AGRICULTURAL FDI, PRODUCTION, AND DEVELOPMENT: EVIDENCE FROM THE PALM OIL SECTOR IN LIBERIA*

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Abstract

This paper examines the effects of agricultural foreign direct investment, in the form of land acquisitions, on agricultural production and local development. We study palm oil concessions in Liberia using a local difference-in-differences design, exploiting satellite-based measures of palm oil cultivation. We document that acquisitions led to a 4 percentage point decline in tree cover and a corresponding increase in land dedicated to palm oil cultivations. Beyond land, we also document an increase in the availability of capital inputs: palm oil fertilizers, harvesting tools, and extraction machinery imports rise following the acquisitions, with no comparable trend in other products. Locally, individuals are less likely to own any agricultural land, agricultural self-employment falls by roughly 10 percentage points, and agricultural wage employment rises by 5–6 percentage points. These findings are consistent with a reallocation of labor from self-employment toward wage employment, a pattern predicted by models of structural transformation (Lewis, 1954), though we find no effect on household wealth over this horizon.

Keywords: land acquisitions, agricultural production, structural transformation
JEL Codes: F18, F63, O13, Q15

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1. INTRODUCTION

By 2022, more than 60 million hectares had been acquired globally through public land deals (equivalent to 4.3% of the world's arable land, a surface larger than Brazil's arable area) and the number of contracts increased by 128% over the previous 13 years.[1] Whether, and how, these acquisitions transform local economies is an open question.[2] Agriculture in much of the developing world remains dominated by small-scale, labor-intensive subsistence farming (Lowder et al., 2016), with low productivity (Restuccia et al., 2008; Gollin et al., 2014) attributed to limited adoption of modern inputs (Duflo et al., 2011) and fragmented farm structures (Adamopoulos & Restuccia, 2014). This paper combines satellite measures of production with staggered local variation in exposure to land concessions to examine whether agricultural FDI promotes production and local development.

Specifically, we examine the effects of palm oil land acquisitions in Liberia. Following the end of its second civil war (1999–2003), the Liberian government sought to leverage the country's natural resource endowments to stimulate recovery, attracting FDI that grew from approximately US$100–150 million annually in 2006–2007 to nearly US$1 billion by 2012–2013 (WorldBank, 2015). A substantial share of this investment went to agriculture, where two firms acquired seven palm oil concessions between 2008 and 2011. This setting is well suited for identification. The boundaries of palm oil concessions are precisely mapped, providing the spatial variation needed for a local difference-in-differences design. The concessions were granted recently enough that geo-referenced household surveys span both the pre- and post-acquisition periods. Most distinctively, measuring agricultural production at a granular level is typically difficult, but palm oil cultivation follows a sequence that is observable from space: forests are cleared and palm oil is planted, and this change is detectable in annual satellite imagery. This allows us to measure the expansion of cultivated area directly, without relying on self-reported or aggregate production statistics.

We proceed in three steps. First, we combine geo-localized data on palm oil concessions and land cover to estimate the effects on agricultural production. We identify concessions using maps from Global Forest Watch, merged with data from the Liberian National Bureau of Concessions, and combine these with the MODIS Vegetation Continuous Fields, which provides percentage coverage data across seventeen mutually exclusive cover classes. We use a pixel-based, staggered, local difference-in-differences design, comparing land cover just outside and just inside (10km) palm oil concessions. The identification assumption is that, absent the acquisitions, land cover would have evolved similarly on both sides of concession boundaries.[3] We estimate a 4 percentage point decline in tree cover within concessions following the acquisitions. To establish that this deforestation reflects palm oil planting rather than mere land clearing, we use a random forest algorithm on satellite imagery to identify the land cover category associated with palm oil plantations, which we find to be "Woody Savannas".[4] We find a corresponding increase in this category, indicating an

[1] Authors' calculations based on FAOSTAT for agricultural FDI inflows; FAO (2009) and GTZ (2009) for investment structures; Land Matrix for land acquisitions; and FAO (2021) for total arable land.

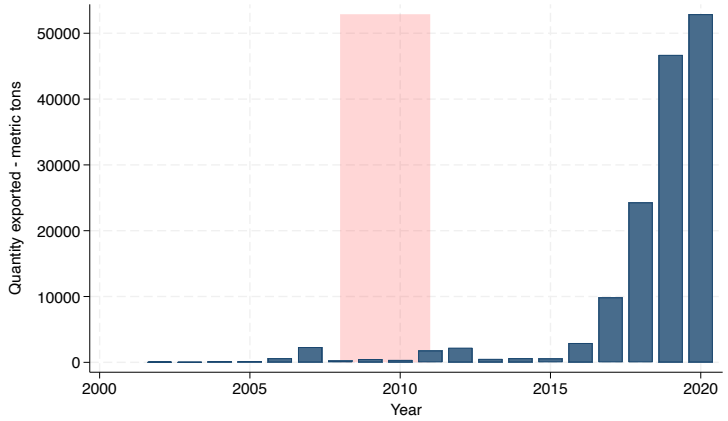
[2] For discussions of potential benefits, see for instance FAO Insights, the Report on FDI in Agribusiness in Armenia by World Bank (2017), the UNCTAD (2009)'s World Investment Report, and the World Bank (2011)'s Agriculture and Rural Development Report. For critiques, see FAO (2012), the Analysis of LandMatrix Data by MISEROR (2021), UNCTAD (2022), and World Bank (2009)'s Agriculture and Rural Development Report.

[3] These areas were specifically designated for palm oil, and their boundaries do not align with administrative ones (as shown in Figure 2 in Appendix A)

[4] This classification is in line with theoretical considerations on palm oil canopy cover and recent evidence;

expansion of palm oil cultivation. Given palm oil's production cycle and estimates of global average yield, we estimate the implied change in production at roughly 43,000 metric tons annually, a figure consistent with the change in Liberian palm oil exports, which increased by 64% between 2011 and 2016, and eleven-fold by 2018 (Figure 1).

Figure 1: Liberian Palm Oil Exports



Notes: Quantity of palm oil exports in metric tons from Liberia during the period from 2000 to 2018. Export data from BACI HS2 Revision 1992, product categories HS: 151110 (Vegetable oils: palm oil and its fractions, crude, not chemically modified, crude) and 151190 (Vegetable oils: palm oil and its fractions, other than crude, whether or not refined, but not chemically modified, possibly refined). The shaded area between 2008 and 2011 indicates the period of palm oil land acquisitions in the sample.

Second, we use product-level import data to examine whether the acquisitions introduced capital inputs beyond land. Palm oil-specialized inputs are not domestically produced in Liberia, so firms must import them, and detailed product-level records allow precise identification of palm oil inputs relative to other products. Following the acquisitions, imports of palm oil-specific inputs (nitrogenous and potassic fertilizers, harvesting tools, and extraction machinery) increase sharply. The magnitude of the fertilizer increase is consistent with the expansion of cultivated area estimated in the first part of the paper. No comparable increase appears for other hand tools (such as drills and saws), similar agricultural machines (wood presses), or unrelated products (such as poultry equipment, telecommunications, and cosmetics).

Third, we use geo-localized household surveys to investigate the effects on local development. We compare individuals from the Demographic and Health Surveys (DHS) in villages just inside and just outside palm oil concessions, before and after the acquisitions. Placebo exercises on ten outcomes unlikely to be affected by the acquisitions, including altitude, literacy, education, and ethnicity, reveal no differential pre-trends between treated and control villages. We document a 10 percentage point decrease in the probability of owning any agricultural land. Self-employment in agriculture falls by roughly 10 percentage points relative to a baseline of 50–60% (outside concessions, before acquisitions), while agricultural wage employment rises by 5–6 percentage points, with heterogeneous effects by gender: husbands reallocate both toward agricultural wage employment and services, while wives reallocate

see Section 4 for additional information.

primarily toward agricultural wage employment, consistent with gender-segmented labor markets within plantation agriculture. These employment results are robust to varying the distance of the control group from concession boundaries, alternative specifications, and different fixed effect structures. Conclusions are also unchanged when excluding the Ebola period, by retaining only the sample before 2014, and restricting to individuals residing in the village for more than 11 years, to rule out endogenous migration. We do not, however, find any change in the wealth of respondents.

These findings suggest that agricultural FDI, in the form of land acquisitions, may promote agricultural production and initiate a Lewisian account of transformation *within* agriculture. Following the acquisitions, more land was dedicated to palm oil production, the export of palm oil increased, palm oil inputs were imported, and local labor market adjusted accordingly: workers moved out of self-employment into wage employment, and some reallocated to non-agricultural occupations. This pattern corresponds to the supply-side mechanism emphasized in models of structural change (Acemoglu & Guerrieri, 2008; Bustos et al., 2016): a shift in factor intensity within a sector that alters local employment equilibria. These findings may extend to other land acquisitions and, more generally, to agricultural FDI in developing countries. 94% of land contracts occur in developing nations (including regions such as Africa, South and Central America, South-Eastern Asia, and Eastern Europe). Notably, 15% of worldwide land deals concern palm oil specifically.[5] Although in the same country, we also find similar employment dynamics close to other agricultural concessions (mostly timber).

This paper contributes to three literatures. First, it provides direct evidence on how agricultural FDI affects local production and employment. The existing literature on land concessions has primarily examined historical settings, documenting negative long-run consequences (Dell, 2010; Bobonis & Morrow, 2014; Lowes & Montero, 2021), with notable exceptions (Dell & Olken, 2020; Méndez & Van Patten, 2022). The closest paper to ours is Méndez and Van Patten (2022), who study the United Fruit Company's concessions in Costa Rica and find positive effects on living standards. We complement their work by focusing on contemporary acquisitions and by tracing the production channel explicitly—from land conversion, capital imports to employment effects.[6]

Second, the paper connects to the literature on FDI and development. The evidence on whether FDI promotes growth in developing countries is mixed, with results depending on initial conditions such as human capital (Borensztein et al., 1998), financial development (Alfaro et al., 2004), and institutional quality (C. Li & Tanna, 2019).[7] Our contribution is to document that agricultural FDI, through land acquisitions, may stimulate production and initiate a process of structural transformation within the sector.

Third, we contribute to the literature on agricultural transformation and structural change. Since Kuznets (1965), economists have studied the drivers of labor reallocation away from agriculture, distinguishing demand-side explanations from supply-side ones such as innovations (Gollin et al., 2002; Bustos et al., 2016), migration costs (Bryan et al., 2014; Bryan & Morten, 2019), and changes in factor intensity (Caselli & Coleman II, 2001; Ace-

[5] Authors' calculations based on Land Matrix data.

[6] A related literature in development studies has documented environmental consequences of land acquisitions, including deforestation (Davis et al., 2015, 2020), fires (Nepstad et al., 1999; Carlson et al., 2012), and water scarcity (Rulli et al., 2013; Johansson et al., 2016), as well as mixed evidence on employment and welfare (Baumgartner et al., 2015; Anti, 2021; Herrmann, 2017).

[7] For broader reviews of this relationship, see Aitken and Harrison (1999); Prasad et al. (2007); Contessi and Weinberger (2009).

moglu & Guerrieri, 2008). Our evidence suggests that foreign capital, entering through land acquisitions, can act as such a supply-side push factor, at least within the confines of a single commodity and country. Whether these local effects aggregate into broader transformation, and whether any welfare gain is realized in the long-run, are questions our data cannot fully answer.

The remainder of the paper proceeds as follows. Section 2 provides background on the palm oil sector in Liberia. Section 3 describes the data. Section 4 presents results on deforestation and land cover. Section 5 examines the import of capital inputs and 6 local development. Section 7 discusses the results. Section 8 concludes.

2. BACKGROUND

Palm oil cultivation in Liberia has a longstanding history (Republic of Liberia & International Trade Center - WTO and UN, 2014). Following the conclusion of Liberia's second civil war (1999–2003), the government sought to leverage the country's natural resource endowments to stimulate economic recovery. FDI in Liberia grew substantially from the mid-2000s, increasing from approximately US$100–150 million annually in 2006–2007 to around US$450–500 million annually in 2010–2011, and reaching nearly US$1 billion annually by 2012–2013. This increase is largely attributable to substantial investments in agriculture and mining made by multinational corporations (WorldBank, 2015). FDIs in these sectors often involve these companies acquiring land concessions for the establishment of large scale plantations.

The push for the expansion of oil palm plantations has been described as "the Liberia Government is inundated with requests for [...] expansion of oil palm plantations for biofuel production [...]", and it has received strong support from the Liberian government, as well as from influential agencies such as US Agency for International Development, the World Bank, and the US Department of Agriculture (Liberian Ministry of Finance, 2008).

This process has corresponded with a redirection of palm oil production towards the international market (Republic of Liberia & International Trade Center - WTO and UN, 2014), positioning palm oil as a strategic sector in Liberia, with exports totalling $90.8 million in 2022. However, Liberia remains a minor player in the global market; in 2022, the leading palm oil exporters included Indonesia (US$ 28.7 billion), Malaysia (US$ 17.7 billion), Thailand (US$ 1.31 billion), the Netherlands (US$ 1.18 billion), and Papua New Guinea (US$ 1.03 billion).[8]

3. DATA

We combine geolocalized data on palm oil concessions, land cover, household surveys, and import data to construct three datasets. The first divides Liberia into a grid of 12 square mile cells, yielding 7,656 cells observed annually from 2001 to 2018. The second contains import data in Liberia on approximately 5,000 products (Harmonized system 6-digit classification) from 2002 to 2018. The third provides cross-sectional data on individuals in georeferenced villages, with observations in 2007, 2009, 2011, 2013, 2016, and 2019.

Palm Oil Concessions. To identify cells containing concessions, we use data from Global Forest Watch, which documents the location, boundaries, and ownership of palm

[8]See, for example, OEC - palm oil data. Last accessed: January 23, 2025.

oil concessions in Liberia.[9] These data do not include concession grant dates. We obtain dates from the Liberian National Bureau of Concessions.[10] Matching across sources yields 19 of 22 concessions belonging to three companies. These concessions are recorded as palm oil operations in official records and have documented grant dates: 2008, 2009, and 2011. However, the contract signed in 2009 was ratified to reinstate a set of concessions that had been granted in 1954, amended in 1985, and abandoned during the Liberian civil war in 2001.[11] We exclude the concessions covered by this contract in the main specifications and provide robustness checks with these concessions included. This yields a sample of seven concessions belonging to two companies. These concessions are quite large, with an approximate average area of 230 square miles. We have a minimum of nine pre-treatment years (treating the grant year as pre-treatment) and seven post-treatment years. The concessions are concentrated in three geographic clusters distributed along Liberia's coastline (Figure 2). Figure A2 in Appendix A shows the timing of all recorded land acquisitions in Liberia from OpenLandContracts.org.

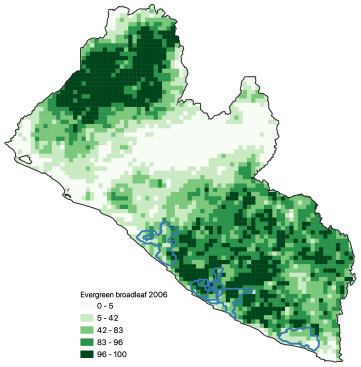
Land Cover Data. We measure land cover using MODIS Vegetation Continuous Fields data (Dimiceli et al., 2015), which provides annual estimates of land cover percentages for the entire globe.[12] The data classify land into 17 mutually exclusive categories defined by the International Geosphere-Biosphere Programme (IGBP), such as "Water Bodies" and "Evergreen Needleleaf Forests" (evergreen conifer trees with canopy >2m). Figure 3 shows the 2006 distribution of "Evergreen Broadleaf Forest", the predominant land cover type in Liberia. Given its dominance, we refer to this category as *tree cover* throughout the paper.

Figure 2: Map palm oil concessions



Notes: The figure presents the map of palm oil concession in the sample.

Figure 3: Percentage Broadleaf 2006



Notes: The figure presents the percentage of each cell covered by "Evergreen Broadleaf Forests" in 2006. The darker the cell, the higher the percentage.

Imports. The BACI database (from CEPII) provides annual data on bilateral trade flows broken down by product (Harmonized System - 6-digit level). It includes imports reported on a CIF (Cost, Insurance and Freight) basis, with quantities expressed in metric

[9] Global Forest Watch. 2019. World Resources Institute. Accessed on 07/23/2020.
[10] Available at: LEITI.org.
[11] The contract can be found here: Open Land Contracts.
[12] We use the MCD12C1 product, layer "Land Cover Type 1 Percent".

tons (possibly estimated). The methodology is described in detail by Gaulier & Zignago, 2010. We extract data for Liberia, and aggregate, for each product, the imported quantity by year. If no quantity is estimated for a given year, we include a null entry for that product-year combination.

Household surveys. We use data from the Demographic and Health Surveys (DHS), which are nationally representative household surveys collecting information on health, demographics, and occupation. We supplement these with the Malaria Indicator Survey (MIS), also administered by the DHS program, which focuses on malaria prevalence and contains fewer variables. The analysis uses individual-level data for men and women aged 15-64. Both surveys provide geographic coordinates for interviewed households, yielding a repeated cross-section of individuals across Liberian villages in 2007, 2009, 2011, 2013, 2016, and 2019. Only the full DHS waves (2007, 2013, and 2019) contain occupation data. Therefore, only the 2007 DHS wave predates all concession grants. Figure A3 in Appendix A shows the geographic distribution of surveyed villages. The sample includes villages both inside and outside concession areas, with observations spanning the periods before and after the initial land acquisitions.

CO2 & N2O. To measure CO2 and N2O emissions we use the Emissions Database for Global Atmospheric Research (EDGAR - European Commission, Joint Research Centre (JRC)). EDGARv8.0 provides worldwide estimates for annual emissions of the three main greenhouse gases (CO2, CH4, N2O) per 0.1 degree $\times$ 0.1 degree.

PM25. To measure PM25 emissions we use the Atmospheric Composition Analysis Group data (ACAG V6GL01 - Washington University in St. Louis). They provide annual ground-level fine particulate matter (PM2.5) for 2000-2019 by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS with the GEOS-Chem chemical transport model, and subsequently calibrating to global ground-based observations using a residual Convolutional Neural Network (CNN).

Population. For population data we use LandScan. This product was made utilizing the LandScan (2006-2018)TM High-Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05- 00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set. This dataset shows the number of inhabitants in 30-arc-second cells (about 1km $\times$ 1km near the Equator). In particular, LandScan aims to "develop a population distribution surface in totality, not just the locations of where people sleep". For this reason, it combines diurnal movements and travel habits in a single variable called *ambient-population*. To construct the data, it uses a "smart interpolation" technique combining census data, primary geospatial input, ancillary datasets, and high-resolution imagery analysis. We take the sum of this variable in each cell-year.

Nighlights. For nightlihts data we use the harmonized DMSP-OLS NTL and VIIRS data by X. Li et al. (2020). The dataset contains: (1) temporally calibrated DMSP-OLS NTL time series data from 1992-2013; and (2) converted NTL time series from the VIIRS data (2014-2021) at a 30 arc-seconds ($\approx$1km) spatial resolution.

Rainfall. Rainfall data come from the Global Precipitation Climatology Project.

See Adler et al. (2016). They provide estimated monthly rainfall data on a 2.5-degree global grid from 1979 to the present. We take the average annual rainfall in each cell-year.

Other concessions. We use AidData (Open Data for International Development) for the other concessions for the placebo exercises. In particular,the geocoded, released for research, shapefile of concessions in Liberia, level 1, version 1.0. This dataset release represents all concession licenses sourced, as of June 15, 2016, from the Liberian Extractive Industries Transparency Initiative (LEITI), the Mining Cadastre Administration System (MCAS), and the Liberia National Concessions Portal (LNCP), along with additional information collected using AidData's "TUFF" open-source data collection methodology. Starting from all concessions, we exclude any those that extracts palm oil, lists palm oil among its products, or indicates "other crops", and hydrocarbon ones, which are offshore.

Descriptive statistics. Table 1 presents summary statistics for the sample period. Panel (a) reports statistics for all grid cells, while Panel (b) restricts to cells located within palm oil concessions. Several patterns are noteworthy. First, tree cover is higher in concession areas than in the full sample, consistent with concessions being located in rural, forested regions. The share of urban cover, as well as the estimated population, are correspondingly lower within palm oil concessions. Second, approximately 3% of grid cells fall within concessions, which accounts for the difference in observations between Panels (a) and (b). Third, turning to household survey data, average age and unemployment rates for both spouses are similar across concession and non-concession areas.

4. DEFORESTATION AND LAND COVER

In this section we study changes in land cover within palm oil concessions following the acquisitions to explore the effects of land acquisitions on agricultural production. The palm oil sector provides a unique setting to study this since cultivations are measurable from satellite data.

4.1. Deforestation

Methodology The first fundamental production stage in the palm oil sector is deforestation. We measure deforestation using changes in "Evergreen Broadleaf Forests", the most common type of tree cover in Liberia. We employ a staggered local difference-in-differences design to examine changes in tree cover within concessions following acquisition. The sample includes all cells within 10 km of a concession boundary, where distance is measured as the shortest path from each cell's centroid to the nearest boundary. Thus, we compare areas just inside and just outside concessions before and after acquisition. The identifying assumption is that, absent the acquisitions, land cover would have evolved similarly just inside versus just outside palm oil concession boundaries. For each cell k, we identify its closest concession c_k and assign that concession's acquisition year as the relevant treatment time. The reduced form model is:

$$P_{kt} = \alpha + \sum_{j \neq -1} \beta_j \times \mathbb{1}[t - \hat{t}_k = j] \times C_k + \mu_k + \mu_{c_k} \times \mu_t + u_{kt} \tag{1}$$

Table 1: Descriptive Statistics

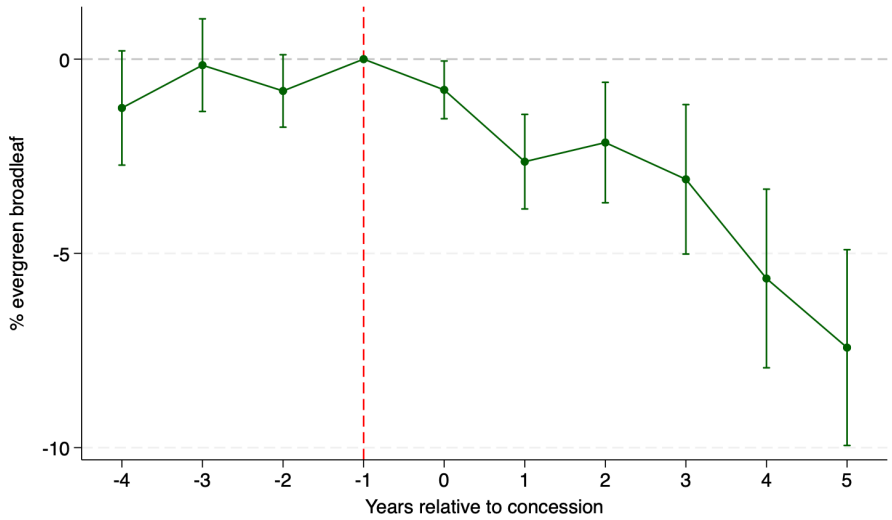
	Obs.	Mean	S.D.	Min	Max
Panel (a): All Sample					
Cell data					
% Evergreen broadleaf	137,808	24.56	35.60	0	100
% Woody Savannas	137,808	35.17	39.18	0	100
% Urban	137,808	0.166	2.101	0	83
Concession	137,808	0.0273	0.163	0	1
Rain	137,808	141.5	92.03	0	461.5
Population	137,808	1,078	5,345	0	329,609
CO2	137,808	1,006	6,484	0	380,747
DHS data					
Age	36,777	29.06	9.600	15	49
Max educ. years	36,777	0.918	0.872	0	9
Unemployed wife	21,329	0.306	0.461	0	1
Unemployed husband	15,789	0.0231	0.150	0	1
Panel (b): Concessions					
Cell data					
% Evergreen broadleaf	3,762	53.87	33.87	0	100
% Woody Savannas	3,762	35.79	30.47	0	100
% Urban	3,762	0.0574	0.639	0	9
Rain	3,762	247.4	41.63	142.9	407.6
Population	3,762	751.1	1,526	0	51,061
CO2	3,762	769.1	1,733	0	13,874
DHS data					
Age	5,180	29.55	9.704	15	49
Max educ. years	5,180	0.717	0.782	0	9
Unemployed wife	3,128	0.339	0.473	0	1
Unemployed husband	2,314	0.0186	0.135	0	1

Notes: The table presents summary statistics for the main variables used in the analysis. Panel (a) reports statistics for all grid cells and DHS respondents in the full sample. Panel (b) restricts to cells and respondents located within palm oil concessions. Cell data are observed annually from 2001 to 2018. DHS data are from the 2007, 2013, and 2019 waves. See Section 3 for variable definitions and data sources.

where P_{kt} indicates the percentage of land cover (in this case, tree cover), T_t are year dummies, C_k equals one for cells inside concessions, and $\hat{t}_k(c_k)$ denotes the acquisition year of cell k closest concession c_k. The acquisition year serves as the reference category (-1), as concessions were granted late in the calendar year. The benchmark specification includes cell (μ_k) and closest concession by year ($\mu_{c_k} \times \mu_t$) fixed effects, with standard errors clustered at the cell level. This compares cells just inside and outside the same concession before and after acquisition. In the benchmark specification we control for the average rainfall in the cell-year.

Results Figure 4 presents the results. The coefficients on the pre-acquisition indicators are small and statistically insignificant, suggesting no differential pre-trends in tree cover near concession boundaries. Following acquisition, tree cover declines progressively in cells inside concessions relative to cells just outside. Figure A4 in Appendix A shows the corresponding raw average percentage of Evergreen Broadleaf cover in cells within concessions over time. Figure A5 presents the difference within and outside palm oil concessions over time. Figure A6 examines sensitivity to the 10 km bandwidth, varying the distance threshold from 5 km to 20 km in 1 km increments.

Figure 4: Percentage of tree cover - Event study



Notes: The figure presents event-study coefficients from equation (1). The dependent variable is tree cover, measured as the percentage of land classified as Evergreen Broadleaf Forest in MODIS land cover data (the primary forest type in Liberia). The coefficient reflects the change in tree cover for cells within concessions, with respect to the control group (10km outside the boundaries). The event year (t=-1) is the year the concession was granted. All specifications include cell and concession × year fixed effects. 95% confidence intervals shown with standard errors clustered at the cell level. Periods before -4 after 6 are included in these time dummies.

To quantify the effect, we estimate a simple difference-in-differences specification comparing cells just inside and just outside concessions (within 10 km of the boundary) before and after acquisition. Table A1 in Appendix B reports the results. Across all specifications, the estimated effect is a decline of approximately 4 percentage points in evergreen broadleaf cover. Column 1 includes cell and year fixed effects with no additional controls. Column 2 adds a control for rainfall. Column 3, the benchmark specification, includes concession-by-year fixed effects. Table A2 in Appendix B examines sensitivity. The estimates remain

stable when correcting standard errors for spatial and temporal correlation, following Conley (1999), when using alternative fixed effect specifications (cell-by-year or cell only), and when including different controls (lagged rainfall, SPEI, nighttime lights, or no controls). To provide context for the magnitude, this 4 percentage point decline corresponds to approximately 70 million trees lost between 2001 and 2018.[13]

Placebo To assess the strength of the identifying assumption, we conduct a placebo exercise using boundaries of other concessions. We obtain data on other concessions in Liberia from AidData (see Appendix 3 for details). Figure A7 in Appendix A shows their geographic distribution. We exclude palm oil concessions, concessions classified as "other crops" (which may include palm oil), and hydrocarbon concessions (which are offshore). The remaining concessions are primarily timber (20%) and gold (19%). We assign each cell an indicator for whether it contains a non-palm oil concession, but use the timing of the nearest palm oil concession as the event time. This specification tests whether deforestation patterns around the palm oil acquisition dates reflect palm oil-specific effects or instead capture broader trends associated with the acquisition period. Figure A8 in Appendix A presents the event study estimates, and Table A3 in Appendix B reports the local difference-in-differences results. The placebo estimates are small and statistically insignificant, indicating that deforestation is specific to palm oil concessions and not driven by unobserved factors correlated with the timing of palm oil acquisitions.

4.2. Land cover

Measurement In this subsection, we examine whether deforestation within palm oil concessions led to increased palm oil cultivation. Satellite data do not directly measure palm oil; instead, we observe 17 land cover classes defined by the International Geosphere-Biosphere Programme (IGBP). We therefore must determine which class corresponds to young palm oil plantations.

IGBP classes are defined by canopy diameter and percentage of tree coverage, both of which vary with tree age and cultivation type. We focus on palm oil trees in their first 4-5 years after planting. Carolita et al. (2017) document the relationship between canopy diameter and tree age for palm oil, which we use to compute average canopy diameter by year since planting (Table A4 in Appendix B). Canopy diameter increases with age but consistently exceeds 2 meters, the IGBP classification threshold. To calculate coverage, we first compute average canopy area for each year since cultivation (column 3 of Table A4). At the optimal planting density of 143 trees per hectare (source: FAO), this yields the area covered by palm oil canopy in each year (column 6). Column 7 shows that palm oil canopy covers approximately 47% of each cell. These characteristics, canopy diameter exceeding 2 meters and coverage between 30-60%, match one IGBP class: "Woody Savannas". Figure A10 in Appendix A presents the geographical distribution of this class in 2006. This classification aligns with Keil (2016), who classify palm oil as "woodland" in the University of Maryland (UMD) system, which corresponds to woody savannas. Palm oil plantations are also commonly characterized as woody crops (SEEA; de Sousa et al., 2020 for Liberia),

[13] Given the density of trees in Liberia per km^2 (285,600, see the Liberia National Forest Inventory 2018/2019), and the size of a cell (30 km^2), approximately $285{,}600 \times 30 \times 0.04 \approx 340{,}000$ trees were cut down per cell. Multiplying this by the total number of cells within concessions (≈ 200), we obtain a tree loss of approximately 70 million trees.

further supporting this classification. Recently, Myint et al., 2025 confirmed the classification of palm oil cultivations in "Woody Savannas" and "Savannas" in Indonesia using very high-resolution (VHR) imagery.

Random Forest To validate this theoretical classification, we use satellite images. Figure A9 presents satellite images of cell 4466 in Maryland Country across three years (2011, 2014, and 2020), illustrating our approach. The concession boundary is marked in red. In 2011, before acquisition, the cell was entirely forested. By 2014, following the 2011 acquisition, a substantial portion had been cleared. By 2020, palm oil trees had matured in the previously deforested area. The fourth image provides a close-up confirming the presence of palm oil trees. MODIS data classify this cell as Woody Savannas during this period. We formalized this approach using a random forest classifier applied to harmonized Landsat 7/8 imagery. Annual dry-season (November–March) median composites were generated from cloud-masked Landsat scenes via Google Earth Engine, with Landsat 7 used for 2001–2012 and Landsat 8 for 2013–2018. Landsat 7 surface reflectance was harmonized to Landsat 8 radiometric space using the transformation coefficients of Roy et al., 2016. Training data consisted of 125 polygons hand-digitized in QGIS over high-resolution 2020 Google Satellite imagery and co-registered to a 2020 Landsat 8 median composite at 30 m resolution. Three land cover classes were defined: Broadleaf Forest, Palm Oil, and Grassland/Savanna. From the six raw Landsat bands (Blue, Green, Red, NIR, SWIR1, SWIR2), 13 spectral features were derived, including vegetation indices (NDVI, EVI, SAVI), moisture indices (NDMI, NBR, TCW), a water index (NDWI), and band ratios (NIR/SWIR2, SWIR1/SWIR2), alongside the Blue, NIR, SWIR1, and SWIR2 bands. The raw Green and Red bands were excluded as their discriminative information was captured by the spectral indices. After removing nodata pixels, the training set comprised 9,868 pixels, which were balanced by subsampling the majority class (Broadleaf Forest) to 2,000 pixels, yielding 4,714 training samples. Model accuracy was assessed through five-fold stratified cross-validation. A pixel-level confidence threshold of 0.5 was applied during classification, rejecting pixels for which no class received a majority probability. The trained model was then applied to each annual composite to produce classified rasters, from which per-class pixel counts and coverage percentages were computed. To assess whether the Landsat 7-to-8 sensor transition in 2013 introduced a spurious discontinuity, a weighted least squares structural break regression was run for each class, with weights proportional to the number of valid pixels per year. Finally, classified rasters were aggregated onto the MODIS MCD12C1 grid to enable cross-comparison with the MODIS land cover product. The random forest classifier achieved an overall accuracy of 0.904 and a Cohen's kappa of 0.852 under five-fold cross-validation. Per-class F1 scores were 0.921 for Broadleaf Forest, 0.890 for Palm Oil, and 0.893 for Grassland/Savanna. The out-of-bag score on the full training set was 0.907. At the 0.5 confidence threshold, 95.8% of pixels were retained, with accuracy rising to 0.921 and kappa to 0.879. Figure 5 presents an example of a satellite image of a palm oil plantation, and Figure 6 presents the binned scatterplot between the percentage of each cell classified as Palm Oil by the random forest algorithm and the percentage classified as Woody Savannas by MODIS. The relationship between the two classifications is strongly positive, although non-linear, highlighting the presence of other land covers in the broader MODIS category.

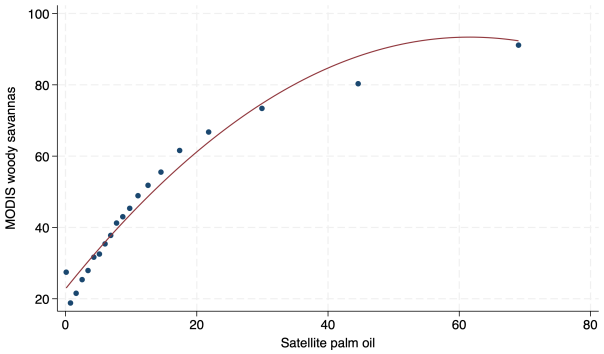
Results Figure 7 presents the staggered local difference-in-difference analysis for the percentage of the cell of the 17 MODIS categories, i.e. using them as P_{kt} in equation (1). The graph shows a steady decrease in the presence of Evergreen Broadleaf Forests, as shown in Figure 4, together with a corresponding increase in Woody Savannas, the category

Figure 5: Palm oil plantation



Notes: The figure presents an example of the satellite image of a palm oil cultivation.

Figure 6: Satellite validation



Notes: The figure presents the bin-scatterplot of the percentage of cell classified as Palm oil by the random forest on satellite images and the percentage of the cell classified as Woody Savannas in the MODIS data.

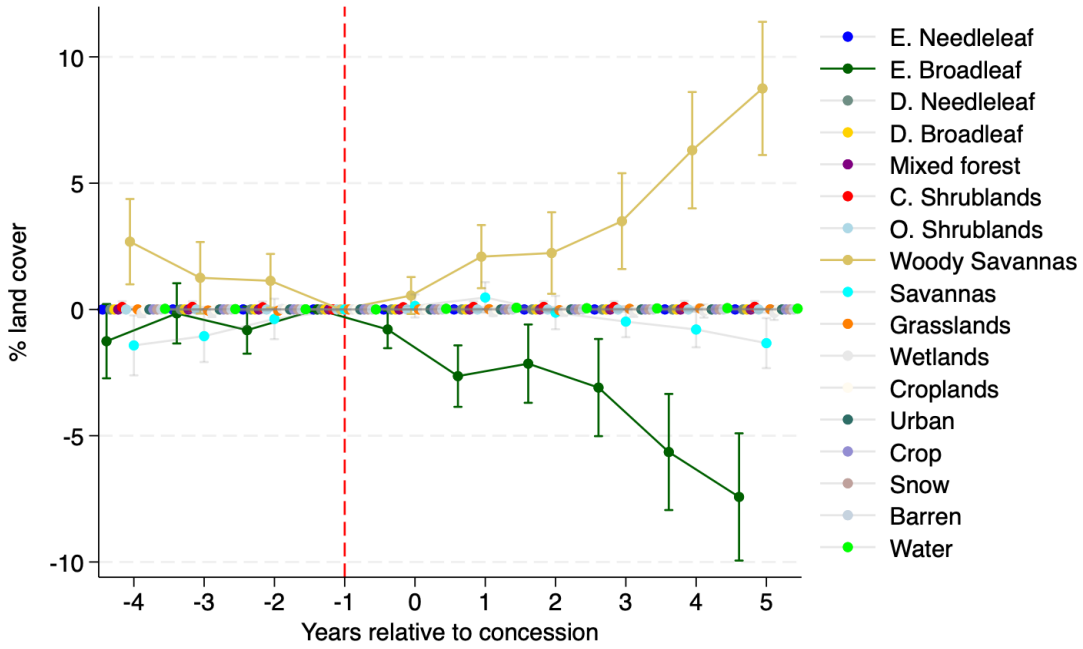
associated with palm oil cultivation. The two trends are not only opposite in direction but also comparable in magnitude, suggesting a substitution between the two categories. Figure A11 in Appendix A shows the corresponding raw averages of the two land covers in cells within concessions over time. Figure A12 presents the difference within and outside palm oil concessions over time. Figure A13 assess robustness to the inclusion of all the matched palm oil companies, regardless of the intent of the contract. Table A5 in Appendix B presents the local difference-in-difference results, with the same structure of Table A1 in Appendix B. The estimated effect is an increase of approximately 4 percentage points in woody savannas cover. Column 1 includes cell and year fixed effects, column 2 controls for rainfall, column 3 includes concession-by-year fixed effects.

To get an idea of the change in production, we perform a small back-of-the-envelope calculation. There are approximately 200 cells within concessions, each covering 12 square miles (approximately 3,000 hectares). A 4 percentage point increase in palm oil cultivation implies roughly 120 hectares of new palm oil area per cell, or about 24,000 hectares in total. The yield of oil palm depends on tree age: palms produce no significant output in years 1-3, increase rapidly in years 4-7, and reach peak production in years 8-15. Trees planted between 2008 and 2011 would be 5-10 years old by 2018/2019, placing them in the transition from early production to maturity. At the global average yield of approximately 2 tonnes (1.8 metric tonnes) of crude palm oil per hectare per year (Woittiez et al., 2017), the estimated new area would produce roughly 43,000 metric tons annually. These figures are broadly consistent with the observed increase in palm oil export, which reached approximately 30,000/50,000 metric tons in 2018/2019 (Figure 1).

These calculations are necessarily rough (they assume uniform planting density, ignore variation in tree age and management quality across concessions, and treat the entire 4 percentage point increase as new commercial plantation). They do, however, suggest that the satellite-based production estimates and the export data tell a mutually consistent story.

Air pollution As additional evidence on the expansion of palm oil cultivations within

Figure 7: Change in land cover - Event study



Notes: The figure presents event-study coefficients from equation (1) for different MODIS land cover categories. Coefficients represent changes inside concessions relative to control cells located (10km outside the boundaries). The event year (t=-1) is the year the concession was granted. All specifications include cell and concession × year fixed effects. 95% confidence intervals shown with standard errors clustered at the cell level.

concessions, we examine air pollution. In Indonesia, palm oil emissions averaged 220 million tonnes of CO2 equivalent annually between 2015 and 2022, accounting for nearly one-fifth of the country's total emissions (SEI, 2024). Therefore, as an indirect test, we examine whether acquisitions increased local air pollution.

Table A6 in Appendix B reports local difference-in-differences estimates for three pollutants: PM2.5, CO2, and N2O. Panel A uses the benchmark 10 km bandwidth; Panel B uses 20 km to account for pollutant dispersion. The estimates indicate increases of 0.4% for PM2.5 and 60% for CO2, and 13% for N2O. Consistent with evidence from Indonesia, palm oil expansion in Liberia is associated with substantial increases in carbon dioxide emissions.

4.3. Conclusions

This section uses a local difference-in-differences approach to estimate the effects of palm oil acquisitions on production. The analysis proceeds in two steps.

First, we document that acquisitions led to substantial deforestation within concession boundaries. Event study estimates show no differential pre-trends in tree cover, followed by a progressive decline of approximately 4 percentage points in the years following acquisition. These estimates are robust to corrections for spatial and temporal correlation in the error structure, alternative fixed effect specifications, and various controls. A placebo exercise using non-palm oil concessions confirms that deforestation is specific to palm oil acquisitions rather than reflecting broader trends during this period.

Second, we establish that deforested areas were converted to palm oil cultivation. Using

agronomic data on palm oil canopy characteristics, we identify young palm oil plantations with the IGBP land cover class "Woody Savannas". Satellite imagery validates this classification. Consistent with this interpretation, woody savanna coverage increases within concessions following acquisition. The two trends are opposite and comparable in magnitude, suggesting a substitution between forests with palm oil cultivations.

Together, this evidence indicates that palm oil acquisitions generated significant increases in palm oil production. The estimates are identified by comparing areas just inside and outside concession boundaries, allowing for concession-specific trends, and are robust across multiple specifications and datasets.

5. FERTILIZERS, HAND TOOLS, AND EXTRACTING MACHINES

The production expansion documented above raises a natural question: what changed with the acquisitions? Did these firms simply acquire land and expand cultivations, or did they also introduce new inputs? This section uses product-level import data to document changes in the availability of capital inputs following the acquisitions. Using a difference-in-difference design that compares imports of palm oil-specific products to other products, before and after the acquisitions, we show that Liberia experienced an increase in imports of fertilizers, harvesting tools, and extraction machinery, with no comparable trend in other agricultural products. Because trade data are measured at the national level, this analysis does not rely on the local variation exploited in the previous section; instead, identification comes from comparing product categories within the same country and time period.

Products To study changes in inputs, we use BACI imports data. This is a comprehensive international trade database that provides bilateral trade flows between countries using the Harmonized System (HS) product classification. The database categorizes traded goods at the 6-digit HS level, allowing detailed analysis of specific products.

The palm oil production process is mainly divided into four phases: (1) seeding and plantation, (2) cultivation and harvesting, (3) oil extraction and primary processing and (4) refining and fractionation. In this section, we discuss our product selection choices. Additional details on product codes and characteristics are provided in Table A7 in Appendix B. Firstly, given that palm oil is indigenous to Liberia, we do not consider seed imports.

For the second phase, we focus on fertilizers (HS: 31) and hand tools for manual work (HS: 8467). Specifically, we concentrate on nitrogenous and potassic fertilizers (HS: 3102 and 3104).[14] It is important to underline that characterizing fertilizers as palm oil-specific or not is challenging, and it is possible that other fertilizers are also used in this cultivation. In contrast, for hand tools we can target the long pole palm oil cutter (in HS: 846729), while excluding unrelated equipment such as drills (HS: 846721) or saws (HS: 846722).

The third phase is carried out mainly using machines with individual functions (HS: 8479). These include machines for "extraction or preparation of animal or fixed vegetable fats or oils" (HS: 846920) and "mixing, kneading, crushing, grinding, screening, sifting,

[14]Nitrogen and potassium fertilizers are by far the most important for oil palm because these nutrients have the highest uptake rates (mature palms require 193 kg/ha/year of nitrogen and 251 kg/ha/year of potassium, which are immobilized in large quantities in vegetative tissue and exported through harvested crops). These two nutrients show significant interactions, with nitrogen being identified as the key limiting element, making them essential for realizing the palm's high genetic growth and yield potential. In contrast, phosphorus and magnesium are needed at much lower rates (50-60 kg/ha and 30-40 kg/ha, respectively), and single responses to these nutrients are rare. Sources: FAO and Dubos, Bonneau, and Flori (2020).

homogenising, emulsifying or stirring" (HS: 846982). Thus, also in this category, we can target palm oil-specific machinery with greater precision than in fertilizers. This allows us to exclude other types of machinery which, although used in agriculture or industry, are not typical of this sector, such as "presses for the manufacture of particle or fiber board" (HS: 847930).

To conclude, we do not include refining in our analysis, as it is only sparsely carried out locally.

Methodology We use import data for two reasons. First, palm oil processing machinery and specialized inputs are not domestically produced in Liberia, so firms must import them. Second, detailed product-level import records allow precise identification of palm oil-specific inputs over time. We compare imports of palm oil inputs to all other imports before and after acquisitions. The estimating equation is:

$$I_{it} = \alpha + \beta_1 P_i + \beta_2 G_t + \beta_3 P_i \times G_t + u_{it} \tag{2}$$

where I_{it} is the imported quantity of product i at time t, P_i equals one if the product is a palm oil input, and G_t equals one from 2008 onward, the year of the first acquisition in the sample.

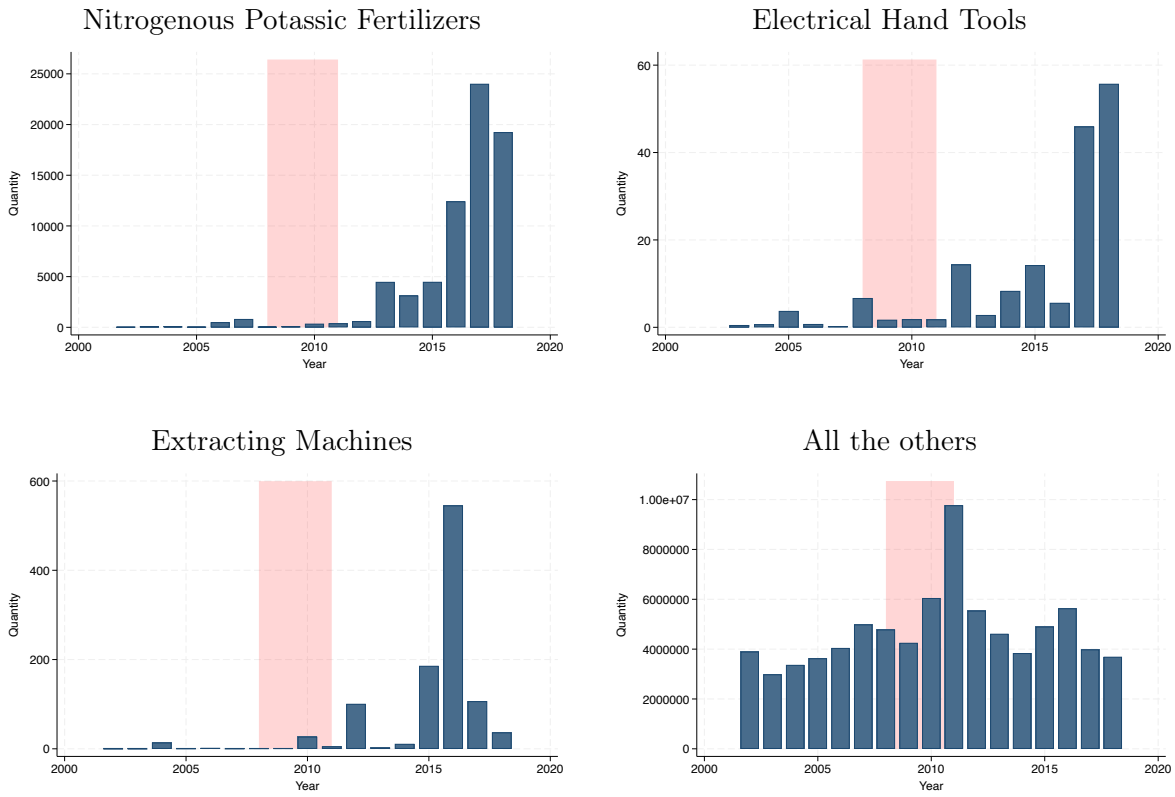
The identification assumption is a standard parallel trends assumption, with palm oil input imports following the same trend as all other Liberian imports absent the acquisitions. Given the aggregate nature of this exercise, identification in this step is significantly weaker. We therefore treat the import results as corroborating evidence rather than as an independent causal estimate. However, the detailed granularity of import data and the consequent ability to target palm oil inputs specifically are reassuring about our ability to identify key correlations in the data.

Results Figure 8 presents the quantities imported for three product categories (nitrogenous/potassic fertilizers, harvesting tools, and extraction machines) over time, as well as all the other imports. Imports of these key palm oil inputs were very low before the acquisitions, but right after the acquisition period, there was a substantial increase in imports across all these product categories. No similar trend appears in other imports. Table A8 in Appendix B reports the difference-in-differences estimates using imports from all other products as the control group. Given the nature of import data (severely skewed with many null values), we use the inverse hyperbolic sine transformation (Panel A) or a simple logarithmic one (Panel B). The results align with the raw import data: a substantial increase in inputs for the palm oil industry after the acquisitions.

This change in fertilizer import data is also roughly consistent with the change in production estimated in Section 4. At recommended application rates of 193 kg/ha of nitrogen and 251 kg/ha of potassium per year for maturing palms (FAO and Dubos, Bonneau, and Flori (2020)), the 24,000 hectares of new plantation would require on the order of 4,500 metric tonnes of nitrogenous and 6,000 metric tonnes of potassic fertilizer annually, magnitudes comparable to the post-acquisition import volumes (combined approximately 5,000/12,000 metric tonnes in 2015/2016).

Table 2 in Appendix B examines whether import increases are specific to palm oil inputs or reflect broader trends in similar product categories. We disaggregate the analysis to the 6-digit product level within the 4-digit categories for hand tools and extraction machines, allowing comparison of palm oil-specific inputs to closely related but non-palm oil products.

Figure 8: Palm oil inputs imports



Notes: This figure imports in Liberia for three categories of products related to the palm oil production: nitrogenous and potassic fertilizers (HS: 3102 and 3104), hand tools used for harvesting (HS: 846729), extracting machines (HS: 846920 and HS: 846982), and all the other imports. The shaded area between 2008 and 2011 indicates the period of palm oil land acquisitions in the sample.

The results indicate that import increases are concentrated in palm oil inputs. For harvesting tools, imports of palm oil-specific equipment increase substantially, while imports of similar tools used in other sectors, such as drills (HS: 846721) or saws (HS: 846722) show no significant change. Similarly, for extraction machinery, palm oil presses exhibit large increases, whereas imports of related equipment used in other agricultural processing, such as wood presses (HS: 847930), remain flat. This pattern is consistent with the hypothesis that import increases resulted from palm oil acquisitions rather than broader sectoral trends, lending credibility to the parallel trends assumption and strengthening the link between documented production expansion and capital inputs.

Placebo Table A9 in Appendix B presents difference-in-differences estimates for placebo products. In particular, *Harvest/Tresh*: HS-843330, 843340, 843351, 843352, 843353, 843359, 843360, 843390; "Poultry": HS-843621, 843629, 843691; "Soil prep.": HS-8432; "Drills": HS-846721; "Telecommunication": HS-8517; "Cosmetics": HS-3304; "Office equ.": HS-8472. The interaction coefficient is small and not statistically different from zero for all these products.

Table 2: BACI categories - difference in difference, 6-digits products

HS Code	Description	Palm oil	DiD coef (std. error)
Harvesting tools [for working in the hand...]			
846711	pneumatic, rotary type		-0.139 (0.387)
846719	pneumatic, other than rotary type		0.124 (0.397)
846721	drills of all kinds		0.451 (0.348)
846722	saws		0.313 (0.464)
846729	other than saws and drills†	✓	1.436*** (0.438)
846781	chain saws		0.463 (0.446)
846789	hydraulic or with self-contained non-electric motor		0.327 (0.489)
846791	parts of chain saws		-0.360 (0.509)
846792	parts of pneumatic tools		-1.232** (0.515)
846799	parts for others		1.261*** (0.428)
Extracting machines			
847910	public works, building or the like		2.136*** (0.709)
847920	extraction or preparation of animal of fixed vegetable fats or oil	✓	2.398*** (0.731)
847930	presses for the manufacture [...]		0.184 (0.256)
847940	for making rope or cable		-0.342* (0.198)
847950	industrial robots		-0.374* (0.206)
847960	evaporative air coolers		0.625 (0.392)
847981	for treating metal		-0.149 (0.209)
847982	for mixing, kneading, crushing, grinding, screening [...]	✓	0.988 (0.617)
847989	having individual functions, n.e.c		0.601 (0.471)
847990	parts, of thos having individual functions		0.855* (0.456)

Notes: OLS regressions, equation 2 (Section 8). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. The difference-in-difference coefficient shown is the interaction term between Treated and Grant. *Grant* is a dummy equal to one after (and including) 2008. *Treated* is a dummy equal to one for products belonging to the relevant products in the table. In each regression the other treatment groups have been excluded from the sample.
† this is the category where the Cantas-type motorized palm oil harvester should be.

6. LOCAL DEVELOPMENT

This section examines whether palm oil acquisitions affected local development, with a focus on employment. We use household survey data to compare individuals in villages just inside and outside concession boundaries before and after acquisition, exploring whether the production increase documented in Section 4 is associated with changes in labor allocation.

Methodology We employ a similar identification strategy to the previous section, comparing individuals in villages just inside and outside concession boundaries before and after acquisition. Figure A14 in Appendix A illustrates the variation for one concession. The identifying assumption is that, absent the acquisitions, individual outcomes would have evolved similarly just inside versus just outside concession boundaries.

The data structure differs from the previous section. The household surveys provide a repeated cross-section of individuals rather than a panel of cells. Different villages and individuals are sampled in each wave, precluding individual or village fixed effects. The estimating equation is:

$$Y_{ict} = \alpha + \beta_1 G_{ct} + \beta_2 G_{ct} \times W_i + \mu_t + W_i \times \mu_c + u_{ict} \tag{3}$$

where Y_{ict} is the outcome for individual i in the area surrounding concession c at time t, G_{ct} equals one if individual if concession c has been granted at t, W_i equals one if individual i's village is inside a concession, μ_t are year fixed effects, and $W_i \times \mu_c$ are concession-by-location fixed effects (separate fixed effects for areas inside and outside each concession). This spec-

ification compares individuals in villages just inside and outside the same concession before and after acquisition, controlling for time-invariant differences between inside and outside areas specific to each concession. Given the sparser distribution of villages relative to grid cells, we increase the bandwidth from 10 km to 20 km. We examine sensitivity to alternative bandwidths and specifications below.[15]

Placebo To assess the plausibility of the identifying assumption, we conduct a placebo exercise examining ten outcomes unlikely to be affected by palm oil acquisitions over this time horizon: altitude, time to water source, age, whether the individual belongs to the Kpelle ethnicity (the largest group, comprising 20% of the sample), whether the individual is Christian (the largest group, 86% of the sample), whether the individual is able to read, years of education, weight over height, average child weight over height, and number of children. This exercise assess both the parallel trends assumption and potential sampling imbalances arising from the repeated cross-sectional design, though imperfectly, as discussed in Section 7. Table A11 and Appendix B and Figure 9 present the results. All the estimated effects are small and statistically insignificant.[16]

Land ownership and urban residency Table A12 in Appendix B examines whether acquisitions affected land ownership and urban residence. In columns 1 and 2, the dependent variable is an indicator equal to one if the respondent owns any agricultural land. In columns 3 and 4, it is an indicator for whether the respondent lives in an urban area. Columns 1 and 3 report estimates without individual controls; columns 2 and 4 add controls for age. Individuals inside concessions are 10 percentage points less likely to own agricultural land following acquisition, consistent with the transfer of land to concession companies. Respondents are also less likely to live in an urban area, consistent with palm oil plantations operating as rural employment hubs that reduce the incentive to migrate to cities, at least over the medium term.

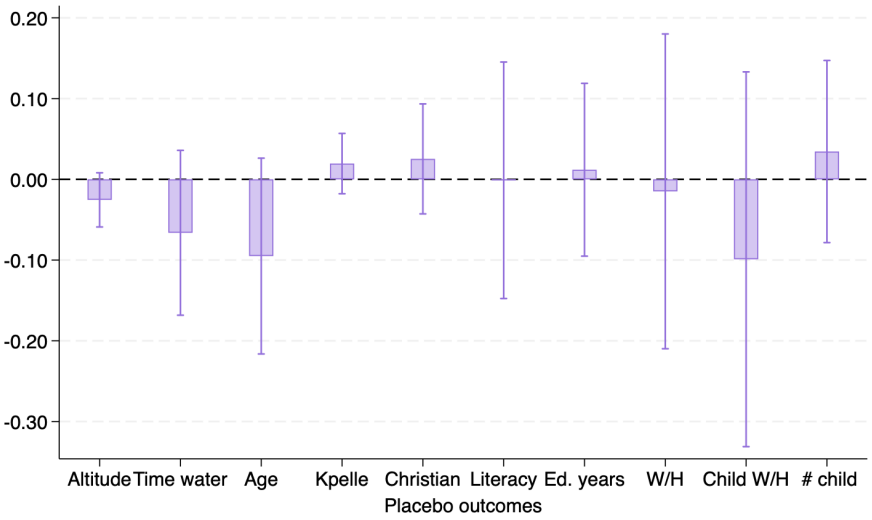
A potential concern with the local identification strategy is violation of SUTVA due to spillovers across concession boundaries. To assess robustness, we replicate the analysis while systematically varying the distance of the control group from concession boundaries (in the spirit of Michalopoulos & Papaioannou, 2014). Beginning with the baseline control group of villages [0km, 20km] from boundaries, we incrementally shift both bounds by 1 km–creating samples of [1km, 21km], [2km, 22km], and so forth. Figure A15 in Appendix A presents the results. The estimated effect on land ownership remains stable through a 5 km shift; beyond 5 km, the coefficient becomes small and statistically insignificant. The estimated effect on urban residence declines with distance but remains statistically significant throughout.

Employment Table 3 reports difference-in-differences estimates for six occupation outcomes: unemployment, sales, self-employment in agriculture, agricultural wage employ-

[15]The pixel-based local difference-in-difference methodology can be applied one last time to study changes on population dynamics and nightlights. The results (Table A10 in Appendix B) show a positive (albeit small, 0.08 standard deviations) effect on the population and no impact on nightlights. However, it is important to note that this widespread measure of economic development has significant limitations when assessing development in rural areas (Keola et al., 2015, Gibson et al., 2021, and Perez-Sindin et al., 2021).

[16]The *Grant* dummy is excluded from the regression for the literacy and weight over height outcomes since it is collinear with the year fixed effect since this is present only in the DHS (2007, 2013, 2019) waves, and therefore only one pre-acquisitions period is present.

Figure 9: Placebo outcomes



Notes: The figure presents the local difference in the difference coefficient from equation 3 (Section 6), for different placebo outcomes. Robust standard errors, year and within × concession fixed effect included. 95% confidence interval shown. Altitude is the altitude of the village; time to water is the time to the nearest water source; age is the age of the DHS respondent; kpelle is a dummy variable indicating whether the individual belongs to the kpelle ethnicity; christian is a dummy variable indicating whether the individual declares to be christian; literacy is a dummy variable indicating whether the respondent can read (part of) a sentence; education years is the years of education the respondent declares to have; We/He is the weight over height of the respondent; Child We/He is the average child weight over height; num. child is the number of children. All dependent variables are standardized.

ment, services, and manual labor.[17][18] Panel A presents results for wives; Panel B for husbands. Control variables are age and years of education. Several patterns emerge. First, self-employment in agriculture decreases by approximately 10 percentage points for both groups, relative to a baseline of 50/60% outside concessions before acquisition. This is consistent with the decline in land ownership documented above. Second, agricultural wage employment increases by roughly 5 percentage points for wives and 8 percentage points for husbands, compared to baseline rates of 1% and 8%, respectively. Results are robust to the exclusion of controls (Table A14 in Appendix B). Figure A16 in Appendix A presents results from the spillover robustness exercise described in the previous subsection. The estimates remain stable as the control group is shifted away from concession boundaries.

Figure A17 in Appendix A examines the sensitivity of the agricultural occupation results to alternative specifications and bandwidths. We report $\hat{\beta}_2$ of equation 3, the difference-in-differences, across 17 specifications and 6 bandwidths (5 km to 30 km in 5 km increments). The specifications vary the fixed effects structure (benchmark, year and concession fixed

[17]These are constructed using the question about occupation. One data limitation merits note: unemployment was not reported in the 2007 occupation question, yielding a probability of unemployment of zero outside concessions before the acquisitions. As a robustness check, Table A13 in Appendix B reports results using both the occupation-based unemployment measure and a separate question on work status (available only for wives). The results are not the same. Therefore, we interpret the results on unemployment with caution.

[18]The *Grant* dummy is excluded from the regression for occupation outcomes since it is collinear with the year fixed effect since these are present only in the DHS (2007, 2013, 2019) waves, and therefore only one pre-acquisitions period is present.

Table 3: Occupation

Dep. Variable	(1) Unemployed	(2) Sales	(3) Agri. self	(4) Agri. empl	(5) Services	(6) Manual
Panel A: wife						
Grant × Within	0.0187	-0.00715	-0.0981**	0.0490***	0.0135	-0.00236
	(0.0223)	(0.0383)	(0.0408)	(0.0157)	(0.0136)	(0.00896)
Observations	3,932	3,932	3,932	3,932	3,932	3,932
R-squared	0.227	0.047	0.343	0.175	0.066	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave × Concession FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Grant = 0 & Within = 0	0.000	0.269	0.623	0.016	0.016	0.011
Panel B: husband						
Grant × Within	-0.0168*	-0.0258	-0.0869**	0.0814***	0.0672***	-0.0127
	(0.00882)	(0.0257)	(0.0439)	(0.0238)	(0.0217)	(0.0290)
Observations	2,841	2,841	2,841	2,841	2,841	2,841
R-squared	0.053	0.024	0.257	0.219	0.023	0.075
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave × Concession FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Grant = 0 & Within = 0	0.000	0.077	0.481	0.081	0.089	0.127

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE), separately for wives (Panel A) and husbands (Panel B). Outcome variables are indicators for: Unemployed = not working; Sales = employed in sales; Agriculture employee = employed in agriculture; Agricultural self-employment = self-employed in agriculture; Services = employed in services; Manual = employed in manual labor. The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is an indicator for individuals residing inside a concession. The *Grant* coefficient is perfectly collinear with fixed effects in this specification, since the DHS waves are 2007, 2013, and 2019 and all the palm oil concessions were granted between 2007 and 2013. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables are age and the years of education.

effects separately, or interacted, simple difference-in-difference with or without concession fixed effect), inclusion of age and years of education controls, sample restrictions (long-term residents only; pre-Ebola period only), and functional form (linear probability versus logit). Coefficients are color-coded: blue indicates the same sign as the benchmark specification and statistical significance at the 5% level; black indicates statistical insignificance; red indicates the opposite sign and statistical significance at 5%. The estimates are stable across most specifications. Results are less stable at the 5 km bandwidth, where the control sample contains relatively few individuals (control = 125, treatment = 2743). This is consistent with either increased sampling variability at narrow bandwidths or potential spillovers very close to concession boundaries. The findings are robust to excluding the Ebola period (waves before 2014), indicating that differential Ebola impacts inside versus outside concessions do not drive the results.[19] They are also robust to restricting the sample to individuals residing in their village for more than 11 years (the time elapsed between the first acquisition and the final survey wave), suggesting that endogenous migration does not drive the occupation shifts.

Wealth Table A15 in Appendix B reports difference-in-differences estimates for the DHS wealth index, with and without controls for age and years of education. The wealth index is a standardized composite measure of household living standards based on asset ownership, housing materials, and access to water and sanitation.[20] The estimated change

[19] Acquisitions occurred 2-4 years before the 2014 Ebola outbreak.

[20] The index is constructed using principal components analysis. Asset scores are standardized using country-wave means and standard deviations, and households are ranked and divided into quintiles. The

is 0.05 standard deviations and statistically indistinguishable from zero.[21] Figure A19 in Appendix A shows that the estimate is robust to varying the bandwidth from 5 km to 30 km.

7. DISCUSSION

Summary This paper uses a local difference-in-differences design to study the effects of palm oil land acquisitions on agricultural production and local development in Liberia. Comparing grid cells and villages just inside and outside concession boundaries before and after acquisition, we document three sets of results.

First, acquisitions led to substantial deforestation within concession boundaries, with cleared land converted to palm oil cultivation. Event study estimates show no differential pre-trends in tree cover, followed by a progressive decline of approximately 4 percentage points after acquisition. The decline in tree cover is matched by a corresponding increase in woody savannas, the land cover category associated with palm oil plantations, a classification we validate using satellite imagery and that is consistent with recent work using very high-resolution imagery (Myint et al., 2025). A back-of-the-envelope calculation places the implied production increase at roughly 43,000 metric tons annually, a figure consistent with the observed increase in Liberian palm oil exports over this period.

Second, using product-level import data, we document an increase in imports of palm oil-specific capital inputs (nitrogenous and potassic fertilizers, harvesting tools, and extraction machinery) following the acquisitions. The increase is concentrated in palm oil inputs: closely related but non-palm oil products (drills, saws, wood presses) and unrelated categories (poultry equipment, telecommunications, cosmetics) show no comparable change. The magnitude of the fertilizer increase is consistent with the expansion of cultivated area estimated in the first part of the paper.

Third, individuals inside concessions are 10 percentage points less likely to own agricultural land following acquisition. Self-employment in agriculture falls by roughly 10 percentage points, while agricultural wage employment rises by 5–6 percentage points. These employment results are robust to alternative specifications and robustness tests. We do not, however, find any change in the DHS wealth index.

Taken together, these results trace a process of structural transformation within agriculture. Foreign firms acquire land, convert it to palm oil cultivation, and introduce capital inputs that were previously unavailable. The local labor market adjusts: self-employment declines and wage employment expands. This pattern is consistent with the mechanism described by Lewis (1954), in which modern sector entry absorbs labor from the traditional sector through the introduction of capital. We do not find evidence of wealth gains over this period. Whether such gains materialize over a longer horizon falls outside the scope of our data, which cover at most a decade following the first acquisition. In this section, we discuss the robustness and limitations of these results.

Measurement To measure the expansion of palm oil cultivation, we use the MODIS "Woody Savannas" land-cover category. This classification is based on canopy size and tree-cover thresholds that are consistent with the structure of young palm oil plantations, as

final index measures standard deviations from the national mean. See DHS Wealth Index website for details.

[21] To put things into perspective, we use the asset scores provided by the 2018 Liberian DHS. This increase is comparable to individuals living within the concessions, after the acquisitions, owning an additional chair (i.e., owning a chair increases the wealth score by 0.04 standard deviations).

discussed in Section 4. Satellite imagery validates this classification and recent work by Myint et al. (2025) confirms that palm oil cultivations are classified as "Woody Savannas" and "Savannas" in the IGBP system using very high-resolution imagery. It is important to note that our estimates rely on comparisons around palm oil-specific boundaries. Although this measure may contain noise (e.g., classification lags or similarities with other woody crops), such misclassification would tend to attenuate effects rather than generate spurious ones. Bias would arise only if misclassification were systematically correlated with concession boundaries.

Internal Validity Throughout the paper, except in the import analysis, the identification assumption is that outcomes would have evolved similarly just inside versus just outside palm oil concession boundaries absent the acquisitions. We assess the strength of this assumption with several robustness checks.

On land cover and production, the event study estimates show no differential pre-trends in tree cover near concession boundaries (Figure 4). Moreover, a placebo exercise using non-palm oil concessions (primarily timber and gold) yields null results for both deforestation (Table A3).

For the import results, identification relies on a standard parallel trends assumption at the aggregate level: in the absence of the acquisitions, imports of palm oil inputs would have followed the same trend as all other Liberian imports. Given the aggregate nature of this exercise, causal identification is weaker than in the local analysis. However, the granularity of the import data allows us to target palm oil-specific products precisely. The fact that increases are concentrated in palm oil inputs—while closely related but non-palm oil products (drills, saws, wood presses) and unrelated categories (poultry equipment, telecommunications, cosmetics) show no change—provides reassurance that the patterns reflect palm oil-specific investment rather than broader import trends.

On employment, two features of the data merit discussion. First, given the identification strategy and the nature of the data, we estimate local changes in labor market equilibria following land acquisitions, as in Autor et al. (2016). The effects we document represent the sum of all changes generated by the acquisitions, including both direct effects (e.g., hiring by plantation companies) and indirect ones (e.g., displacement of self-employed farmers, emergence of local service activities). Second, the household surveys provide a repeated cross-section rather than a panel of individuals. Different villages and individuals are sampled in each wave, precluding individual fixed effects. This means that changes in sample composition across waves could, in principle, confound the estimates. To address this, we conduct placebo tests on outcomes unlikely to be affected by acquisitions (Table A11). Nevertheless, we cannot fully rule out imbalances in unobserved characteristics.

An additional potential concern is that the 2014 Ebola epidemic, which severely affected Liberia, could have had differential impacts just inside versus outside concession boundaries, confounding our estimates. Several features of the data alleviate this concern. First, all palm oil concessions in our sample were granted between 2008 and 2011, two to four years before the epidemic. The deforestation event studies show that tree cover began declining immediately after grant dates, well before the outbreak. Second, the employment results are robust to excluding the Ebola period entirely, retaining only the 2007 (pre-acquisition), 2011, and 2013 (post-acquisitions, pre-Ebola) DHS waves (Figure A17). Third, for the Ebola epidemic to confound our estimates, it would need to have had systematically different labor market effects on individuals residing just inside versus just outside concession boundaries, a selection mechanism for which we have no evidence and which the placebo outcomes do

not support.

Another potential threat comes from spillovers across boundaries (SUTVA violations), a common concern in local identification designs. For deforestation and land cover, spillovers would most likely bias our estimates downward, as clearing may extend beyond formal boundaries. For employment outcomes, the direction of the bias is less clear. To assess the extent of spillovers, we progressively shift the control group to more distant locations (Figure A16). Estimates remain stable or become stronger as the control group moves farther from boundaries, consistent with attenuation bias at close distances. Nonetheless, we cannot fully rule out bias in either direction. To address the possibility that endogenous migration drives the results, we show that estimates are robust to restricting the sample to long-term residents (Figure A17).

External Validity The generalizability of these results to other land acquisitions, and more generally to agricultural FDI, depends on the characteristics of the acquisitions examined.

A first consideration relates to the context of *Liberia*. As a low-income, post-conflict country with low baseline land use, land acquisitions here primarily expanded cultivated area. In settings where land is already intensely used, such as high- or middle-income countries, agricultural FDI may instead reallocate land across crops rather than increase total cultivation. A second consideration is that this study focuses on *palm oil* acquisitions. Large-scale palm oil is an extensive woody crop, and these characteristics may influence the observed effects.

Taken together, these findings are most directly relevant for agricultural FDI in extensive crops within developing countries. This describes a substantial share of global land acquisitions: 94% of deals occur in developing regions, and 71% target extensive monoculture crops, with 15% in palm oil alone (authors' calculations using Land Matrix data). Within Liberia, we find suggestive evidence that the patterns extend beyond palm oil. Figures A20 and A21 compare employment equilibria just inside and just outside non-palm oil concessions, including agricultural concessions (mostly timber and rubber). The employment dynamics are similar, though these exercises lack the temporal variation that identifies the main results.

8. CONCLUSIONS

After Liberia's second civil war, foreign direct investment surged from approximately $100–150 million per year in 2006–2007 to about $1 billion annually by 2012–2013, largely driven by multinational investments in agriculture and mining (WorldBank, 2015). In these sectors, FDI typically involves land acquisitions.

This paper studies the effects of palm oil land acquisitions on agricultural production and local development in Liberia. Using a local difference-in-differences design that compares areas just inside and outside concession boundaries before and after acquisition, we document that these investments reallocated land from forest to palm oil cultivation, shifted local employment from agricultural self-employment toward wage labor, and were accompanied by increases in imports of industry-specific capital inputs. Together, these results suggest that agricultural FDI, in the form of land acquisitions, can serve as a push factor for structural transformation within agriculture, consistent with a Lewisian framework (Lewis, 1954).

The findings are most directly relevant for land acquisitions in developing countries involving extensive crops, which account for roughly two-thirds of global land deals. Future

research could investigate how the effects of agricultural FDI depend on the type of crop, the availability of uncultivated land, and the institutional environment governing land rights and labor protections.

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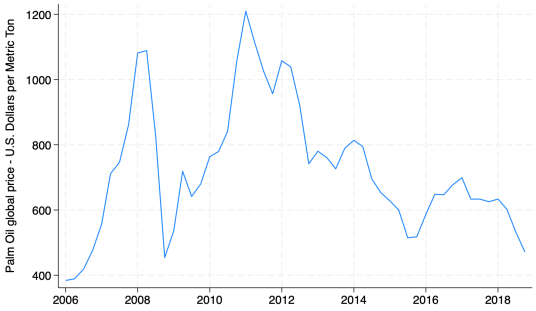
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APPENDIX

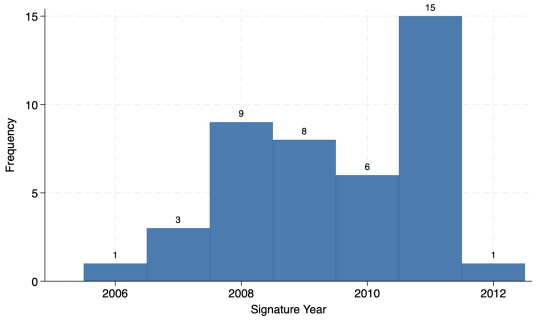
A. ADDITIONAL FIGURES

Figure A1: Palm oil global price



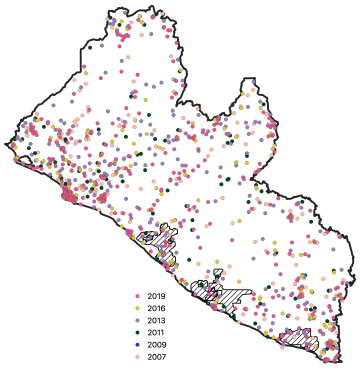
Notes: The figure presents the trend of palm oil global price (U.S. dollars per metric ton) over the period 2006-2020. Data from FRED.

Figure A2: Number of land contracts



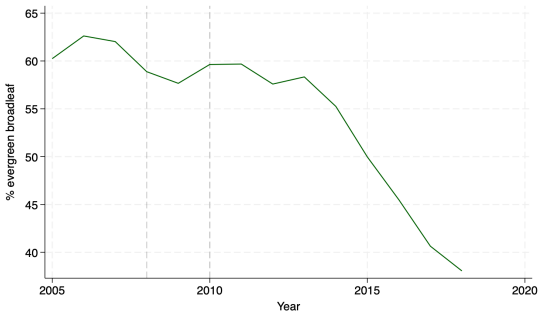
Notes: The figure presents the number of land contracts recorded on OpenLand Contracts between 2006 and 2018.

Figure A3: DHS villages



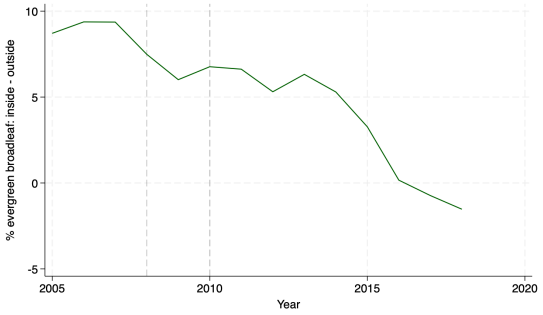
Notes: The figure presents the geographical distribution villages surveyed by the DHS (and MIS).

Figure A4: Broadleaf cover over time



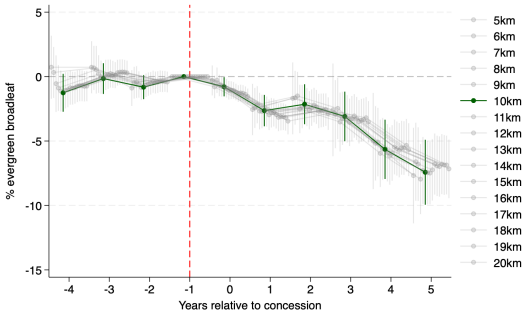
Notes: The figure presents the percentage of cell covered by "Broadleaf Evergreen Forest" within concessions over years. The two gray lines represent the granting years.

Figure A5: Broadleaf cover - comparison



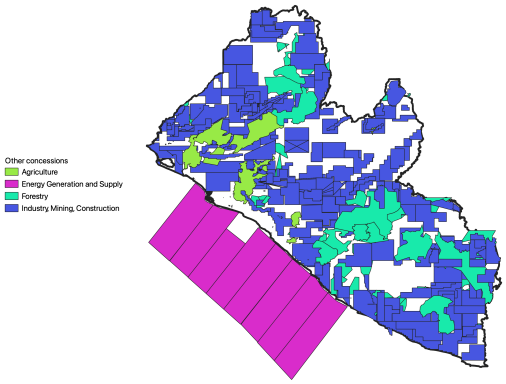
Notes: The figure presents the difference in the percentage of cell covered by "Broadleaf Evergreen Forest" within and outside concessions. The two gray lines represent the granting years.

Figure A6: Percentage tree cover - event study, sensitivity



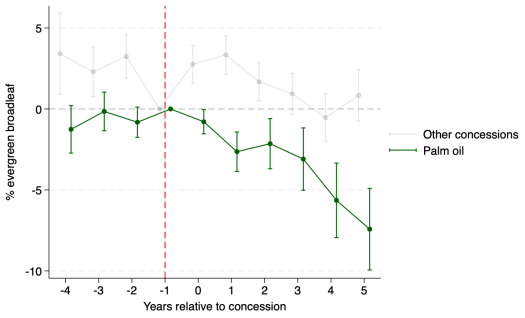
Notes: The figure presents the sensitivity of event-study coefficients from equation 1 (Section 4), to changes in the control bandwidth from 5km to 20km. 95% confidence interval shown. Dependent variable is the percentage of cell covered by "Broadleaf Evergreen Forest". 95% confidence intervals shown with standard errors clustered at the cell level.

Figure A7: Map other concessions



Notes: The figure presents the map of other land concessions in Liberia.

Figure A8: Percentage tree cover - event study, placebo



Notes: The figure presents the event-study coefficients from equation 1 (Section 4), for palm oil concessions (in green) and other land concessions (in gray). 95% confidence interval shown. Dependent variable is the percentage of cell covered by "Broadleaf Evergreen Forest". 95% confidence intervals shown with standard errors clustered at the cell level.

Figure A9: Pixel 4466



(a) Pixel 4466 - 2011



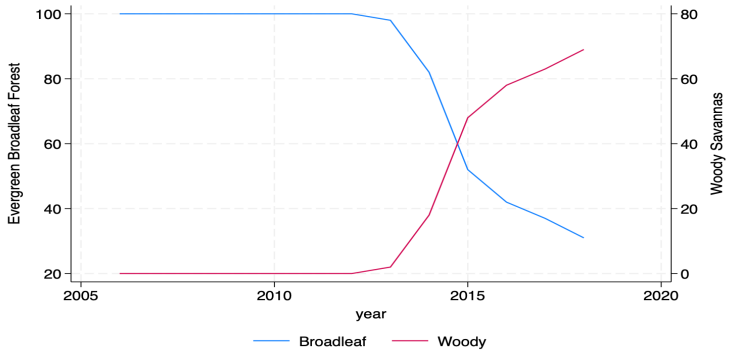
(b) Pixel 4466 - 2014



(c) Pixel 4466 - 2014, zoom



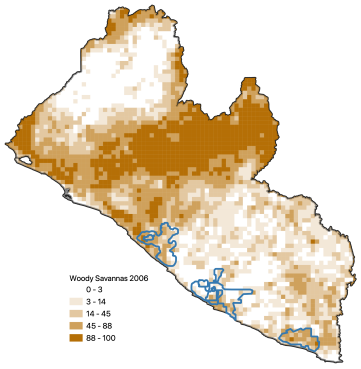
(d) Pixel 4466 - 2020



(e) Pixel 4466 - land cover

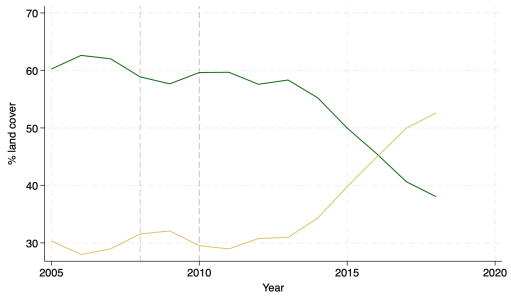
Notes: The figure shows satellite images (Google Earth) of pixel 4466 in Maryland County across three time points (2011, 2014, 2020) and a zoomed-in view. The images illustrate the transition from forest to deforested land and then to palm oil plantation after the acquisition. The last picture shows the *Evergreen Broadleaf Forest* and *Woody Savannas* land cover categories over the sample period.

Figure A10: Map Woody Savannas 2006



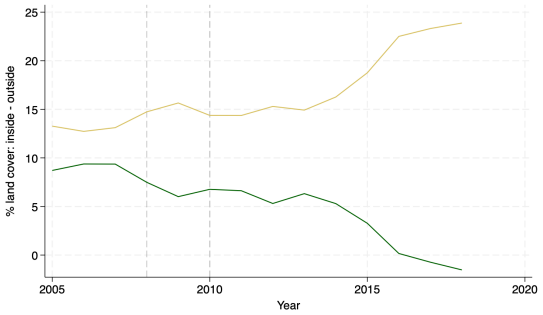
Notes: The figure presents the percentage of each cell covered by "Woody Savannas" in 2006. The darker the cell, the higher the percentage.

Figure A11: Land cover over time



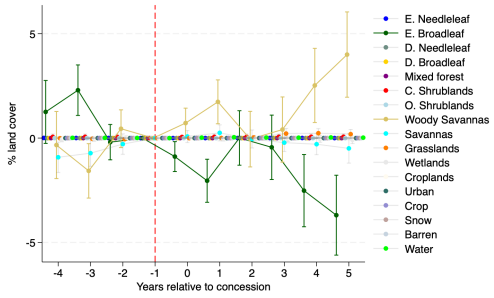
Notes: The figure presents the percentage of cell covered by "Broadleaf Evergreen Forest", in green, and "Woody Savannas", in yellow, within concessions over years. The two gray lines represent the granting years.

Figure A12: Land cover - comparison



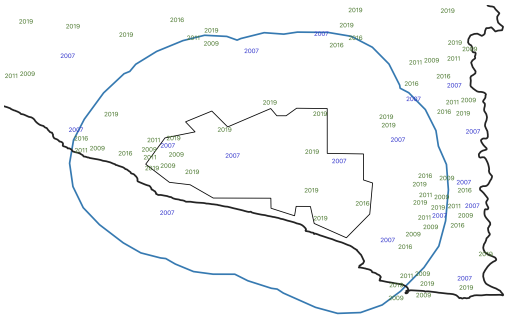
Notes: The figure presents the difference in the percentage of cell covered by "Broadleaf Evergreen Forest", in green, and "Woody Savannas", in yellow, within and outside concessions. The two gray lines represent the granting years.

Figure A13: Land cover - all palm oil companies



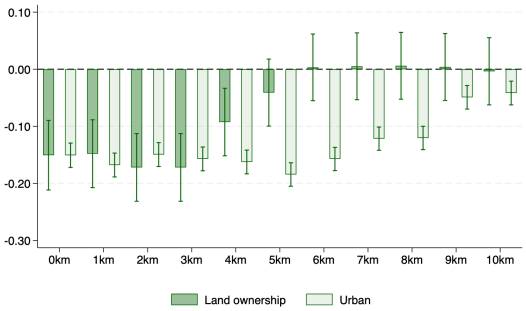
Notes: The figure presents event-study coefficients from equation (1) for different MODIS land cover categories. Coefficients represent changes inside concessions relative to control cells located (10km outside the boundaries). The event year (t=-1) is the year the concession was granted. All specifications include cell and concession × year fixed effects. 95% confidence intervals shown with standard errors clustered at the cell level. All three palm oil companies considered.

Figure A14: DHS villages - zoom



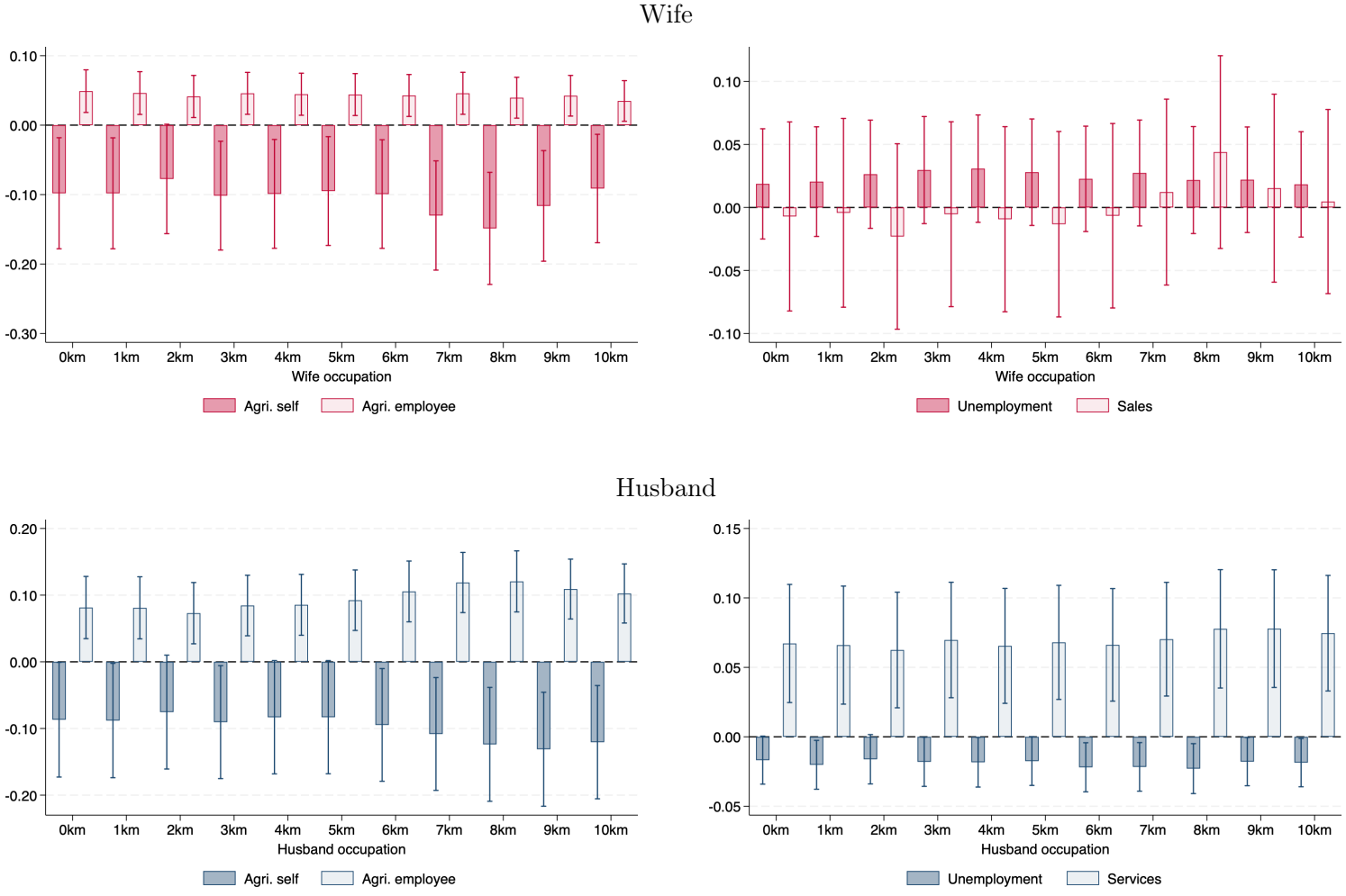
Notes: The figure presents the geographical distribution of villages surveyed by the DHS (and MIS) around a palm oil concession. The 20km buffer in blue. Villages before 2008 in blue, villages after 2010 in green.

Figure A15: Land - sensitivity buffer



Notes: The figure presents the local difference in the difference coefficient from equation 3 (Section 6), for different buffer zones. Due to data availability, for this outcome *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. The dependent variable are land ownership, a dummy variable equal to 1 if the household owns any agricultural land, and the urban dummy, indicating whether the individual lives in an urban place. 95% confidence interval shown. Robust standard errors. Year and concession × within FE included. Within is a dummy variable equal to 1 if the village is within the palm oil concession. The x-axis indicates the amount of km between the control group and the boundary of the closest palm oil concession. Control is age.

Figure A16: Occupation - sensitivity buffer



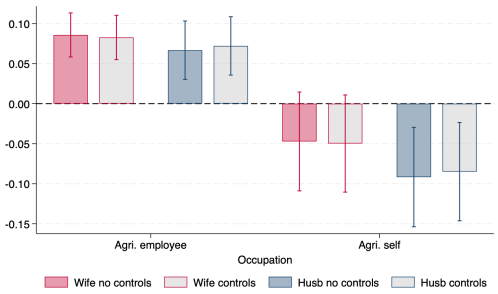
Notes: The figure presents difference-in-differences coefficients from equation 3 (Section 6), for different buffer zones, shown separately for wives and husbands. Outcome variables are indicators for agriculture employment, agricultural self-employment, unemployment, sales for wives, and services per husbands. All specifications include year and concession × within fixed effects, where Within indicates villages located inside the palm oil concession. 95% confidence intervals shown with robust standard errors. The x-axis indicates the amount of km between the control group and the boundary of the closest palm oil concession. Controls are age and years of education.

Figure A17: Occupation - sensitivity



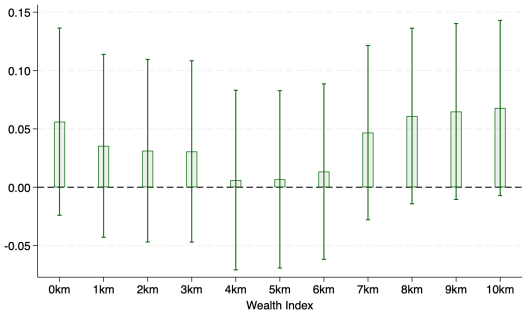
Notes: The figure presents robustness checks for the difference-in-differences coefficients from equation 3 (Section 6). Outcome variables are indicators for agriculture employment and agricultural self-employment, shown separately for wives and husbands. Each panel shows results using a different control group bandwidth: villages within 5km, 10km, 15km, 20km, 25km, 30km, and 35km of concession boundaries. Each row represents a different model specification (see Section 6 for details). Color coding indicates: blue = same sign as benchmark specification and statistically significant at 5% level; black = not statistically significant; red = opposite sign from benchmark and statistically significant at 5% level. The benchmark specification is the first.

Figure A18: Occupation - all palm oil companies



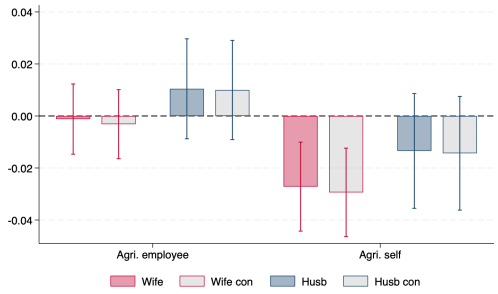
Notes: The figure presents the difference-in-differences coefficients from equation 3 (Section 6) considering all three palm oil concessions. Outcome variables are indicators for agriculture employment and agricultural self-employment, shown separately for wives and husbands. Controls are age and years of education.

Figure A19: Wealth - sensitivity buffer



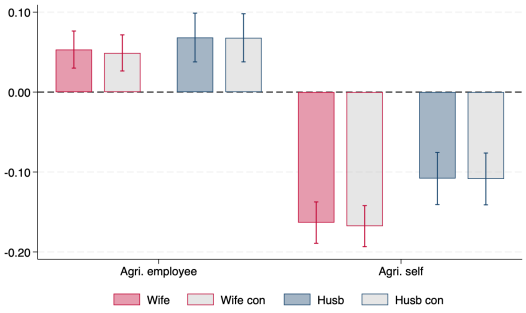
Notes: The figure presents the local difference in the difference coefficient from equation 3 (Section 6), for different buffer zones. The dependent variable is the DHS wealth index, standardized. Robust standard errors. Year and concession × within FE included. Within is a dummy variable equal to 1 if the village is within the palm oil concession. The x-axis indicates the amount of km between the control group and the boundary of the closest palm oil concession. Controls are age and years of education.

Figure A20: Other concessions



Notes: The figure presents coefficients comparing employment outcomes inside versus outside other (non-palm oil) concessions, shown separately for wives and husbands. A concession is considered active only in years between its grant year and expiry year. Outcome variables are indicators for agriculture employment and agricultural self-employment. The sample is restricted to DHS respondents living within 20km of these concession boundaries. All specifications include year and concession fixed effects. 95% confidence intervals shown with robust standard errors. Controls are age and years of education.

Figure A21: Other concessions - agriculture



Notes: The figure presents coefficients comparing employment outcomes inside versus outside other (non-palm oil) concessions, shown separately for wives and husbands. A concession is considered active only in years between its grant year and expiry year. Outcome variables are indicators for agriculture employment and agricultural self-employment. The sample is restricted to DHS respondents living within 20km of these concession boundaries. All specifications include year and concession fixed effects. 95% confidence intervals shown with robust standard errors. Controls are age and years of education. Sample restricted to agricultural concessions (rubber and timber).

B. ADDITIONAL TABLES

Table A1: Percentage tree cover

Dep. Variable	(1) % Evergreen Broadleaf	(2) % Evergreen Broadleaf	(3) % Evergreen Broadleaf
Grant × Concession	-3.473***	-3.464***	-3.970***
	(0.806)	(0.807)	(0.944)
Observations	6,660	6,660	6,642
R-squared	0.948	0.948	0.951
Cell FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Concession × Year FE	No	No	Yes
Rain	No	Yes	Yes
Mean y | Grant = 0 & Concession = 0	40.501	40.501	40.501

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variable is the percentage of cell covered by "Evergreen Broadleaf Forest" (MODIS). The sample is restricted to grid cells within 10km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Concession* is an indicator for cells located inside a palm oil concession. Standard errors (in parentheses) are clustered at the cell level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Percentage tree cover - Sensitivity

Dep. Variable	(1) Coefficient	(2) Standard error
Benchmark	-3.970***	(0.944)
Robust s.e.	-3.970***	(0.426)
Conley s.e.	-3.970***	(1.423)
Cell Year FE	-3.464***	(0.807)
Cell FE	-3.945***	(0.641)
No controls	-3.947***	(0.944)
Nightlights	-5.345***	(1.019)†
SPEI	-4.776***	(1.258)
Lag rain	-4.157***	(0.961)

Notes: The table presents the Grant × Concession coefficient from column (1) of Table A1, re-estimated using different specifications. Conley std. with 250km of possible spatial correlation and 100 years of time correlation. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
† This regression is done on a sample from 2006 to 2018 due to sample availability of nightlights.

Table A3: Percentage tree cover - Placebo concessions

	(1) Palm oil	(2) Others
Grant × Concession	-3.970***	0.309
	(0.944)	(0.338)
Mean y | Grant = 0 & Concession = 0	46.623	50.409
Cell FE	Yes	Yes
Concession × Year FE	Yes	Yes
Rain	Yes	Yes

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variable is the percentage of cell covered by "Evergreen Broadleaf Forest" (MODIS). The sample is restricted to grid cells within 10km of concession boundaries. Column (1) compares cells inside palm oil concessions to nearby cells outside any concession. Column (2) compares cells inside other (non-palm oil) concessions to nearby cells outside any concession, excluding palm oil concessions from the sample. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Concession* is an indicator for cells located inside a palm oil concession. Standard errors (in parentheses) are clustered at the cell level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Palm oil characteristics

Age	Canopy diameter	Canopy area	Optimal density	Num trees	Area covered	Perc covered
1 y	4.2 m	13.19 m^2	143 t/ha	429000 t	5.65 km^2	18%
2 y	5.3 m	22.39 m^2	143 t/ha	429000 t	9.60 km^2	32%
3 y	6.4 m	31.97 m^2	143 t/ha	429000 t	13.71 km^2	46%
4 y	7.4 m	42.84 m^2	143 t/ha	429000 t	18.38 km^2	61 %
5 y	8.3 m	53.87 m^2	143 t/ha	429000 t	23.11 km^2	77 %

Notes: The table presents the estimated canopy diameter, canopy area, and the resulting coverage of a standard MODIS pixel at different years since palm oil plantation. The calculations assume an optimal planting density of 143 trees per hectare and use data on canopy diameter by age from Carolita et al. (2017).

Table A5: Woody savannas cover

Dep. Variable	(1)	(2)	(3)
	% Woody Savannas		
Grant × Concession	4.093***	4.090***	4.306***
	(0.788)	(0.788)	(0.937)
Observations	6,660	6,660	6,642
R-squared	0.907	0.907	0.913
Cell FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Concession × Year FE	No	No	Yes
Rain	No	Yes	Yes
Mean y | Grant = 0 & Concession = 0	17.61	17.61	17.61

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variable is the percentage of cell covered by "Woody Savannas" (MODIS). The sample is restricted to grid cells within 10km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Concession* is an indicator for cells located inside a palm oil concession. Standard errors (in parentheses) are clustered at the cell level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Air pollution

Dep. Variable	(1) PM2.5	(2) CO2	(3) N2O
Panel A: 10km sample			
Grant × Concession	0.204**	174.7*	0.0873**
	(0.0857)	(101.3)	(0.0364)
Observations	5,994	6,642	6,642
R-squared	0.984	0.871	0.939
Cell FE	Yes	Yes	Yes
Concession × Year FE	Yes	Yes	Yes
Rain	Yes	Yes	Yes
Mean y | Grant = 0 & Concession = 0	42.932	281.245	0.651
Panel B: 20km sample			
Grant × Concession	0.177***	172.6**	0.0805***
	(0.0664)	(81.60)	(0.0298)
Observations	9,126	11,502	11,502
R-squared	0.981	0.870	0.936
Cell FE	Yes	Yes	Yes
Concession × Year FE	Yes	Yes	Yes
Rain	Yes	Yes	Yes
Mean y | Grant = 0 & Concession = 0	43.218	284.672	0.667

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variables are PM25, the average PM2.5 emission in the year-cell (ACAG B6GL01 data), CO2, the average CO2 emission in the year-cell (EDGAR v8.0 data), and N2O, the average N20 emission in the year-cell (EDGAR v8.0 data). The sample is restricted to grid cells within 10km of concession boundaries, in Panel A, and 20km in Panel B. *Grant* is a dummy equal to one after the year the closest palm oil concession was granted. *Concession* is a dummy equal to one for cells in a concession. Standard errors (in parentheses) are clustered at the cell level in columns (1)-(4). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A7: BACI categories (HS02)

HS Code	Description	Palm oil
Fertilizers → Fertilizers		
310100	fertilizers, produced by the mixing or chemical treatment of animal or vegetable products	
310210	nitrogenous, urea, whether or not in aqueous solution	✓
310221	nitrogenous, ammonium sulphate	✓
310229	nitrogenous, other than ammonium sulphate	✓
310230	nitrogenous, ammonium nitrate, whether or not in aqueous solution	✓
310240	ammonium nitrate with calcium carbonate or other inorganic non-fertilizing substances, mixtures thereof	✓
310250	nitrogenous, sodium nitrate	✓
310260	nitrogenous, double salts and mixtures of calcium nitrate and ammonium nitrate	✓
310270	nitrogenous, calcium cyanamide	✓
310280	nitrogenous, mixtures of urea and ammonium nitrate in aqueous or ammoniacal solution	✓
310290	nitrogenous, other kinds including mixtures not specified in the foregoing subheadings	✓
310310	phosphatic, superphosphates	
310390	phosphatic, n.e.c. in heading no. 3103	
310420	potassic, potassium chloride	✓
310430	potassic, potassium sulphate	✓
310490	potassic, n.e.c. in heading no. 3104	✓
310510	in tablets or similar forms or in packages of a gross weight not exceeding 10kg	
310520	containing the three fertilizing elements nitrogen, phosphorus and potassium	
310530	diammonium hydrogenorthophosphate (diammonium phosphate)	
310540	ammonium dihydrogenorthophosphate (monoammonium phosphate) and mixtures thereof [...]	
310551	containing nitrates and phosphates	
310559	containing the two fertilizing elements nitrogen and phosphorus, other than nitrates and phosphates	
310560	containing the two fertilizing elements phosphorus and potassium	
310590	n.e.c. in heading no. 3105	
Tools for working in the hand [...] → Harvesting tools		
846711	for working in the hand, pneumatic, rotary type (including combined rotary-percussion)	
846719	for working in the hand, pneumatic, other than rotary type	
846721	for working in the hand, with self-contained electric motor: drills of all kinds	
846722	for working in the hand, with self-contained electric motor: saws	
846729	for working in the hand, with self-contained electric motor: other than saws and drills	✓
846781	for working in the hand, chain saws with self-contained non-electric motor	
846789	for working in the hand, (other than chain saws), hydraulic or with self-contained non-electric motor, (not pneumatic)	
846791	for working in the hand, parts of chain saws, with self-contained non-electric motor	
846792	for working in the hand, parts of pneumatic tools	
846799	for working in the hand, parts thereof for other than chain saws and pneumatic tools	
Machines and mechanical appliances having individual functions → Extracting machines		
847910	for public works, building or the like	
847920	for the extraction or preparation of animal or fixed vegetable fats or oils	✓
847930	presses for the manufacture of particle or fibre building board of wood or other ligneous materials [...]	
847940	for making rope or cable	
847950	industrial robots, n.e.c. or included	
847960	evaporative air coolers	
847981	for treating metal, including electric wire coil-winders	
847982	for mixing, kneading, crushing, grinding, screening, sifting, homogenising, emulsifying or stirring	✓
847989	having individual functions, n.e.c. or included in this chapter	
847990	parts, of those having individual functions	

Table A8: Imports

Dep. Variable	(1) Fertilizers	(2) Extracting machines	(3) Harvesting tools
Panel A: inverse hyperbolic sine transformation			
Palm oil	-0.097	-0.564**	-0.376
	(0.224)	(0.272)	(0.265)
Grant	0.574***	0.574***	0.574***
	(0.015)	(0.015)	(0.015)
Palm oil × Grant	0.966***	1.696***	1.439***
	(0.368)	(0.500)	(0.438)
Observations	79,679	79,509	79,560
Mean y | Grant = 0 & Palm oil = 0	1.050	1.050	1.050
Panel B: log + 1			
Palm oil	-0.076	-0.49**	-0.349*
	(0.194)	(0.220)	(0.201)
Grant	0.498***	0.498***	0.498***
	(0.014)	(0.014)	(0.014)
Palm oil × Grant	0.916***	1.420***	1.136***
	(0.329)	(0.431)	(0.370)
Observations	79,679	79,509	79,560
Mean y | Grant = 0 & Palm oil = 0	0.877	0.877	0.877

Notes: OLS regressions, equation 2 (Section 5). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. Dependent variable is the inverse hyperbolic sine transformation (panel A) or the log + 1 (panel B) of the quantity imported in Liberia. *Grant* is a dummy equal to one after (and including) 2008. *Palm oil* is a dummy equal to one for products belonging to the relevant products in the palm oil production process indicated in the column, more information in Table A7. In each regression the other palm oil products have been excluded from the sample.

Table A9: Imports - placebo

	(1) Harvest/Thresh	(2) Poultry	(3) Soil Prep	(4) Drills	(5) Telecom	(6) Cosmetic	(7) Office
Panel A: inverse hyperbolic sine transformation							
Product	-0.791***	-0.732**	-0.611***	0.435	0.232	1.706***	-0.169
	(-8.75)	(-2.89)	(-5.12)	(1.61)	(1.14)	(3.42)	(-0.63)
Grant	0.574***	0.574***	0.573***	0.574***	0.574***	0.573***	0.573***
	(37.40)	(37.42)	(37.34)	(37.41)	(37.41)	(37.40)	(37.38)
Product × Grant	-0.287*	-0.310	0.371	0.453	-0.275	0.556	0.791
	(-2.03)	(-0.96)	(1.81)	(1.30)	(-0.94)	(0.90)	(1.46)
Observations	79,475	79,475	79,475	79,475	79,475	79,475	79,475
Mean y | Grant = 0 & Product = 0	1.051	1.051	1.051	1.051	1.051	1.051	1.051
Panel B: log + 1							
Product	-0.685***	-0.614**	-0.544***	0.262	0.149	1.511***	-0.184
	(-9.79)	(-2.83)	(-5.82)	(1.27)	(0.89)	(3.42)	(-0.85)
Grant	0.499***	0.498***	0.498***	0.498***	0.499***	0.498***	0.498***
	(36.86)	(36.88)	(36.81)	(36.87)	(36.87)	(36.86)	(36.84)
Product × Grant	-0.263*	-0.300	0.278	0.345	-0.208	0.502	0.746
	(-2.33)	(-1.11)	(1.67)	(1.25)	(-0.84)	(0.91)	(1.57)
Observations	79,475	79,475	79,475	79,475	79,475	79,475	79,475
Mean y | Grant = 0 & Product = 0	0.887	0.887	0.887	0.887	0.887	0.887	0.887

Notes: OLS regressions, equation 2 (Section 5). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Grant* is a dummy equal to one after 2008. Dependent variable is the inverse hyperbolic sine transformation of the quantity imported in Liberia. *Product* is a dummy equal to one for products belonging to the relevant products indicated in the column. In particular, *Harvest/Tresh*: HS-843330, 843340, 843351, 843352, 843353, 843359, 843360, 843390; "Poultry": HS-843621, 843629, 843691; "Soil prep.": HS-8432; "Drills": HS-846721; "Telecommunication": HS-8517; "Cosmetics": HS-3304; "Office equ.": HS-8472. Palm oil products excluded from the control group, more information on these products in Table A7.

Table A10: Nightlights and Population

Dep. Variable:	(1) Nightlights	(2) Population
Grant × Concession	-0.000971	0.0803**
	(0.0697)	(0.0370)
Observations	4,797	6,642
R-squared	0.327	0.673
Cell FE	Yes	Yes
Concession × Year FE	Yes	Yes

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variables are nightlights, nighttime light density from harmonized DMSP-VIIRS data (Li et al., 2020), and population, count from LandScan satellite-detected population data. The regression in model (1) is done on a sample from 2006 to 2018 due to sample availability. Both dependent variables are standardized to have mean zero and standard deviation one. The sample is restricted to grid cells within 10km of concession boundaries. *Grant* is a dummy equal to one after the year the closest palm oil concession was granted. *Concession* is a dummy equal to one for cells in a concession. Standard errors (in parentheses) are clustered at the cell level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A11: DHS placebo outcomes

Dep. Variable	(1) Altitude	(2) Time to water	(3) Age	(4) Kpelle	(5) Christian	(6) Literacy	(7) Edu years	(8) We/He	(9) Child We/He	(10) Num. child
Grant	0.0669***	0.0840	0.0705	-0.101***	-0.0539		-0.0688			0.390***
	(0.0177)	(0.0756)	(0.0616)	(0.0278)	(0.0351)		(0.0593)			(0.0669)
Grant × Within	-0.0255	-0.0662	-0.0950	0.0195	0.0253	-0.00118	0.0119	-0.0149	-0.0990	0.0344
	(0.0171)	(0.0521)	(0.0619)	(0.0191)	(0.0347)	(0.0747)	(0.0546)	(0.0994)	(0.118)	(0.0575)
Observations	5,216	6,305	7,177	3,345	7,155	4,454	7,175	2,848	1,480	7,177
R-squared	0.187	0.029	0.003	0.024	0.008	0.036	0.036	0.006	0.012	0.044
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within × Concession FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). Altitude is the altitude of the village; time to water is the time to the nearest water source; age is the age of the DHS respondent; kpelle is a dummy variable indicating whether the individual belongs to the kpelle ethnicity; christian is a dummy variable indicating whether the individual declares to be christian; literacy is a dummy variable indicating whether the respondent can read (part of) a sentence; education years is the years of education the respondent declares to have; We/He is the weight over height of the respondent; Child We/He is the average child weight over height; num. child is the number of children. All dependent variables are standardized to have mean zero and standard deviation one. The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is an indicator for individuals residing inside a concession. All specifications include year and within × concession fixed effects. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A12: Land ownership

Dep. Variable:	(1) Land	(2) Land	(3) Urban	(4) Urban
Grant	0.0146	0.0103	0.0133	0.0134
	(0.0218)	(0.0217)	(0.0125)	(0.0125)
Grant × Within	-0.167***	-0.151***	-0.151***	-0.151***
	(0.0312)	(0.0311)	(0.0109)	(0.0109)
Observations	9,597	9,597	39,993	39,993
R-squared	0.095	0.100	0.153	0.153
Year FE	Yes	Yes	Yes	Yes
Within × Concession FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean y | Grant = 0 & Within = 0	0.254	0.254	0.396	0.396

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The dependent variable is an indicator equal to one if the household owns any agricultural land in models (1) and (2), and an indicator equal to one if the household lives in an urban area in models (3) and (4). The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is a dummy equal to one for individuals within a concession. All specifications include year and within × concession fixed effects. Control variable (where indicated) is respondent's age. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A13: Unemployment - check

Dep. Variable	(1) Unemployed	(2) Unemployed	(3) Not working	(4) Not working
Grant × Within	0.0201	0.0187	0.143***	0.126***
	(0.0194)	(0.0223)	(0.0385)	(0.0385)
Observations	3,932	3,932	4,447	4,445
R-squared	0.130	0.227	0.038	0.132
Year FE	Yes	Yes	Yes	Yes
Wave × Concession FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean y | Grant = 0 & Within = 0	0.000	0.000	0.567	0.567

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE), for wives. Outcome variables are indicators for (1-2) the individual reports to be not working in the occupation variable, and (3-4) the individual reports to be not working in the working variable. The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is an indicator for individuals residing inside a concession. The *Grant* coefficient is perfectly collinear with fixed effects in this specification, since the DHS waves are 2007, 2013, and 2019 and all the palm oil concessions were granted between 2007 and 2013. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables (where indicated) are age and years of education.

Table A14: Occupation - no controls

Dep. Variable	(1) Unemployed	(2) Sales	(3) Agri. self	(4) Agri. empl	(5) Services	(6) Manual
Panel A: wife						
Grant × Within	0.0201	-0.00722	-0.0986**	0.0482***	0.0134	-0.00239
	(0.0194)	(0.0382)	(0.0414)	(0.0149)	(0.0135)	(0.00896)
Observations	3,932	3,932	3,932	3,932	3,932	3,932
R-squared	0.130	0.037	0.323	0.115	0.061	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave × Concession FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Grant = 0 & Within = 0	0.000	0.269	0.623	0.016	0.016	0.011
Panel B: husband						
Grant × Within	-0.0158*	-0.0214	-0.0942**	0.0731***	0.0690***	0.00331
	(0.00876)	(0.0258)	(0.0441)	(0.0237)	(0.0217)	(0.0290)
Observations	2,841	2,841	2,841	2,841	2,841	2,841
R-squared	0.052	0.017	0.237	0.199	0.019	0.047
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave × Concession FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Grant = 0 & Within = 0	0.000	0.077	0.481	0.081	0.089	0.127

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE), separately for wives (Panel A) and husbands (Panel B). Outcome variables are indicators for: Unemployed = not working; Sales = employed in sales; Agriculture employee = employed in agriculture; Agricultural self-employment = self-employed in agriculture; Services = employed in services; Manual = employed in manual labor. The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is an indicator for individuals residing inside a concession. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A15: Wealth

Dep. Variable	(1) Wealth Index	(2) Wealth Index
Grant	0.118**	0.138***
	(0.0534)	(0.0488)
Grant × Within	0.0559	0.0562
	(0.0425)	(0.0409)
Observations	7,177	7,175
R-squared	0.134	0.250
Year FE	Yes	Yes
Within × Concession FE	Yes	Yes
Controls	No	Yes

Notes: The table presents results from a linear regression with high-dimensional fixed effects (HDFE) estimated using the method of within fixed effects (MWFE). The outcome variables is the DHS wealth index. The sample is restricted to DHS respondents living within 20km of concession boundaries. *Grant* is an indicator equal to one for years after the nearest palm oil concession was granted. *Within* is an indicator for individuals residing inside a concession. Robust standard errors shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables are age and years of education.