish the necessary infrastructure, hire workers, prepare land, plant oil palms, then harvest the first fruit. Smallholders need time to switch livelihood, prepare land, plant trees, then wait for their first harvest around two and a half years later.[15] It takes five to seven years for an oil palm to reach a productive state and the price paid for a fresh fruit bunch increases with tree maturity.[16]

A causal interpretation of $\widehat{\beta}$ relies on an assumption of parallel trends, common to all difference-in-difference-type approaches. Consistent estimates are obtained if no problematic time-varying omitted variables (i.e., correlated with oil palm expansion and poverty) systematically shift poverty trends within island groups after allowing for differential trends by initial income and poverty levels. While oil palm expansion is governed by complex administrative processes subject to a high degree of randomness (discussed further in Section 5.1), the main concern is oil palm being endogenously planted due to different underlying economic conditions, with expanders on different growth and poverty reduction paths. I turn to IV estimation to identify causal effects.

[15]While smallholders can often intercrop (i.e., farm different crops on their land), this is much less common for oil palm smallholders than for other food and cash crops farmers (BPS, 2013). The time from planting to first harvest is shorter if germinated seedlings are planted instead of seeds, a common practice on industrial plantations but not for smallholders.

[16]Prices are set weekly and published in local newspapers; differencing and allowing different regional trends likely captures any systematic differences across markets.

4.1 Instrumental variable strategy

My identifying variation comes from a rich geo-spatial dataset on agricultural productivity: the Food and Agriculture Organization's (FAO) Global Agro-Ecological Zones (GAEZ) data. I instrument the change in the share of district area used for oil palm from 2001–2009 with average district agro-climatically attainable oil palm yield, measured in kilograms per hectare. Exploiting the variation in oil palm expansion arising from crop-specific agro-climatic suitability isolates the effect of developing oil palm on areas where it is makes the most sense to develop it.

The GAEZ dataset uses state-of-the-art agronomic models and high-resolution data on geographic characteristics and climatic conditions to predict attainable yields for 1.7 million grid cells—5 arc-minutes and 30 arc-seconds each—covering the Earth's surface. Estimates are available for different crops on every piece of land regardless of whether the land is cultivated or growing the crop, informing farmers and policy makers on how productive they would be at crops they are not currently growing. Exogenous variables known for every grid cell (e.g., soil types and conditions, elevation, land gradient, rainfall, temperature, humidity, wind speed, and sun exposure) feed into agronomic models predicting how these variables affect the micro-foundations of each crop's growth processes, explaining how a given set of growing conditions map to potential yields at each grid cell. GAEZ provide different sets of productivity predictions for different input scenarios. I opt for the median options: medium man-made inputs and rain-fed water supply.[17]

[17] Time-varying variables (i.e., humidity, temperature, rainfall, windspeed) are measured at a high frequency and their levels and variation over the period 1960–1990 are used in the models. Predictions for yields at the end of the 20th century are based on a large number of past realizations of these variables over the 20th century. Using rain-fed irrigation minimizes measurement error from historical changes in irrigation intensity and technologies (Nunn and Qian, 2011), although alternative input assumptions give a similar spatial distribution so do not affect my results. See Fischer et al. (2002), Nunn and Qian (2011), and Costinot et al. (2016) for further details on the FAO GAEZ data.

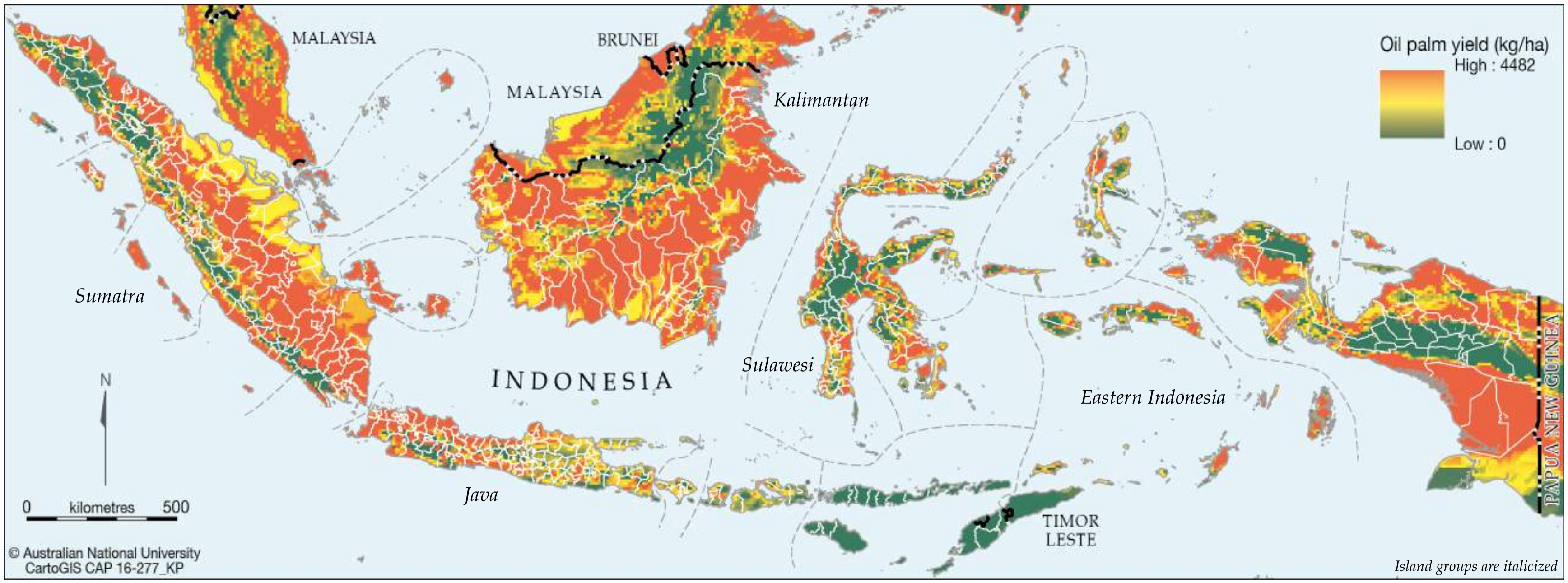
Pixel-level data for attainable palm oil yield across every field in Indonesia is presented in Figure 7. Each major region has some districts suitable for palm oil production with only rainfall irrigation and a medium level of inputs. I mapped the gridded data on attainable yield of each of Indonesia's main agricultural commodities to official district administrative boundaries from the 2010 Population Census using geographical information systems (GIS), calculated each district's mean, then collapsed districts back to 2001 definitions using area weights. The granularity and the continuous nature of the data provide a rich source of variation: a different value for every potential palm oil producing district.

Instrument relevance and strength

Oil palms only grow under certain agro-climatic conditions—humid low-land tropics—and potential yields and profits in each district affect the likelihood that district will have oil palms planted. The IV is thus theoretically relevant. First-stage coefficients on potential palm oil yield are positive and statistically significant at the 0.1 per cent level (presented with main results). A weak instrument problem can be present even with highly significant first-stage coefficients (Bound et al., 1995), so I report the Kleibergen and Paap (2006) *rk* Wald F statistic against the relevant Stock and Yogo (2005) critical values and use the Fuller (1977) median-unbiased limited information maximum likelihood (LIML) estimator for all IV estimates.[18] I provide additional confidence intervals and hypothesis tests using Moreira's (2003) conditional likelihood ratio (CLR) procedures, which outperform traditional Anderson and Rubin (1949) weak-instrument-robust-inference tests (Andrews, Moreira, and Stock, 2006; 2007).

[18] I prefer the Fuller estimator over the standard two-stage least squares (2SLS) IV estimator because (a) a few IV estimates have scope for a weak IV problem and LIML point estimates are more reliable for inference under a potentially weak IV (Murray, 2006), and (b) I prefer to use the same estimator throughout. 2SLS gives consonant results and these are reported in the appendix).

Figure 7: Attainable Palm Oil Yield Across Indonesia



Exogeneity and exclusion

A causal interpretation is only obtained if average attainable district palm oil yields do not affect changes in poverty through any channel other than oil palm expansion. GAEZ potential yield predictions do not involve estimating any sort of statistical relationship between observed inputs, outputs and agro-climatic conditions, so are exogenously determined with respect to district economic and poverty conditions. The two theoretically endogenous factors shaping GAEZ data—irrigation and man-made inputs—are set equal for all districts, so uncorrelated with poverty trends across districts.[19]

The main empirical concern is that a key input to the oil palm GAEZ productivity model could affect productivity of similar tropical crops and therefore welfare through agricultural productivity in other sectors: a common challenge with external instruments, particularly those relating to weather and climate (Bazzi and Clemens, 2013; Sarsons, 2015). Using a crop-specific instrument reduces this threat, but I go a step further. GAEZ attainable yield data are available for most of Indonesia's major agricultural crops. By controlling for other key crops' potential yields (i.e., wet land rice, dry land rice, tea, coffee, cocoa, and cassava), I further restrict the identifying variation to that relating only to oil palms and not shared suitability characteristics with other crops (i.e., tropical, humid, non-mountainous, lowlands with sufficient rainfall less suitable for other tropical cash crops that could be grown in similar areas to oil palm). Even with this precaution, a potential omitted variable problem cannot be ruled out and I rely on the assumption that districts suitable for oil palm are not systematically good at something else setting them on different poverty trends for a reason other than oil palm not captured by initial levels of development and suitability for other crops.

[19] Actual irrigation settings are likely to be correlated with poverty trends and economic development. Setting irrigation equal could underestimate yield potential under actual irrigation settings in better-irrigated wealthier areas, and would overestimate in poorer areas. As actual variation in irrigation settings does not enter the GAEZ model, I do not consider this a problem for estimation, i.e., the variation in potential yields across districts is agnostic to actual irrigation and other economic characteristics observed in districts on the ground.

5 Main results

My main result is presented in Table 1. Districts that converted more of their land to oil palm plantations in the 2000s have achieved more rapid poverty reduction than districts of similar initial poverty levels and per capita incomes in the same region. Oil palm appears to be better rural land use than alternatives for poverty alleviation in Indonesia.

Column 1 of Table 1 presents Equation 1 estimated with least squares. A district experiencing a ten percentage point increase in the share of land used for oil palm over the 2000s, at the mean (e.g., from 10 to 20 percent of district area), had a poverty rate 12 percent lower than otherwise similar districts in 2010. Columns 2–5 of Table 1 present the IV estimates. Positive first stage coefficients confirm oil palm expansion has been most pronounced where most productive. Column 2 shows a ten percentage point increase in district oil palm land share over the 2000s corresponds to over a thirty percent greater reduction in the poverty rate. That the estimate in Column 2 is almost three times the magnitude of least squares is not surprising. Any income driven effects are likely to be more pronounced where potential yields are higher.[20] The CLR confidence interval reported under the main coefficient does not overlap with zero, rejecting the null hypothesis that the coefficient equals zero with 97% confidence.

In Column 3 of Table 1 I control for the attainable yield of two of Indonesia's most important non-cash crop agricultural commodities: rice (wet and dry land) and cassava. The first stage coefficient in Column 3 is virtually the same and the second stage coefficient slightly larger; this is expected, as rice is typically produced in regions with different agro-climatic conditions and so should not share much of the identifying variation with

[20]While oil palm is grown in areas less suitable—notably a few poorer mountainous areas—such growers (i.e., "non-compliers") account for a very small component of total oil palm area and production. Monotonicity is likely satisfied by design: it seems highly unlikely that a district more suitable for oil palm will reduce its land used for the crop. I drop island dummies for IV estimates, as more parsimonious IV models tend to provide a stronger first stage identification in finite sample estimates and, in this context, most of the regional variation is captured by the instrument, suitability for other crops, initial conditions controls, and differencing out time invariant factors. Estimates including island dummies are qualitatively similar but with weaker first stages and larger standard errors, as expected.

Table 1: Poverty Impacts of the 2001–2010 Oil Palm Expansion

Dependent variable			*Δ log district poverty rate*			
Estimator	OLS	IV	IV	IV	IV	IV
Column	1	2	3	4	5	6
Δ oil palm land / district area	-0.012***	-0.034***	-0.040***	-0.046***	-0.078***	-0.033***
	(0.003)	(0.013)	(0.012)	(0.012)	(0.023)	(0.013)
CLR 95% confidence interval	N/A	[-0.19, -0.003]	[-0.133, -0.008]	[-0.12, -0.02]	[-0.20, 0.009]	[-0.17, 0.006]
CLR p-value (H0: B=0)	N/A	0.03	0.01	0	0.08	0.08
Potential rice and casava yields	N	N	Y	N	Y	N
Potential coffee, cocoa, tea yields	N	N	N	Y	Y	N
First-stage coefficients and diagnostics						
Log potential palm oil yield	N/A	0.690***	0.690***	0.893***	0.584***	
Log palm oil suitability index	N/A					0.506***
Kleibergen-Paap Wald *rk* F stat	N/A	13.41	13.12	20.25	9.08	10.83
30 per cent max Fuller bias critical value	N/A	12.71	12.71	12.71	12.71	12.71
10 per cent max Fuller bias critical value	N/A	19.36	19.36	19.36	19.36	19.36
Observations	335	308	303	303	303	309

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. All IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses and conditional likelihood ratio-based confidence intervals in square brackets.

oil palms (e.g., compare Java to Kalimantan, or the rice-growing deltas of south-east Asia to neighboring tropical islands growing cash crops). In Column 4 I separately include average district-specific attainable yields for three of Indonesia's key tropical cash crops: cocoa, coffee, and tea.[21] The first-stage coefficient increases to 0.89 and the excluded-F statistic to 20.25, exceeding the Stock-Yogo critical value of 19.36 for ten percent maximum Fuller bias. The second-stage coefficient restricting the identifying variation to suitability to oil palms but none of Indonesia's other major cash crops (i.e., controlling for agro-climatic suitability for cocoa, coffee, and tea) is 0.046, suggesting an additional ten percentage point increase in oil palm land share where it is most suitable has almost halved the poverty rate over the decade. The CLR test rejects the null that the coefficient equals zero with almost 100% confidence. In Column 5, I include potential yield for all six additional crops as controls. Identification is significantly weaker (with an excluded F statistic of 9.08) and the estimated coefficient on oil palm expansion much larger at 0.078. The CLR test however still rejects the null hypothesis that the coefficient is equal to zero at the ten percent level. Instrumenting oil palm expansion with GAEZ's oil palm suitability index instead of potential yield gives a similar result in Column 6.

The reduction in the poverty rate observed in Table 1 could be due to people near the poverty line being lifted just above, with little effect on those further down the income distribution. The poverty rate would fall but the gap between the average poor person and the poverty line (i.e., poverty depth) increase. To evaluate this potential explanation, I estimate impacts on poverty depth in Table 2. Results are similar to Table 1, confirming benefits from oil palm expansion tend to reach the average person living below the poverty line in rural districts.

[21] Agro-climatic suitability data for rubber, replaced in many areas by oil palm, was not available at the time of this study.

Table 2: Impacts of the 2001–2010 Oil Palm Expansion on the Poverty Gap

Dependent variable	*Δ log district poverty gap index*					
Estimator	OLS	IV	IV	IV	IV	IV
Column	1	2	3	4	5	6
Δ oil palm land / district area	-0.015***	-0.038**	-0.038**	-0.054***	-0.132***	-0.046**
	(0.005)	(0.019)	(0.018)	(0.018)	(0.049)	(0.020)
CLR 95% confidence interval	N/A	[-0.130, 0.013]	[-0.110, 0.006]	[-0.146, -0.011]	[-0.282, 0.017]	[-0.244, 0.017]
CLR p-value (H0: B=0)	N/A	0.122	0.085	0.016	0.084	0.12
Potential rice and casava yields	N	N	Y	N	Y	N
Potential coffee, cocoa, tea yields	N	N	N	Y	Y	N
First-stage coefficients and diagnostics						
Log potential palm oil yield	N/A	0.695***	0.82***	0.902***	0.584***	
Log palm oil suitability index	N/A					0.508***
Kleibergen-Paap Wald *rk* F stat	N/A	13.54	13.77	20.53	9.08	10.83
Observations	335	308	303	303	303	309

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. All IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses and conditional likelihood ratio-based confidence intervals in square brackets.

In Table 3 I explore the robustness of the main long difference least squares estimate to controlling for local economic growth and changes in the natural environment, partialling out any effects through these two potential channels. In Columns 1 and 2 of Table 3 I control for the decadal change in log per capita output. The coefficients on regional gross domestic product growth are statistically insignificant and the coefficients on oil palm land share similar to those in Table 2, implying areal oil palm expansion has been a particularly pro-poor (i.e., redistributive) activity.

Like many equatorial developing countries, Indonesia was mostly tropical forest half a century ago and over half of Indonesian and Malaysian palm oil plantations in 2005 were forests in 1990 (Koh and Wilcove, 2008). The forestry landscape can often change alongside or prior to oil palm expansion, potentially biasing my estimates.[22] In Columns 3 and 4 I control for the initial level and 2000–2010 change in tree cover using pixel-level Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery data.[23] Similar poverty impacts from oil palm land expansion are observed holding tree cover constant and the coefficients on tree cover variables statistically insignificant, suggesting conversion of primary forest into palm oil plantations is unlikely to explain the observed poverty reduction. The stability of my coefficient of interest to the inclusion of these two key factors associated with oil palm expansion—economic growth and changes in the natural environment—and their limited explanatory power for poverty reduction also provides suggestive evidence against a potential omitted variable problem.

[22]For example, income from forestry and logging taking place in the same districts as oil palm expansion could bias my estimates downwards, and social harms like conflict and malaria associated with deforestation could bias estimates upwards. If such factors arise from oil palm expansion, their influence is included in the net effect in my main estimates.

[23]Data are taken from Wheeler et al. (2013). While MODIS data cannot disentangle primary forest from plantations (i.e., it is distinctly not a measure of deforestation in the Indonesian context), it is still a useful proxy for observed changes in forest and the natural environment. Wheeler et al. (2013) discuss MODIS data in detail.

Table 3: Additional Covariates and Placebo Tests

Dependent variable	Δ*log district poverty rate, 2000s*				Δ*log poverty, 1990s*	
Estimator	OLS	IV	OLS	IV	OLS	IV
Column	1	2	3	4	5	6
Δ oil palm land / district area	-0.0120***	-0.044***	-0.011***	-0.044***	-0.003	0.035
	(0.003)	(0.012)	(0.004)	(0.017)	(0.008)	(0.022)
Δ log RGDP per capita (IDR)	-0.048	-0.137				
	(0.074)	(0.086)				
Δ tree cover (pixels)			(0.000)	(-0.000)		
			(0.000)	(0.000)		
Kleibergen Paap-Wald rk F stat		20.71		6.239		20.03
Observations	335	303	181	159	292	264

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. All IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample in Columns 1–4 is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). Sample in Columns 5–6 is the same but with the change in the log district poverty rate from 1987–2001 as the dependent variable. Initial period district definitions are used throughout. Changes in samples size are due to data availability and district proliferation. Each regression includes as control variables log poverty and log per capita output in the initial period and the least squares estimates include island dummies. IV estimates additionally control for potential coffee, cocoa, and tea yields. Change in tree cover refers to the change pixels of tree cover measured by MODIS satellite data, and estimates in Columns 3–4 additionally control for initial period tree cover. Heteroskedasticity-robust standard errors are in parentheses.

The main identifying assumption for my preferred long difference IV estimate is that agro-climatically suitable oil palm expansion districts are not on different poverty trends for a reason other than oil palm. I conduct two empirical exercises to probe the credibility of this exclusion restriction. I first examine poverty trends in the period preceding the dramatic scale up of oil palm production in Columns 5 and 6 of Table 3. I regress oil palm expansion on the change in district poverty rate from 1987 through to 2001, the first year of the panel used in my main estimates. Coefficients are not statistically different from zero suggesting districts highly suitable for oil palm were not on different trajectories prior to the oil palm boom of the 2000s.[24] Second, similar to Nunn and Wantchekon (2011) I perform a falsification test looking at the reduced form relationship between agro-climatic suitability for oil palm and poverty reduction in regions with significant oil palm expansion and those with much less or none. If agro-climatic suitability for oil palm affects poverty reduction only through planting oil palms and producing palm oil, then there should be no relationship between potential oil palm yields and poverty reduction in regions that did not increase their planted area. This is precisely what we observe. In Column 1 of Table 4 I estimate a statistically insignificant relationship between potential oil palm yield and poverty reduction in Java and Eastern Indonesia (Southeast), a relatively untreated sample with little oil palm planted but still considerable variation in potential yields. In Column 2, I find a economically significant and precisely estimated relationship in the other three island groups (Northwest) where the oil palm expansion mostly took place, consistent with my IV estimates. Finally as long differences can sometimes be sensitive to start and finish year, in Columns 3–6 of Table 4 I show how results are similar using alternative start and finish years. Further robustness checks are provided in the appendix: excluding Java, excluding cities, using only palm oil producing districts, and using alternative functional forms.

[24] Regressing oil palm expansion over the 2000s on poverty reduction from 1987 until just before the Asian Financial Crisis also shows no statistically significant effect.

Table 4: Alternative Samples

Dependent variable: Δlog district poverty rate						
Sample	Southeast	Northwest	Late first year (2003)		Early final year (2009)	
Estimator	OLS	OLS	OLS	IV	OLS	IV
Column	1	2	3	4	5	6
Log potential palm oil yield	0.009	-0.071***				
	(0.009)	(0.018)				
Δ oil palm land / district area			-0.013***	-0.045***	-0.014***	-0.050***
			(0.004)	(0.012)	(0.004)	(0.015)
Kleibergen Paap-Wald rk F stat				22.44		20.28
Observations	188	235	336	304	334	302

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. Overall sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Sample in Column 1 is only districts on Sumatra, Kalimantan, and Sulawesi, and in Column 2 only Java and Eastern Indonesia. Columns 3–4 is 2003–2010, and Columns 5–6 2002–2009. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimates includes island dummies and IV estimates potential yield for coffee, cocoa, and tea. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Heteroskedasticity-robust standard errors are in parentheses.

5.1 Short-run and dynamic effects

I have focused on the total changes in oil palm plantation land and poverty over the 2000s. But the relationship between growth in the palm oil sector and poverty could vary over the crop's life cycle. I now use alternative panel estimators to examine short-run impacts. My preferred panel estimator takes the form:

$$ln(y_{d,t}) = \beta P_{d,t-1} + \delta_d + \tau_{i,t} + \gamma X_{d,t-1} + \varepsilon_{d,t} \quad (2)$$

$y_{d,t}$ denotes poverty in district d at time t. $P_{d,t-1}$ is the oil palm land percentage of total district area, with additional lags in some estimates. β is the effect of an additional percentage point of oil palm land on poverty. δ_d are district fixed effects, removing time invariant district-specific sources of confoundedness. $\tau_{i,t}$ are island-by-year fixed effects capturing time varying factors common to each island group (e.g., economic growth and business cycles, international commodity prices for an island's commodities, political shocks, regional infrastructure investments, and other major policy changes).[25] Island–year fixed effects focus my comparison to districts within the same island group, relaxing the parallel trends assumption to more flexible regional trends. $\gamma X_{d,t-1}$ is a vector of potential time and district varying controls. Standard errors are adjusted for heteroskedasticity and clustered by district to allow arbitrary correlation within districts over time.[26]

[25]Social policy in Indonesia is strongly targeted towards the poor, but its spatial distribution is relatively unchanged from 2001–2010 and mostly captured by district fixed effects. New social programs were mostly implemented nationally (e.g., the Raskin rice subsidy, PNPM, unconditional cash transfers, and scholarships) so captured by island–year fixed effects, or piloted in a few villages before national roll-out.

[26]Bertrand et al. (2004) discuss problems arising in panel estimates when serial correlation is unaddressed. I consider larger cluster robust errors a more conservative basis for inference and hypothesis testing, with weaker assumptions and better finite sample properties than more efficient counterparts.

$\widehat{\beta}$ in Equation 2 has a causal interpretation if there are no time and district varying omitted variables correlated with $y_{d,t}$ and $P_{d,t-1}$ influential enough to systematically shift poverty trends within island groups, a reasonable assumption for two reasons. Equation 2 focuses on the poverty response from the *timing* of district oil palm expansions, so the critical issue is what determines the timing. Oil palm land declared by the Department of Agriculture reflects plantation sector land use decisions made through the large, decentralized bureaucracy: each step in the process is influenced by idiosyncratic factors resulting in highly unpredictable delays.[27] Second, focusing on timing, the main concern is districts receiving more timely oversight on their requests for land conversion for reasons other than oil palm. But island–year fixed effects appear sufficient to eliminate such bias from unobserved time varying characteristics. In-time placebo tests using leads instead of lags and regressing poverty lags on oil palm provide no evidence of such divergent trends, and the coefficient on oil palm land is remarkably stable when I include additional time and district varying correlates of poverty.[28]

I estimate Equation 2 with first differences and mean deviations (i.e., within estimation), both with distributed lags. Column 1 of Table 5 presents the annual first difference. Assuming an effect within the same year, a ten percentage point increase in the district share of land used for oil palm in one year corresponds to a three per cent reduction in the poverty rate the next year, statistically significant at the five per cent level. Assuming the land data is accurate and timely in its reporting, immediate effects must come from planting more mature seedlings (c.f., seeds) or through channels other than the

[27]Indonesian land use regulations are complicated. The *Regional Autonomy Laws 1999* saw district forest departments become answerable to *bupatis* (district heads) instead of the central government. *Bupatis* apply to the central government for approval to convert land into oil palm plantations, a process involving identifying areas for plantations, attracting investors, gaining district parliament approval, making a formal request to the central government, central agencies working through the request, the district receiving approval, and land being converted. Burgess et al. (2012) similarly highlight how administrative lags from central to district governments could render district splits exogenous to province and district outcomes. The processes driving official and unofficial land conversion to oil palm are arguable more obscure than those to create new administrative units, which has strict criteria (see, e.g., Bazzi and Gudgeon, 2016).

[28]If there were divergent trends we would expect current outcomes to be correlated with future oil palm expansion, but coefficients are small and statistically insignificant. These estimates are all reported in the appendix.

Table 5: Short-run and Dynamic Poverty Impacts

Dependent variable: log district poverty rate							
Estimator	First difference			Within FE			
Columns	1	2	3	4	5	6	7
Oil palm land / district area (%)	-0.003**	-0.004***	-0.004**	-0.007***	-0.005**	-0.007***	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
First lag		-0.003	-0.002		-0.003		
		(0.002)	(0.003)		(0.003)		
Second lag		-0.009***	-0.008**		-0.007**		
		(0.003)	(0.004)		(0.003)		
Third lag		-0.006***	-0.005*		-0.005		
		(0.002)	(0.003)		(0.003)		
Σ coefficients		-0.022***	-0.019***		-0.020***		
District fixed effects	N	N	Y	Y	Y	Y	Y
Island-specific time trends	N	N	N	N	N	Y	N
Province-specific time trends	N	N	N	N	N	N	Y
Observations	3040	2371	2371	3386	2717	3386	3386

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level. Sample is an annual 341 district panel from 2002–2010. Oil palm land is lagged one period. 2001 district boundaries are used, with new districts collapsed into year 2001 parent districts. Changes in sample size are due to data availability. Island–year fixed effects are included throughout, with island groupings defined Java, Sumatra, Kalimantan, Sulawesi, and Eastern Indonesia. The within FE estimator refers to the mean differenced (within-district) fixed effects estimator. Significance reported for sum of the coefficients relates to the test that the sum of the coefficients on oil palm is equal to zero.

production and sale of the crop (e.g., payments to communities or waged labor to establish plantations. The land conversion and planting stage is the most labor intensive part of the oil palm life cycle for smallholders and companies). In Column 2 I include the first three lags of the annual first difference. The second and third lags have much larger coefficients, reflecting the crop's life cycle (e.g., heavy upfront investment, and long gestational period). The sum of the coefficients on oil palm land is 0.022, between long difference estimates obtained from least squares and IV. As the evolution of oil palm land has been gradual, I follow Ciccone (2011) in Column 3 and take first differences and include district-fixed effects (i.e., exploiting deviations in these differences from their within district means) to extract the "shock" component of the changes in oil palm land. Coefficients are similar.

In Columns 4–7 of Table 5 I adopt the mean differenced "within" estimator. Unlike the first differences in Columns 1–3, coefficients reflect the effect of variation over time within each district (c.f., at a particular point in time across districts). As within estimation also picks up level effects, this is a more appropriate flexible estimator than first differences (i.e., due to the lags in the palm oil production process). Column 4 of Table 5 presents my preferred panel estimate. A ten percentage point increase in the share of land used for oil palm at the mean corresponds to a seven per cent reduction in the poverty rate in the short run. Column 5 includes lags, summing exactly to the least squares long difference in Column 1 of Table 1. Columns 6 and 7 include time trends for each island and province. Results are almost identical with these rich control vectors. Results are similar for poverty depth (see appendix).

5.2 Effect heterogeneity

I now briefly explore effect heterogeneity across private, government, and smallholder sectors, and across regions. Despite smallholder managed oil palm generating more jobs per hectare, smallholders struggle to exploit economies of scale and can have per hectare yields up to 40 per cent lower than industrial estates due to their poorer agricultural practices (Hasnah et al., 2004; Lee et al., 2013). Industrial plantations, on the other hand, are usually between 5,000–20,000 hectares and intensively managed to maximize efficiency (Corley and Tinker, 2015). Although industrial and smallholder sectors are heavily dependent on one another for supply and processing, they could heterogeneously affect the poor.

FIGURE 8: SECTOR HETEROGENEITY

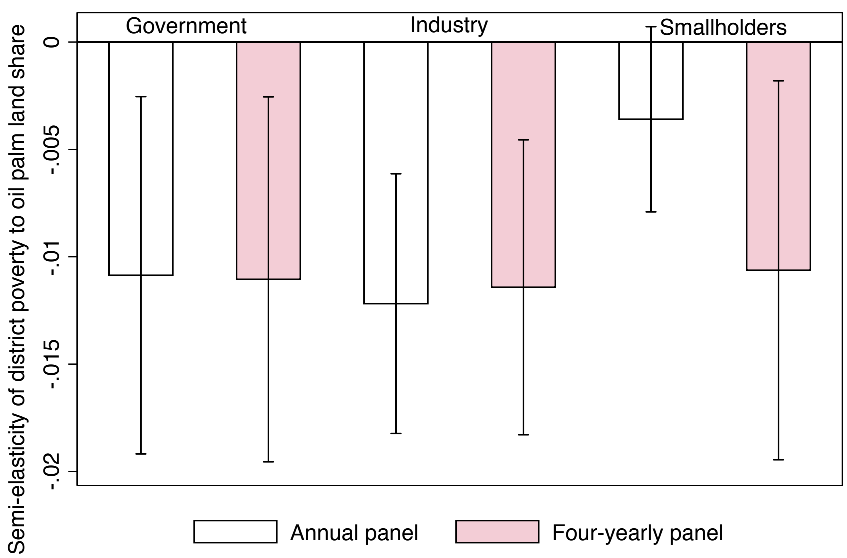


Figure 8 compares the poverty impacts of additional government, industry, and smallholder managed oil palm land. Sub sector oil palm data are only available for some years so I use the within estimator (i.e., Equation 2) with island-by-year fixed effects and shift between an annual (clear bars) and four-yearly (light cranberry bars) panel to assess dynamics. The semi-elasticity of district poverty to oil palm land is similar whether land is managed by state owned plantation companies, private industry, or smallholders.[29] The immediate response to smallholder oil palm expansion is the exception, with no detectable short-run relationship between more smallholder land and district poverty rates. Large state and company plantations immediately hire labor to establish and work on plantations, often building local infrastructure and community facilities for their workers. Companies also tend to plant already germinated seedlings, which yield fruit considerably faster than when planted as seeds. By contrast, independent smallholders tend to bear establishment costs, plant poorer quality seeds, and see little profit for at least two years, relying on alternative livelihoods. A similar pattern is observed for poverty depth (see appendix).

Indonesia is a diverse country characterized by regional heterogeneity, and the country's palm oil sector is no exception. Oil palm plantations were introduced by the Dutch to North Sumatra in the colonial era of the early 1900s. Today the island of Sumatra is the most mature palm oil production region, with new expansion mostly through smallholders. Kalimantan and eastern Indonesia (e.g., Sulawesi and Papua) tend to be characterized by recent clearing of primary forests to establish industrial plantations, although mills in these areas are still highly dependent on smallholder supply.[30]

[29]Recall a palm oil supply shed is roughly a 50km radius from the mill and there are few smallholder owned mills, so the industrial and smallholder sectors tend to colocate and grow together. Most mills require a steady supply of fruit from smallholders to operate efficiently.

[30]Smallholders enter the market around these estates in much the same way as Sumatra, by planting on idle land, switching to oil palm from other sources of livelihood, or being incorporated into the plantation system with the company, often within concession areas.

Figure 9: Regional Heterogeneity

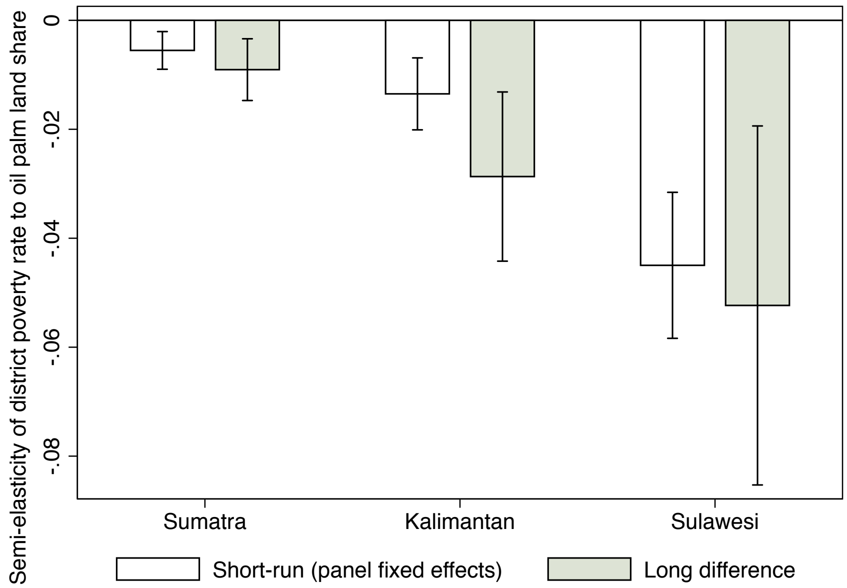


Figure 9 compares effects across Indonesia's three main palm oil producing regions of Sumatra, Kalimantan, and Sulawesi. I use the full sample within (i.e., Equation 2 estimated with an annual panel; clear bars) and long difference estimators (Equation 1; light green bars), estimated with least squares and interacting the island dummies with my main oil palm land share variable to provide marginal effects by region.[31] Considered with the maps presented in Figures 3 and 5, a clear pattern emerges. Oil palm related poverty reduction has been strongest in the east where the sector is less mature and initial poverty rates were higher. That the 11 oil palm producing districts in Sulawesi on average experienced the largest reductions in district poverty rates highlights how it is not just regions with relatively low poverty driving my results, but highly remote districts with high poverty rates making commensurate proportional poverty reductions.

[31] I drop the main (not interacted) effects to allow a more straightforward interpretation of the estimated coefficients. Results in Tables 1 and 5 are weighted averages of these. Estimates on regions not producing much palm oil are statistically indistinguishable from zero, as expected following the falsification exercises in Table 4. These are provided in the appendix as complete tabulated estimates and by island group sub sample.

6 A migration story?

District poverty rates can fall either due to real consumption growth for the poor, or through changes in population. Population changes contaminating my interpretation include inward migration of non-poor people and outward migration of poor people; both would also alter poverty rates in my comparison pool if migration is to and from districts not producing palm oil. Critics of the palm oil sector highlight a story of displacement, where "land grabbing" drives forest dwellers, indigenous people, and poor farmers off their land (Gellert, 2015; Cramb and McCarthy, 2016). I do not dispute the existence of such cases and have heard them first hand. But could population movements, by choice or by force, explain the reductions in district poverty rates documented in this article?[32]

I investigate the plausibility of a migration-based alternative explanation in three steps. I first identify the quantum of migration needed to explain my main estimates in the context of official internal migration statistics and relevant contextual information gathered from field visits. I then pursue province-level estimates, less exposed to the issue of migration given the larger size of provinces vis-a-vis districts. I finally estimate district-level impacts of oil palm expansion on population change and on the number of poor people in a district (c.f., the poverty rate).

The 2010 Indonesian Population Census reported 2.5 per cent of the population living in a different province to where they lived at the time of the previous census (BPS, 2010). In resource rich provinces, the rate can be higher (around 6 per cent in Riau and East Kalimantan) or closer to the national average, even below (4 and 1.8 per cent in Jambi and South Sumatra). The highest rate is in West Papua, the least densely populated province, but still under 8 per cent. It is important to note the magnitude of migration flows in the

[32]Understanding the scale and scope of local migration in Indonesia is difficult. Reliable internal migration data are collected in the decadal population census, with no information on income level and only information on inter-province movements made public. I do not have the original census data, which I understand may have details on districts of birth. SUSENAS and the labor market surveys (SAKERNAS) do not include information on migration, and the Indonesian Family Life Surveys (IFLS) which do are not representative across regions, let alone at the district level. Meng et al. (2010) and Bazzi (2016) detail recent and historical migration patterns in Indonesia.

average oil palm district would have to be around four times the national average rate of recent migrants to explain my long difference estimate (i.e., 10 per cent), a further four times that to explain my preferred IV estimate, and predominately involve poor people leaving or non-poor people coming. Contrast this to the tendencies of lower income people to move to booming regions seeking economic opportunities, and of wealthy beneficiaries of natural resource sectors to be based in capital cities.

Two other contextual issues bear a mention. First, the popular displacement narrative relates to agroindustrial frontier expansion. But smallholders manage around half of Indonesia's planted oil palm area, accounting for most of the increase in planted oil palm area over the period of this study. Plasma scheme smallholders mostly moved in during the transmigration program, which ceased in 2000 (Bazzi et al., 2016). Independent smallholders accounting for much of the rapid areal expansion over the 2000s tend to be local people without government or company support, less affluent and hesitant to move.

Second, a district is a large geographic unit, on average comprising over 200 villages. When villages are forcefully moved or formal relocation agreements reached, communities tend to be relocated nearby or incorporated into plantation activities within the same subdistrict (*kecamaten*) or the existing village area if large, often on unfavorable terms. Relocation to other districts is rare, and a displaced poor individual is unlikely to move farther than the district or provincial capital, in no small part because of financial constraints.

Estimating analogous models at a greater level of spatial aggregation is a useful way to remove the influence of any within province migration. Province-level estimates are presented in Table 6. Columns 1 and 2 present short-run effects, focusing on changes within each province over time. Column 1 includes island-specific poverty trends and Column 2 island–year fixed effects. The magnitude of the estimate in Column 2 is similar to the analogous district-level estimate (Column 4 of Table 5). A long difference estimate with island fixed effects is presented in Column 3. Provinces with a ten percentage point

TABLE 6: PROVINCE RESULTS

Dependent variable: log district poverty rate (%)			
Estimator	FE	FE	LD
Column	1	2	3
Oil palm land / district area (%)	-0.014*	-0.007**	-0.013**
	(0.006)	(0.003)	(0.004)
Linear island trends	Y	N	N
Island–year fixed effects	N	Y	N
Island fixed effects	N	Y	Y
Observations	319	319	30

Notes: Stars denote statistical significance at the 10, 5, and 1 per cent levels. Sample is an annual balanced panel of Indonesian provinces from 2002–2010, with oil palm land lagged one period. Estimates are the within estimator with province fixed effects (FE) and the long difference least squares estimator (LD). Heteroskedasticitiy-robust standard errors are in parentheses. Data taken from the World Bank (2015).

increase in their share of oil palm land have experienced, on average, a 13 per cent greater reduction in the poverty rate from 2002–2010. Province-level estimates are similar to district-level estimates, suggesting intra province migration is not substantially affecting my findings.

In Table 7 I present results from least squares fixed effects, long difference, and long difference IV estimators using logged population (Columns 1–3) and logged number of poor people (Columns 3–6) as dependent variables. Column 1 provides no evidence of any short-term population change arising from areal oil palm expansion. The least squares estimate in Column 2 indicates that over the nine years districts with greater oil palm expansion tended to have slightly larger populations, but this effect reduces in magnitude and becomes statistically insignificant when estimated with IV in Column 3. Columns 4, 5, and 6 show more oil palm land corresponds to a large reduction in the total number of poor people in each district. I cannot rule out poor people systematically leaving oil palm districts and being replaced by non-poor inward migrants, but this seems highly unlikely to fully explain the falling poverty rates identified in this article. Finally, in Columns 7–9 of Table 7 I include per capita palm oil production, highly statistically significant and of a large magnitude. Per capita palm oil production renders the oil palm land share coefficient insignificant in Columns 7 and 8, highlighting the "dose–response" relationship between areal expansion and production and implying that palm oil production is indeed the principal channel through which areal expansion reduced district poverty.[33]

[33]Estimates in Columns 1–6 are simple decompositions of estimates in Tables 1 and 5 using the log poverty rate as the dependent variable. Land expansion expansion is omitted from the final IV estimate, as I am only using the one instrument.

Table 7: Population, Poor People, and Production

Dependent variable	*Log district population*			*Log number of poor*			Log district poverty rate		
Estimator	FE	LD	LD IV	FE	LD	LD IV	FE	LD	LD IV
Column	1	2	3	4	5	6	7	8	9
Oil palm land / district area (%)	-0.001	0.003*	0.001	-0.012***	-0.009***	-0.041***	-0.004*	-0.007	
	(0.001)	(0.001)	(0.007)	(0.003)	(0.003)	(0.013)	(0.002)	(0.004)	
Per capita palm oil production (tons)							-0.190***	-0.125**	-0.847***
							(0.054)	(0.054)	(0.229)
Kleibergen Paap Wald rk F Stat			20.25			20.25			15.4
Districts	341	335	303	341	335	303	341	335	303
Observations	3689	335	303	3045	335	303	3386	335	303

Notes: Stars denote statistical significance at the 10, 5, and 1 per cent levels. Sample is an annual 341 district panel from 2002–2010. Oil palm variables are lagged one period. 2001 district boundaries are used, with new districts collapsed into year 2001 parent districts. Variations in the sample size are due to data availability. Estimators refer to within fixed effects (FE), long differences (LD), and long difference instrumental variable (LD IV) estimators. FE estimates include island–year fixed effects. LD and LD IV regressions include log poverty and log per capita output in the initial period as control variables, with least squares (LD) estimates additionally including island dummies and the LD IV estimates additionally including potential coffee, cocoa, and tea yields. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level for panel estimators.

7 Mechanisms

I now explore some of the potential channels outlined in my conceptual framework. I focus on direct labor income effects, rural public goods related to agricultural manufacturing, and impacts on economic output by sector. I use my preferred long difference IV estimator throughout.

Columns 1–3 of Table 8 estimate the impact of oil palm expansion on average per capita household expenditures, calculated directly from the national socioeconomic survey (SUSENAS). The point estimate in Column 1 corresponds to a 4,407 rupiah increase in district mean per capita household expenditures per month, although imprecisely estimated and statistically insignificant at conventional levels. Column 2 turns to average per capita expenditure in agricultural households. Agriculture is the largest sector and primary source of employment across rural districts. The estimated coefficient in Column 2 suggests a ten percentage point increase in share of district area used for palm oil has corresponded to around an eight thousand rupiah increase in expenditure per person employed in the agricultural sector per month: more than an extra day's consumption per person each month around district poverty lines. Rising consumption for agricultural households is consistent with an explanation of greater labor income for those directly employed in the sector and more general upwards pressure on agricultural wages. Column 3 finds the bottom 20 percent have on average experienced around a 2000 rupiah increase in consumption per month from a ten percentage point increase in oil palm land over the decade, as expected with falling poverty rates.[34]

[34] A direct examination of impacts on oil palm laborers, smallholders managing their own plots, traders, transport workers, and other agricultural households would be more useful than examining impacts on the average agricultural household. Unfortunately recent industry classifications in SUSENAS and SAKERNAS only disaggregate to more general levels of agricultural work and do not allow such an assessment. SUSENAS is sampled to be representative at the district level and the veracity of the data is significantly reduced in such sub-district analysis, even as I have done in Columns 2 and 3. higher yields for smallholders switching out of less productive agriculture, higher incomes for rural people expanding their landholdings or converting forest and secondary jungle to productive agriculture, long time smallholders earning more from rising prices, and waged labor employment opportunities on plantations and working for larger smallholders are all examples of potential income related mechanisms touched on in my conceptual framework that are consistent with my result in Columns 2 and 3 of Table 8.

Table 8: Mechanisms

Dependent variable	*Per capita household expenditure (IDR)*			*% villages where main road is..*		
	District average	*Agricultural workers*	*Bottom 20 %*	*Dirt*	*Gravel*	*Asphalt*
Column	1	2	3	4	5	6
Δ oil palm land / district area	4407	7849*	2179***	0.016	-0.020*	0.026**
	(4327)	(4012)	(658)	(0.013)	(0.012)	(0.012)
Kleibergen-Paap Wald rk F stat	21.567	19.973	21.537	8.938	12.266	15.667
Observations	283	264	287	176	208	248
Dependent variable	*% households with access to..*		*Log district sectoral RGDP per capita (IDR)*			
	Electricity	*Safe drinking water*	*Primary*	*Secondary*	*Tertiary*	*All*
Column	7	8	9	10	11	12
Δ oil palm land / district area	0.016***	-0.003	0.017*	0.037**	0.007	0.014*
	(0.005)	(0.006)	(0.009)	(0.016)	(0.008)	(0.008)
Kleibergen-Paap Wald rk F stat	21.388	21.117	22.186	21.441	21.441	21.441
Observations	290	290	289	304	304	304

Notes: Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is the long difference cross section of all available districts from 2002–2010. Oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Fuller's limited information maximum likelihood estimator is used throughout, and each regression controls for log per capita output and poverty in the initial period. Dependent variables are all taken from the publicly available calculations at the World Bank (2015), with the exception of household expenditure for people working in agriculture which I calculated directly from SUSENAS. Heteroskedasticity-robust standard errors are in parentheses.

Columns 4–6 of Table 8 turn to roads, often an important constraint to rural economic development and a key logistic requirement in the farm-to-mill stage of the palm oil supply chain. The dependent variable in each column is the share of villages in each district where the main road is made of dirt, gravel, or asphalt, calculated from the triennial census of village heads (PODES) and aggregated to the district level. Column 4 shows no discernible impact on the number of villages with dirt roads. Columns 5 and 6 show a decrease in the share of villages with gravel roads but an increase in the share of villages with asphalt roads greater than the loss, evidence suggestive of primary road upgrading. Columns 7 and 8 examine the percentage of households in each district with access to gridded electricity and safe drinking water (both are calculated from SUSENAS). Oil palm expansion increased households' access to electricity, but had no statistically significant effect on access to clean drinking water. Considered with the estimates in Columns 4–6, oil palm expansion corresponds to greater provision of public goods closely related to the agricultural manufacturing operations (i.e., transport and utilities), but not other essential services.[35] Road networks and electricity mark a potentially important distinction from family farmed cash and food crops not requiring such linkages.

The final four columns of Table 8 use my primary long difference estimator to assess whether areal oil palm expansion affected district economic output by sector and in aggregate. RGDP are taken from official BPS subnational accounts by sector and converted into per capita terms. I use the standard United Nations primary (agriculture and mining), secondary (industry), and tertiary (services) sector classifications, and log the dependent variable for a growth interpretation. Columns 9 and 10 of Table 8 show statistically significant impacts on the output growth in the two sectors most directly involved in

[35] In the absence of a plausible theoretical channel from the oil palm sector to other service delivery and multidimensional poverty outcomes (c.f., roads and utilities), they are best thought of as placebo outcomes: any effect arising from increase in consumption are likely to be heavily lagged, more so in remote areas. Similar results to Columns 7–8 are obtained using alternative electricity and service delivery variables, specifically district electrical generation capacity reported by the state owned utility PLN (positive effects) and collected by Sparrow et al. (2015) and data on other service delivery indicators (no effects) calculated from SUSENAS and PODES (e.g., access to improved sanitation).

palm oil production: the primary sector (planting and harvesting) and industry (milling and refining). That the decadal growth boost has been more than twice as strong in the industrial (secondary) sector is not surprising. Even though oil palms are lucrative for farmers, most of the value adding happens at the mills. The secondary (industry) sector also captures construction, electricity, gas, water, and other utilities services essential for plantation sector operations. Contrary to Foster and Rosenzweig's (2004) findings in rural India, I do not find much district-level evidence that agricultural development and industrialization are substitutes in the Indonesian countryside. Column 11 finds no statistically significant within district economic linkages to the formal services sector (c.f., informal services are typically low wage and difficult to gauge from national accounts).[36] Column 12 finds that increasing the share of district land used for oil palm by 10 percentage points corresponds to an average increase in per capita output of 14 per cent relative to districts without oil palm expansion. Any local crowding out of other economic activities by oil palm—for example through localized "Dutch disease" effects—appears at least fully offset in the medium term, with positive net economic effects at the district level. Oil palm expansion districts thus experienced annual economic growth a few percentage points stronger over this decade when national economic growth was just 3.5 percent per year. Collectively Table 8 suggests my main findings can be explained by both a direct labor income story and local economic development related to electrification, roads, and rural manufacturing.

[36] Note that professional services directly related to plantation sectors are mostly based in regional capitals and Jakarta, not likely captured within districts expanding their planted area.

8 Conclusion

This article's objective was to quantify the contribution of oil palm expansion to local poverty reduction in Indonesia. While there have been clear environmental consequences associated with Indonesia's rapid increase in palm oil production, rural Indonesian districts using more land for oil palm have on average experienced more rapid poverty reduction over the 2000s, a period when national poverty reduction has dramatically slowed relative to previous decades. Indonesia's recent smallholder-led oil palm expansion thus provides an important case study of how geographically dispersed pro-poor growth can reach remote rural regions. But how significant is this contribution for national poverty reduction?

Table 9 presents the ten districts with the largest proportional oil palm land expansions. Columns 3 and 4 compare the actual poverty rate to a simulated counterfactual poverty rate without oil palm expansion based on my most conservative least squares estimate (i.e., setting oil palm expansion to zero and using a semi-elasticity of 0.012). All but one of these districts reduced poverty below its estimated counterfactual poverty rate in the absence of oil palm expansion. Of the more than 10 million Indonesians lifted from poverty over the 2000s, my most conservative estimate suggests at least 1.3 million people have escaped poverty exclusively due to growth in the oil palm sector. Reconciling the sector's past environmental–economic trade-offs though a shift to more sustainable production will likely lead to considerably better development outcomes than a concerted shift away from the sector and its millions of smallholder farmers.

Table 9: Estimated Contribution to Poverty Reduction, 2002–2010

District	Δ oil palm/area (% point)	Poverty rate (%), 2010		Δ poor (no. people)
		Actual	Counterfactual	
Column	1	2	3	4
Rokan Hulu	36	13	20	-28,526
Asahan	34	12	13	-47,012
Labuhan Batu	34	13	12	-43,457
Tanah Laut	24	5	7	-4,509
Deli Serdang	21	7	9	-50,281
Simalungun	20	11	15	-26,463
Kampar	19	10	13	-16,303
Kuantan Singingi	19	13	19	-11,003
Pasaman	17	10	12	-13,077
Langkat	17	11	16	-29,751
Σ estimated poverty reduction for all districts (no. poor people)				-1,319,369

Notes: Districts are ten largest oil palm expansions, as measured by the 2001–2009 change in district area allocated to oil palm and defined by 2001 district boundaries. Counterfactual poverty rates are estimated by predicting each district poverty rate with oil palm expansion set to zero using the most conservative least squares estimator (Column 1, Table 1). The estimated poverty reduction is calculated from the difference between the estimated poverty rate and its counterfactual. The sum in the final row is for all districts for which data are available.

In this article I focused on the macro-level, reduced-form impacts of oil palm expansion on local poverty. My focus on effects *within* the same district tends to miss spillovers across regions or nationally. My findings do not imply oil palm is the best way to reduce *national* poverty. Future research could model how Indonesia's unique plantation sector—or agricultural manufacturing more generally—relates to economic development through changing local economic geography, labor market dynamics, and agglomeration. For example, Fafchamps, Koelle, and Shilpi (2016) show how areas around gold mines in Ghana show early signs of urbanization; this could be tested in the context of agricultural manufacturing plants. Recent work on local multipliers (e.g., Moretti, 2010; Hornbeck and Keskin, 2015) also provides a useful framework to study local labor markets and, to my knowledge, has not yet been extended to a developing country context (i.e. with imperfect substitutability between imports and local consumables, immobile factors of production, and abundant unskilled labor). Indonesia has continued to rapidly urbanize since its 1998 decentralization without much further industrialization, a phenomenon common to many resource dependent countries (Vollrath, Gollin, and Jedwab, 2015). Most palm oil companies are based in capital cities and general equilibrium effects are not well understood, particularly consumption linkages to cities' non-tradable sectors where windfall profits are mostly spent. The long-term consequences of pro-poor agricultural sector growth also warrant further study. There is no mutual inconsistency between primary sector growth having positive short-run impacts whilst undermining longer-term development trajectories, particularly through negative impacts on human capital, institutions, and broader political economy issues.

I conclude with three caveats for future developments in Indonesia and across the rest of the tropics where the oil crop revolution continues to unfold. First, productivity gaps remain widespread within Indonesia, between Indonesia and Malaysia, and between Asia and other regions. The gap for Indonesia's independent smallholders is particularly large, and improving productivity is often as simple as upgrading inputs, particularly high quality seeds, and adopting improved agricultural practices (Alwarritzi et al, 2015; Soliman et al, 2016). Knowledge of good agricultural practices is not widespread for smallholders and the transfer of knowledge between nucleus and plasma schemes has been problematic at best. Many smallholders remain vulnerable to poverty and one can only imagine what the poverty impacts of the boom would have been without the yield gap (Cahyadi and Waibel, 2016). Existing production targets can be met by closing the gap (i.e., without additional extensive expansion into forested areas). Recent *Village Law 2014* reforms further decentralizing power and funding to villages could provide an opportunity to address these challenges.[37]

[37] Lewis (2015) and Antlov et al (2016) discuss the *Village Law 2014* in detail.

Second, evidence of poverty reduction does not necessarily mean oil palm expansion is always socially desirable. Any future extensive expansion must be weighed against potential environmental costs, particularly emissions and biodiversity loss. There is a strong economic and environmental case for future extensive expansion to focus on existing agricultural or degraded land already identified as suitable for oil palm to evade or at least minimize the environmental costs (Gingold et al., 2012; Austin et al., 2015; Pirker et al., 2016). There are likely to be large welfare gains from farmers continuing to switch to more productive crops and addressing market failures inhibiting crop switching (e.g., incomplete credit markets, insufficient public infrastructure, or restrictive land use practices) is a promising area for reform.

Finally, Indonesia's uniquely large share of smallholder farmers engaged in plantation-based agriculture has been central to this story. Generalizing my findings to other prospective plantation developments with different levels of smallholder engagement would be injudicious.

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Supplementary Appendix Tables: Tropical Oil Crops and Rural Poverty

NOT FOR PUBLICATION

Table 1: Panel Summary Statistics

Variable		2002	2010	All years	Mean difference
Palm oil land / district area (%)	Mean	0.58	2.65	1.3	2.07
	SD	1.61	6.35	4.01	4.74
	N	341	341	3386	
District poverty rate (%)	Mean	19.94	13.82	16.74	-6.12
	SD	11.57	7.3	9.5	-4.27
	N	335	341	3386	

Summary statistics are for the balanced panel of constant geographic units, where district boundaries are reset to those at the start of the panel period (2001) for consistency. Palm oil land as a share of district area is lagged by one year, as it is in my estimates. Data are official Indonesian Government data, obtained through the World Bank's Indonesian Database for Policy and Economic Research.

Table 2: Main Results using Production Instead of Areal Expansion

Dependent variable	Δ log district poverty rate					Level
Estimator	OLS	IV	IV	IV	IV	FE
Column	1	2	3	4	5	6
Δ per capita palm oil production (tons)	-0.210***	-0.751**	-0.823***	-0.980***	-0.741**	-0.212***
	(0.051)	(0.292)	(0.303)	(0.271)	(0.297)	(0.054)
Potential rice and casava yields	N/A	N	Y	N	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N	N
Index-based instrument	N/A	N	N	N	Y	N
Kleibergen-Paap Walk rk F stat	N/A	9.571	9.715	14.977	7.264	N/A
Observations	335	308	303	303	309	3386

Notes: This table shows that the effects observed for additional palm oil land as a share of total district area carry over to per capita palm oil production in tons. Stars denote statistical significance at the 10, 5, and 1 percent levels. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Columns 1–5 includes log poverty and log per capita output in the initial period as control variables, the least squares estimate includes island dummies, and the final column is a many-way panel fixed effects estimate, no longer using the long difference but the whole panel in level terms and including island-by-year fixed effects. Island groupings are defined as Java, Sumatra, Kalimantan, and Sulawesi, with remaining districts grouped together. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level in Column 6.

TABLE 3: MAIN RESULTS DROPPING DISTRICTS ON JAVA

Dependent variable	Δ log district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ oil palm land / district area	-0.012***	-0.037***	-0.052***	-0.054***	-0.033***
	(0.003)	(0.012)	(0.017)	(0.013)	(0.011)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	15.559	9.208	20.363	13.133
Observations	230	205	200	200	206

Notes: This table shows that results are similar if I remove the districts of Indonesia's populous island of Java, where very little palm oil is produced. Stars denote statistical significance at the 10, 5, and 1 percent levels. All IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

Table 4: Main Results Dropping Cities, i.e., Kota

Dependent variable	Δ log district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ oil palm land / district area	-0.005*	-0.022***	-0.024***	-0.030***	-0.021***
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	25.845	27.255	30.299	24.583
Observations	261	253	248	248	253

*Notes:*This table shows that the main results are similar if I remove all cities (kota) from the sample, leaving only rural districts. Stars denote statistical significance at the 10, 5, and 1 percent levels. All IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

Table 5: Main Results using Only Palm Oil Producing Districts

Dependent variable	Δ log district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ oil palm land / district area	-0.003	-0.013	-0.021***	-0.029**	-0.012
	(0.003)	(0.009)	(0.007)	(0.013)	(0.009)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	10.788	11.717	7.625	11.519
Observations	93	88	85	85	88

Notes: This table presents my main estimates restricting the sample to only districts that produce palm oil, i.e., using only treated units with varying treatment intensity. Stars denote statistical significance at the 10, 5, and 1 percent levels. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

Table 6: Main Results using 2SLS instead of LIML

Dependent variable	Δ log district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ oil palm land / district area	-0.012***	-0.037***	-0.043***	-0.049***	-0.037**
	(0.003)	(0.014)	(0.016)	(0.013)	(0.015)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	13.410	13.123	20.252	10.825
Observations	335	308	303	303	309

Notes: This table shows that the main results are similar if I use the conventional two-stage least squares estimator instead of Fuller's limited information maximum likelihood estimator. Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

TABLE 7: MAIN RESULTS USING A LINEAR-LINEAR FUNCTIONAL FORM

Dependent variable	Δ district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ palm oil land / district area (%)	-0.108***	-0.643**	-0.551***	-0.535***	-0.608**
	(0.037)	(0.261)	(0.212)	(0.174)	(0.258)
Potntial rice and casava yields	N	N	Y	N	N
Potential coffee, cocoa, tea yields	N	N	N	Y	N
Suitability index IV	N	N	N	N	Y
Kleibergen-Paap Wald rk F stat	N/A	12.70	12.76	20.97	10.76
Observations	335	308	303	303	309

*Notes:*This table shows that the main results are similar if a linear-linear functional form is used (i.e., not log poverty). Stars denote statistical significance at the 10, 5, and 1 percent levels. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

TABLE 8: MAIN RESULTS USING A LINEAR-LOG FUNCTIONAL FORM

Dependent variable	Δ district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ log oil palm land / district area	-0.004	-0.441*	-0.306*	-0.315**	-0.398*
	(0.017)	(0.240)	(0.162)	(0.151)	(0.218)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	8.872	15.970	14.530	5.991
Observations	335	308	303	303	309

*Notes:*This table shows that similar results are obtained if I use a linear-log functional form, with the exception of the least squares estimate which is rendered statistically significant. Stars denote statistical significance at the 10, 5, and 1 percent levels. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

Table 9: Main Results using a Log-log Functional Form

Dependent variable	Δ log district poverty rate				
Estimator	OLS	IV	IV	IV	IV
Column	1	2	3	4	5
Δ log oil palm land / district area	-0.002	-0.031***	-0.028***	-0.033***	-0.028**
	(0.002)	(0.012)	(0.010)	(0.010)	(0.011)
Potential rice and casava yields	N/A	N	Y	N	N
Potential coffee, cocoa, tea yields	N/A	N	N	Y	N
Index-based instrument	N/A	N	N	N	Y
Kleibergen-Paap Walk rk F stat	N/A	8.872	15.970	14.530	5.991
Observations	335	308	303	303	309

Notes: This table shows that broadly similar results are obtained if I use a log-log functional form, with the exception of the least squares estimate which is rendered statistically insignificant. Stars denote statistical significance at the 10, 5, and 1 percent levels. IV estimates use Fuller's limited information maximum likelihood estimator with a Fuller parameter of one. Sample is the long-difference cross-section of all available districts from 2002–2010, and oil palm land is lagged one period (2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in samples size are due to data availability. Each regression includes log poverty and log per capita output in the initial period as control variables and the least squares estimate includes island dummies. Heteroskedasticity-robust standard errors are in parentheses.

Table 10: Short-run and Dynamic Impacts on Poverty Depth

Dependent variable: log poverty gap index								
Estimator		First-difference			Within FE			FE IV
Columns	1	2	3	4	5	6	7	8
Oil palm land / district area (%)	-0.010***	-0.009***	-0.012**	-0.014***	-0.009**	-0.014***	-0.006***	-0.021***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)	(0.007)
First lag		0.000	-0.005		0.001			
		(0.004)	(0.007)		(0.004)			
Second lag		-0.006	-0.010		-0.003			
		(0.004)	(0.007)		(0.005)			
Third lag		-0.011**	-0.014**		-0.010**			
		(0.004)	(0.006)		(0.005)			
Σ coefficients		-0.026***	-0.041***		-0.023***			
First stage coefficient								0.478***
Kleibergen-Paap Wald *rk* F stat								12.17
District fixed effects	N	N	Y	Y	Y	Y	Y	Y
Island-specific time trends	N	N	N	N	N	Y	N	N
Province-specific time trends	N	N	N	N	N	N	Y	N
Observations	2705	2036	2036	3051	2382	3051	3386	3051

Notes: This table presents panel estimates using the depth of poverty as a dependent variable. Results are similar. Stars denote statistical significance at the 10, 5, and 1 percent levels. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level. Sample is an annual 341-district panel from 2002–2010. Oil palm land is lagged one period. 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Changes in sample size are due to data availability. Island-year fixed effects are included throughout, with island groupings defined Java, Sumatra, Kalimantan, Sulawesi, and the rest. The within estimator refers to the mean-differenced (within-district) fixed effects estimator. Significance reported for sum of the coefficients relates to the test that the sum of the coefficients on oil palm is equal to zero.

Table 11: Determinants of Changing Oil Palm Land Shares

Dependent variable	Palm oil land / district area (%)		
Estimator	Pooled OLS	Within FE	Within FE
Column	1	2	3
Lag electricity capacity	-0.0004**	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)
Lag electricity capacity nearby	-0.0003*	-0.0003*	0001
	(0.0001)	(0.0002)	(0.0001)
Lag access to electricity	-0.010	0.046***	0.016
	(0.010)	(0.015)	(0.019)
Lag human development index	-0.180***	0.243***	0.220
	(0.058)	(0.086)	(0.243)
Lag child immunisation rate	-0.168***	0.003	-0.0001
	(0.036)	(0.010)	(0.010)
Lag adult literacy rate	0.245***	-0.088**	-0.036
	(0.026)	(0.036)	(0.036)
Lag skilled birth	0.046***	0.001	0.005
	(0.015)	(0.013)	(0.013)
District FEs	N	Y	Y
Island-year FEs	N	N	Y
Observations	1019	1019	1019

Notes: This table shows that island-year fixed effects render other potential time-varying correlates of short-term changes in palm oil land statistically insignificant. Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is an annual 341 district panel, 2002–2010. Palm oil land is lagged one period (i.e., 2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level. Covariates are taken from the World Bank (2015) Indonesia Database for Economic and Policy Research and Sparrow et al. (2015).

Table 12: Panel Robustness Checks

Dependent variable	Palm land	Log district poverty rate							
Column	1	2	3	4	5	6	7	8	9
Palm oil land / district area		0.001	-0.006***	-0.008***	-0.010***	-0.009***	-0.007***	-0.011***	-0.004*
		(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Lag log poverty rate	0.235		0.412***						
	(0.362)		(0.057)						
2nd lag log poverty rate	0.451								
	(0.617)								
In-time placebo	N	Y	N	N	N	N	N	N	N
Lag poverty controls	N	N	Y	N	N	N	N	N	N
Electricity controls	N	N	N	Y	N	N	N	N	N
Political, fiscal, oil, gas controls	N	N	N	N	Y	N	N	N	N
Forest & political controls	N	N	N	N	N	Y	N	N	N
Income and revenue controls	N	N	N	N	N	N	Y	N	N
Correlates of poverty controls	N	N	N	N	N	N	N	Y	N
District-by-district time trends	N	N	N	N	N	N	N	N	Y
District and island-year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2359	2704	2699	2321	1445	1445	3386	1333	3386

Notes: This table presents a series of robustness exercises for short-run panel estimates. Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is an annual 341 district panel, 2002–2010. Palm oil land is lagged one period (i.e., 2001–2009). 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. The within estimator with district and island–year FEs is used for all estimates. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level. Columns 1 and 2 probe the parallel trends assumption, looking for divergent trends. Column 1 regresses poverty lags on palm land and the in-time placebo test in Column 2 uses future palm oil land values. Electricity controls refer to district and neighboring district power capacity, taken from Sparrow et al (2015). Political, fiscal, oil, and gas controls are taken from Burgess et al (2012) and forest controls from Wheeler et al (2013). Other covariates are taken from the World Bank (2015) Indonesia Database for Economic and Policy Research.

Table 13: Heterogeneity–Regional Interaction Terms

Dependent variable	*Log poverty rate*		*Log poverty gap*	
Estimator	FE	LD	FE	LD
Column	1	2	3	4
Java*oil palm land share	0.013	-0.040	-0.063	-0.122*
	(0.015)	(0.041)	(0.040)	(0.065)
Sumatra*oil palm land share	-0.006***	-0.010***	-0.012***	-0.011**
	(0.002)	(0.003)	(0.003)	(0.004)
Kalimantan*oil palm land share	-0.014***	-0.029***	-0.027***	-0.039***
	(0.004)	(0.008)	(0.007)	(0.012)
Sulawesi*oil palm land share	-0.045***	-0.052***	-0.044***	-0.031***
	(0.007)	(0.017)	(0.008)	(0.008)
Other*oil palm land share	-0.036	0.060	-0.162	0.098
	(0.128)	(0.062)	(0.174)	(0.118)
District and year fixed effects	Y	N	Y	N
Initial conditions controls	N	Y	N	Y
Observations	3386	335	3051	335

Notes: This table presents the tabulated results of the estimates presented in Figure 9. Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample sample is an annual district panel from 2002–2010. Oil palm land is lagged one period. 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Island groupings are defined as districts from Java, Sumatra, Kalimantan, Sulawesi, and with remaining islands grouped together. Estimators are within fixed effects estimator (FE) with district and year fixed effects, and the long difference estimator (LD) with initial log poverty and log per capita income controls. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level for FE estimates. Island*palm interaction terms interact the island dummy for each island with the main oil palm land share variable. Main effects (not interacted) are dropped for a more straightforward interpretation.

Table 14: Heterogeneity–Regional Sub-Samples

Dependent variable: log district poverty rate			
Sample	Island	Island	All
Estimator	FE	LD	FE
Column	1	2	3
Panel A: Java			
Palm oil land / district area	0.015	-0.035	-0.007***
	(0.016)	(0.047)	(0.002)
Island–palm interaction			0.021
			(0.015)
N observations	1091	105	3386
Panel B: Sumatra			
Palm oil land / district area	-0.007***	-0.011***	-0.016***
	(0.002)	(0.004)	(0.005)
Island–palm interaction			0.010**
			(0.005)
N observations	960	96	3386
Panel C: Kalimantan			
Palm oil land / district area	-0.007*	-0.009**	-0.006***
	(0.003)	(0.004)	(0.001)
Island–palm interaction			-0.008**
			(0.004)
N observations	379	37	3386
Panel D: Sulawesi			
Palm oil land / district area	-0.05***	-0.05***	-0.006***
	(0.008)	(0.016)	(0.002)
Island–palm interaction			-0.039***
			(0.007)
N observations	450	45	3386
Panel E: Other islands			
Palm oil land / district area	-0.039	0.345**	-0.007***
	(0.130)	(0.171)	(0.002)
Island–palm interaction			-0.026
			(0.128)
N observations	506	51	3386

Notes: This table presents results by regional (island group) sub-samples. Stars denote statistical significance at the 10, 5, and 1 percent levels. Full sample (Column 3) is an annual 341 district panel, 2002–2010. Palm oil land is lagged one period (i.e., 2001–2009). 2001 district boundaries are used, with new districts collapsed into year 2001 parent districts. Estimators are the within estimator (FE) with district and year fixed effects, and the long-difference (LD) estimator with initial log poverty and log per capita income controls. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level.

Table 15: Heterogeneity—Land Ownership

Sector	State		Private		Smallholder	
Panel width	Annual	4-year	Annual	4-year	Annual	4-year
Column	1	2	3	4	5	6
Panel A: log poverty rate						
Oil palm land/district area (%)	-0.011**	-0.011**	-0.012***	-0.011***	-0.004	-0.011**
	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.004)
Panel B: log poverty gap index						
Oil palm land/district area (%)	-0.012**	-0.015**	-0.014***	-0.011**	-0.004	-0.014**
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.006)
Observations	3009	1004	3009	1004	3009	1004

Notes: This table presents tabulated estimates of the results presented in Figure 8. Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is an annual 341 district panel (2002–2010) Oil palm land is lagged one period. 2001 district boundaries are used, with new districts collapsed into year-2001 parent districts. Heteroskedasticity-robust standard errors are in parentheses, clustered at the district level. A within estimator with district and island–year fixed effects is used throughout.

Table 16: Heterogeneity–Land Quality

Dependent variable: log district poverty rate									
Palm oil land quality		Damaged			Immature			Mature	
Panel width	Annual	2-yearly	4-yearly	Annual	2-yearly	4-yearly	Annual	2-yearly	4-yearly
Column	1	2	3	4	5	6	7	8	9
Palm oil land/ district area (%)	-0.142**	-0.141**	-0.074	-0.025***	-0.025***	-0.035***	-0.014***	-0.014***	-0.011**
	(0.066)	(0.069)	(0.083)	(0.009)	(0.009)	(0.013)	(0.004)	(0.005)	(0.004)
Observations	3009	1674	1004	3009	1674	1004	3009	1674	1004

Notes: This table presents results for palm oil land of different quality, showing how increasing the share of district land used for damaged plantations has the largest short-term impacts on district poverty, tapering off over time. Immature and mature plantations have broadly consistent impacts over 4 years: the former slightly increases (perhaps from "learning by doing and the increased productivity from trees coming of age) and the latter slightly decreases (as poverty gains would have already been made). Stars denote statistical significance at the 10, 5, and 1 percent levels. Sample is an annual 341 district panel, 2002-2010. Palm oil land is lagged one period (i.e., 2001-2009). 2001 district boundaries are used, with new districts collapsed into year 2001 parent districts. Heteroskedasticitiy-robust standard errors are in parentheses, clustered at the district level. The within panel estimator with district and island-by-year fixed effects is used throughout.