Large Scale Land Acquisitions: Trees, Trade, and Structural Change*

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Abstract

By 2022, large-scale land acquisitions, a key component of agricultural foreign direct investment, covered more than 4% of the world's arable land. This paper examines their impact on agricultural production, environmental outcomes, and local communities. To identify these effects, we exploit an exogenous increase in palm oil land acquisitions driven by the Ebola epidemic in Liberia. We find a substantial increase in land dedicated to palm oil cultivation and increased imports of palm oil-specific inputs, suggesting a transition from traditional to industrial production. This is associated with a subsequent significant increase in palm oil exports. The expansion of this tradable industry generated modest positive effects on the local economy and spurred structural transformation: women transitioned from agriculture to service and sales jobs, while men shifted into manual labor positions. The expansion also entailed negative environmental consequences, including increased deforestation, air pollution, and forest fires.

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

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1 Introduction

Resource-based concessions represent an important component of investment structures in developing economies, which experienced an overall growth of foreign direct investment of approximately 10% yearly between 2000 and 2017, peaking at $15 billion in 2015. The primary form of these investments is the acquisition or long-term leasing of land, commonly referred to as large-scale land acquisitions (LSLAs)—another term for land concessions. By 2022, over 60 million hectares were acquired globally through public large-scale land deals (4.3% of the world's arable land—more than the total arable land in Brazil, which ranks fifth globally in arable land area), and the number of large-scale land contracts increased by 128% over the past 13 years.[1] Since their inception, these concessions have sparked significant debate.[2] Advocates highlight potential benefits such as increased productivity, capital inflows, and positive impacts on local economies. Critics emphasize negative environmental consequences, the absence of production gains, and detrimental effects on local economies.[3] However, empirical evidence on their effects remains scarce, as suggested by the call for further research by Liao et al. (2016). Indeed, the sparse nature of concession data, combined with their endogenous allocation, makes it particularly difficult to identify their effects.

This paper documents an exogenous increase in LSLAs and leverages this increase to examine its consequences on agricultural production, environmental outcomes, and local communities. We perform our analysis in the palm oil sector in Liberia. The country's unique bureaucratic procedures for granting land concessions and the specificities of the palm oil production process enable us to detect variations in land acquisitions, usually unobserved, through changes in deforestation. Our results may be extended to land acquisitions in developing countries characterized by extensive monocultures, accounting for more than 65% of all land deals recorded as of the end of 2024.[4] Notably, 15% of worldwide LSLA deals involve palm oil exclusively. Therefore, our findings speak to the consequences of a large transformation process affecting the agricultural sector in developing countries.

We combine geo-localized data on tree coverage, palm oil concessions, household surveys, and additional ancillary data. The resulting dataset is structured as a comprehensive grid of Liberia, comprising 30,114 cells, each covering approximately 5 km^2 over a nine-year period. To measure deforestation, we use

[1] Authors' calculations based on data from FAOSTAT for FDI inflows; FAO report on FDI in agriculture (FAO, 2009) and German Federal Ministry for Economic Cooperation and Development (GTZ, 2009) for investment details; Land Matrix for data on land acquisitions; and FAO (2021) for world's arable land (1.38 billion hectares in 2019).

[2] This phenomenon is more prevalent in developing countries, particularly in Africa (Deininger & Byerlee, 2011; De Schutter, 2011; Nolte et al., 2016). Although less widespread, these acquisitions also occur in developed countries. For instance, in Romania, more than 35% of agricultural land is owned by foreign investors (European Economic and Social Committee, 2015).

[3] 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.

[4] Authors' calculations based on data from Land Matrix. Developing countries include those in Africa, South and Central America, South-Eastern Asia, and Eastern Europe. Extensive monoculture crops are defined here as corn, wheat, cotton, palm oil, timber, and rubber trees, which share similar production characteristics.

MODIS Vegetation Continuous Fields, which provides percentage coverage data across seventeen mutually exclusive land cover classes. This enables us to quantify both deforestation and palm oil cultivation. To define the concessions, we rely on maps provided by Global Forest Watch. To examine the effects of LSLA on local communities, we use data from the Demographic and Health Surveys (DHS) data. These nationally representative household surveys collect a wide range of indicators on health, demographics, education, and employment.

The analysis consists of three steps. First, we document an exogenous increase in LSLA contracts, driven by the 2014 Ebola epidemic, through changes in deforestation. Deforestation allows us to measure LSLAs, although land contracts are unobserved.[5] We do so by employing a local difference-in-difference design, using areas outside the concessions—up to 10 km from the border—as a control group. Our identification assumption is that the Ebola epidemic had no differential impact *locally*, just outside and just inside areas *designated for LSLA*, other than LSLAs itself. The local nature of our strategy is key for identification. These areas were specifically designated for palm oil LSLA contracts, and their boundaries do not align with administrative ones (as shown in Figure A4 in Appendix A).[6] This implies that the only factor discontinuous at the border is the possibility of signing large-scale land contracts. By comparing pixels located just outside and just inside the areas of interest before and after the Ebola outbreak, we observe a 3% decrease in the percentage of evergreen broadleaf cover (more than 100 million trees lost). The staggered local difference-in-difference analysis reveals no significant pre-trend in deforestation. These results indicate an increase in LSLA contracts within the areas of interest driven by the outbreak of the Ebola epidemic. We document one potential mechanism that may explain this pattern: the diversion of NGOs' attention—previously focused on protecting locals' land rights—towards the health crisis. In Section 4.1, and more in detail in Appendix E, we provide detailed supporting evidence for this explanation.

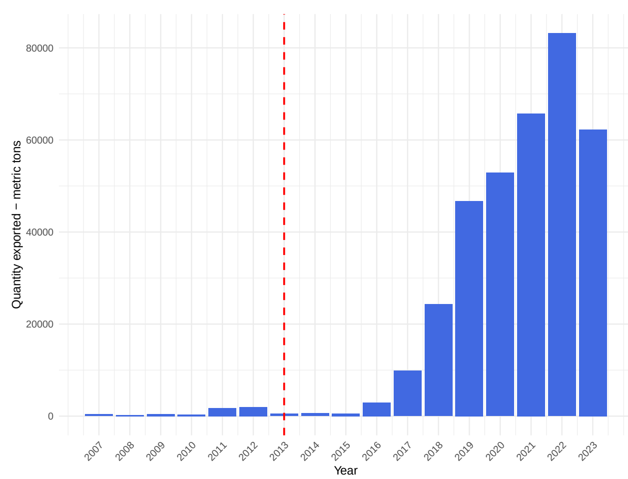
Second, we leverage this exogenous increase to examine the consequences of LSLAs on palm oil production. We focus on two main production inputs: land and capital. Using the same specification and identification assumption as in the previous analysis, we find an increase in palm oil land cover that precisely offsets the decrease in forest cover, indicating an increase in cultivation. To complement this evidence, we also use additional data that allows us to study the proportion of land allocated to each crop. We find that in these areas land was already being used to produce cereals, palm oil, and roots, and that, following the Ebola outbreak, there was a substantial increase in land dedicated to palm oil cultivation. For capital, we study imports of palm oil inputs. We compare these imports with other imports before and after the health crisis. The identification strategy relies on a standard parallel trends assumption: in the absence of the health crisis, imports of palm oil inputs would have followed the same trend as all other

[5]Deforestation is the essential initial step in palm oil production. Furthermore, only palm oil companies are permitted to operate within concession areas in Liberia. Although concessions may have already been granted, companies cannot expand production in these areas without signing new agreements with local communities. Consequently, within palm oil concessions in Liberia, deforestation serves as a necessary and sufficient condition for LSLA contracts. Section 4.1 provides a detailed explanation of this context.

[6]As a result, land use (Figure 4), wealth and health of individuals (Table 2), and their occupation (Table 3), were balanced across the boundaries before the Ebola outbreak.

Liberian imports. Due to the aggregate nature of this analysis, however, causal identification remains more limited at this stage. Nevertheless, the detailed granularity of the import data and the resulting ability to target palm oil inputs specifically are reassuring about our ability to identify key correlations in the data. We find an increase in the imports of fertilizers, harvesting tools, and palm oil extracting machines. As a placebo exercise, we explore the effects on other non-agricultural and agricultural imports, finding null effects. Most importantly, we observe no increase in similar products used in agriculture but not in the palm oil sector (such as milling machines). These results suggest a substantial expansion in land allocated to palm oil cultivation, and a transition from a traditional, labour intensive, production equilibrium to a more industrial one. This is associated, approximately three to four years after the epidemic—the time required for plantations to mature, comparing the mean before 2013 to the mean in 2016 and 2017—with a 1064% increase in the quantity of palm oil exported from Liberia (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. It takes 3-4 years for a plantation to become productive, which explains the lag between the Ebola outbreak (2014) and the increase in exports. Export data from BACI HS6 Revision 1992 (1995 - 2018), 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).

Third, we explore the effects of this increase in LSLA on the environment and the local economy. By comparing pixels just outside and just inside concessions, before and after the Ebola outbreak, we find a 12% increase in carbon dioxide emissions, consistent with other palm oil contexts, a 1% increase in PM2.5 and no change in N2O. We also find a significant increase in fire events, which is in line with the increase in PM2.5, although the precision of the estimate varies across specifications. To conclude, we look at the effects on the local economy with survey data (the DHS). We compare individuals living in villages just outside and just inside the same concession, before and after the Ebola outbreak. Placebo tests (e.g., age, religion, ethnicity) confirm no pre-existing differences or time trends. We document a 12% decline in land ownership, confirming the link between deforestation and LSLAs in the Liberian palm oil sector. At the same time, wealth and health indicators improve modestly, with increases in the wealth index (0.34 standard deviations), education levels (13%), and weight-for-height (0.176 standard deviations), despite no pre-Ebola differences in these outcomes. We find no significant change in unemployment rates, but sectoral shifts. After the outbreak, agricultural employment declines by 25% for wives and 20% for husbands in the affected areas. Wives transition primarily to sales and services (up 32%), while husbands shift to manual labor (up 33%). All results are robust to different specifications and robustness checks. For example, when limited to the subsample of individuals who had lived in the village for at least 6 years–the minimum time period between the last year of our sample (2018) and the Ebola outbreak (2013)–or when we gradually restrict the control sample to increasingly distant villages to assess potential violations of the SUTVA assumption.

Overall, the findings suggest that LSLAs have significantly expanded palm oil production (both by reallocating land from forests to this cultivation and by shifting the production equilibrium from a traditional to a more industrial, capital intensive one), targeting global markets (in line with the predetermined goals: Republic of Liberia & International Trade Center - WTO and UN, 2014). The expansion of this tradable industry has brought modest improvements in wealth, health, and education outcomes for residents in the affected areas. Additionally, it appears to have initiated a structural transformation, with some individuals transitioning out of agriculture into sectors such as sales, services, and manual labor, likely reflecting changes in the relative use of inputs within the sector. However, these developments are accompanied by increased deforestation, higher CO2 emissions, and forest fires. These findings may extend to LSLAs, and, more generally, agricultural FDIs in extensive crops within developing countries. Notably, 94% of LSLAs occur in developing nations (including regions such as Africa, South and Central America, South-Eastern Asia, and Eastern Europe), with 71% focused on extensive monoculture crops such as corn, wheat, cotton, palm oil, timber, and rubber.

This paper relates to two related strands of literature. The primary one focuses on the effects of resource concessions on local economies. Although mainly developed outside economics, this literature has primarily examined historical concessions, highlighting negative consequences for long-run development (e.g. Dell, 2010; Bobonis & Morrow, 2014; Lowes & Montero, 2021) with some exceptions (Dell & Olken, 2020).[7] Within this literature, the closest paper to ours is Méndez and Van Patten (2022), which demonstrates positive effects of land concessions on living standards in Costa Rica. We complement their work by examining effects on agricultural production and environmental outcomes, while also providing an alternative mechanism for these effects: changes in production inputs and the consequent structural

[7] The majority of scholars have highlighted the negative environmental consequences of this phenomenon, ranging from controlled fires (e.g., Nepstad et al., 1999; Carlson et al., 2012), to deforestation (e.g., Davis et al., 2015, 2020; Probst et al., 2020), and water scarcity (e.g. Rulli et al., 2013; Johansson et al., 2016; Chung, 2019). Few scholars in development studies have presented often contrasting evidence on employment (e.g., Baumgartner et al., 2015 and Nolte & Ostermeier, 2017 document negative effects, while Anti, 2021 null effects) and welfare (e.g., negative effects as documented by Rulli & D'Odorico, 2014 and Anti, 2021, and positive as highlighted by Herrmann, 2017).

transformation.

Looking at this question from a different perspective, it can be associated with the classical literature exploring the relationship between foreign direct investment and development.[8] The evidence on this relationship is mixed, with contrasting results on capital accumulation (Prasad et al., 2007; Morrissey & Udomkerdmongkol, 2012), productivity (Aitken & Harrison, 1999; Aghion et al., 2006; H. Hansen & Rand, 2006; Contessi & Weinberger, 2009), conflict (e.g., Martin et al., 2008b; Gehring et al., 2022; Sonno, 2024), and overall a complex causal relationship between FDI and growth in developing countries (e.g., Aitken & Harrison, 1999; Chakraborty & Basu, 2002).[9] Starting conditions–such as initial income (Blomstrom et al., 1992), initial human capital (Borensztein et al., 1998), sufficient financial development (Alfaro et al., 2004, 2010), and institutional quality (C. Li & Tanna, 2019)–have been studied as determinants for the mixed results in the literature. This paper contributes to this literature by providing evidence that large-scale land acquisitions may stimulate production, improve local economic conditions, and promote a process of structural transformation by opening access to foreign markets. However, this development comes with an environmental cost.

The second strand of literature is the one on structural transformation. Since the seminal works of Kuznets (1965, 1971, 1973), economists have linked economic development with an employment transition away from agriculture (e.g., Chenery, 1960; Rostow, 1990).[10] More recently, the literature has focused on the drivers of this process, which can be divided in two groups. Changes of demand resulting from changes in real income, i.e. *demand-side* explanations, and cross-sector differences in production costs-technology, i.e. *supply-side* explanations.[11] These last ones could be determined, for example, by innovations (e.g., Gollin et al., 2002; Ngai & Pissarides, 2007; Alvarez-Cuadrado & Poschke, 2011; Bustos et al., 2016), geographical production dispersion and migration costs (Field, 2007; Bryan et al., 2014; Munshi & Rosenzweig, 2016; Bryan & Morten, 2019; Asher & Novosad, 2020; Morten & Oliveira, 2024), or changes in factor supply and sectoral differences in factor intensity (e.g., Caselli & Coleman II, 2001; Acemoglu & Guerrieri, 2008). This paper contributes to this literature by highlighting another *supply-side* driver of structural change: large-scale land acquisitions, and, more generally, capital-intensive agricultural

[8]The link between trade and economic activity has long been a major subject of enquiry in theories of international trade and economic growth, often highlighting a positive relationship, due to lifts in productivity (e.g., Krugman, 1979; Helpman, 1981), access to foreign markets (e.g., Arrow, 1962; Krugman, 1979; Romer, 1990), and competition/reallocation (e.g., Melitz, 2003; Bernard et al., 2007). Empirically, trade liberalization has often being linked with output growth (e.g., Sachs, 1995; Alesina et al., 2000), productivity increase (e.g., Edwards, 1998; Frankel & Romer, 1998), capital accumulation (e.g., Alvarez, 2017), and ambiguous effects on the labour market (e.g., Hoekman, 2005; Autor et al., 2016). More closely related to the research question of this paper, trade openness has a close association with FDI inflows in developing economies (e.g., Lucas, 1990; Aghion et al., 2006; Buchanan et al., 2012).

[9]Other important contributions on this literature were made by Barbieri (1996); Martin et al. (2008a); Morelli and Sonno (2017); Iacoella et al. (2021); La Ferrara and Zufacchi (2024).

[10]Other important contributions on this link were made by Reynolds (1983); Parente and Prescott (1994, 1999); Laitner (2000); Kongsamut et al. (2001); Gollin et al. (2002)

[11]For the *demand-side* explanations, see Pasinetti (1983); Echevarria (1997); Laitner (2000); Zweimüller (2000); Caselli and Coleman II (2001); Kongsamut et al. (2001); Gollin et al. (2002); Greenwood and Seshadri (2002); Gollin et al. (2007); Foellmi and Zweimüller (2008); Duarte and Restuccia (2010); Boppart (2014). For the *supply-side* explanations, see Baumol (1967); Baumol et al. (1985); Ngai and Pissarides (2007); O'Mahony and Timmer (2009); Herrendorf et al. (2014).

FDIs. Indeed, these could change the employment equilibrium, possibly by shifting the factor intensity in the agriculture industry.

The paper is structured as follows. Section 2 presents the background. Section 3 describes the data. Sections 4 and 5 present and discuss the results, and Section 6 concludes.

2 Background

Palm oil cultivation in Liberia has a longstanding history, traditionally carried out through a labor-intensive system. Palm trees were integrated into diverse landscapes, coexisting with forested areas and other crops. The fruits were harvested and processed locally into red palm oil. The kernels were manually converted into soap or other products, while the sap from the trees was used for palm wine production (Carrere, 2013). As a result, palm oil production in Liberia predominantly served local consumption and was characterized by a polycultural, labor-intensive approach (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, commonly referred to as large scale land acquisitions.[12]

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 Ininternational Development, the World Bank, and the US Department of Agriculture (Liberian Ministry of Finance, 2008). As a result of this process, there is evidence suggesting a shift in Liberian palm oil production from the traditional system to an *industrial system*. This is characterized by oil palm monoculture and high chemical inputs, including fertilizers, to enhance crop growth.[13] Although palm harvesting is still predominantly done manually—particularly by using chisels for younger palms and harvesting sickles on telescopic poles for taller, mature palms (Pashkevich et al., 2024)—the processing of the fruit into palm oil and other secondary products is now centralized in large-scale mechanized industrial plants (Carrere, 2013).

This structural change towards a more capital-intensive monoculture approach has corresponded with

[12]The Liberian palm oil sector comprises seven companies, six of which are part of large multinational groups, collectively owning approximately 10,000 km^2 in palm oil concessions—an area larger than the total surface of a small country, such as Cyprus.

[13]See the article "Palm Oil Cultivation - a West African Story" in Cambridge-Africa (2023).

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).[14]

The bureaucratic procedure for granting land concessions is unique in Liberia, making this setting a unique laboratory to study the effects of large-scale land acquisitions, as we discuss in Section 4.1. To establish large-scale palm oil production in Liberia, companies have to follow a two-step procedure. First, lease land from the central government. For example, two major palm oil agreements signed in 2009 and 2010 granted 440,000 ha to two companies. These large tracts of land are called "areas of interest" and represent our *treatment group*. However, the agreement does not grant any production rights to the companies. Before converting land into plantations, companies must obtain the consent of local communities. Specifically, the company must sign a Memorandum of Understanding with the village living on the land to transform a portion of the area of interest into a working concession. Only once the contract is signed, the designated portion of the area of interest is converted into a concession, allowing the company to deforest and start production (Lowenstein, 2017).

3 Data

To study the effects of LSLA, we combine geolocalized data on the percentage of tree coverage, palm oil areas of interest, agricultural productivity, and household surveys, together with other ancillary data. The main dataset is structured as a full grid of Liberia. Each cell has an area of approximately 5 km^2, for a total of 30,114 cells observed over nine years.

Land Cover Data. The primary source of data is MODIS Vegetation Continuous Fields (Dimiceli et al., 2015), which provides a quantitative representation of the annual percentage of land cover at a 0.05-degree pixel resolution (approx. 5 km^2) for the entire globe for the period 2000-2020. Specifically, for each pixel, we observe the percentage covered by each class as recorded by the International Geosphere-Biosphere Programme (IGBP). This programme categorizes types of land cover into 17 mutually exclusive and precisely defined classes, such as "Water Bodies" (permanent water bodies) and "Evergreen Needleleaf Forests" (evergreen conifer trees with a canopy >2m), among others. Figure A3 in Appendix A shows a cross-sectional plot of the most widespread class in Liberia in 2010, namely "Evergreen Broadleaf Forests". This is our main dependent variable, and since Evergreen Broadleaf Forest is the most common type of tree cover in Liberia, the term "percentage of tree cover" will hereafter refer to the percentage of Evergreen Broadleaf Forest without loss of generality. Thus, we will measure deforestation as a decrease in the percentage of tree cover. Crucially, this dataset also allows for the measurement of changes in other land cover

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

types, ultimately allowing us to measure palm oil land cover.[15]

Palm Oil Areas of Interest. To determine whether a cell belongs to an area of interest, we use data from Global Forest Watch, which provides information on the shape, location, and ownership of palm oil areas of interest in Liberia.[16] No information about the dates of a concession is provided. Therefore, we utilized the ownership data to retrieve this information. Based on several technical reports, we can conclude that all of the areas of interest in our sample were granted by 2010.[17] To avoid potential endogeneity arising from the opening of new areas, we restrict our sample to the period between 2010 and 2018. More information about the palm oil companies can be found in Appendix D.

Individual Level Outcomes. To study the effects of LSLA on local communities, we use the Demographic and Health Surveys (DHS) data. The DHS surveys are nationally representative household surveys that gather a wide range of indicators on health, demographics, and education. We combine these surveys with the Malaria Indicator Survey (MIS), also administered by the DHS program, which focuses more specifically on malaria. From both surveys, we use individual data for men and women aged 15-64. The data provides the geographic coordinates of the households interviewed, allowing us to observe a repeated cross-section of individuals in different villages in Liberia across different waves: before the Ebola outbreak in 2007, 2009, 2011, and 2013, and after it in 2016 and 2019. Figure A4 in Appendix A illustrates the geographical distribution of the DHS-surveyed villages. Figure A5 in Appendix A zooms in on one area of interest to also show the time variation. We observe villages both outside and inside the areas of interest before and after the Ebola outbreak. Consequently, we can compare individuals in villages just outside and just inside these areas before and after the health crisis. From these surveys, we will extract demographic characteristics (age, whether they live in a town or not, whether the head of the household is a male, religion, ethnicity), wealth and education indicators (whether they own any land, the DHS wealth index, the maximum level of education achieved, the ration weight/height, and the same ratio for children), and occupational outcomes (whether they are employed and the sector of occupation, categorized as sales, agriculture, services, manual jobs, or other).

Other data. We complete our set of data with additional sources of data, such as BACI exports, SPAM, population, and weather. See Appendix F for a detailed description of these data.

Descriptive statistics. Table A1 in Appendix B presents descriptive statistics for the sample period. Panel (a) displays the summary statistics for the entire sample, while Panel (b) focuses specifically on the areas of interest. A few features of the data are worth mentioning. First, the average percentage of tree cover is lower in areas of interest than in the full sample, which is expected, as concessionaires must first deforest in order to plant palm oil trees. Conversely, the average percentage of a cell covered by woody savannas is higher within these areas. Second, there is no substantial difference in rainfall between cells inside and outside the areas of interest. Third, Panel (a) indicates that approximately 10% of the cells are located in areas of interest and, indeed, Panel (b) has about 10% as many observations as Panel (a). This is an

[15] Additional details can be found in Section 4.2.1 and Appendix C.

[16] Global Forest Watch. 2019. World Resources Institute. Accessed on 07/23/2020.

[17] For example, "Making concessions in Liberia - Agriculture" (The Africa Report, 2012).

impressive figure, considering that the total land area covered by concessions is approximately 10 thousand km^2. To put this into perspective, this area is larger than the total surface area of a small country like Cyprus, and only slightly smaller than the total surface area of Lebanon. Fourth, the percentage of urban land is higher in Panel (a) than in Panel (b), which is consistent with these areas being predominantly rural. Fifth, turning to DHS data, individuals in concessions are less educated and significantly poorer.

4 Results

In this paper, we study the impact of LSLAs on agricultural, environmental, and local communities. The ideal experiment would consist of a comprehensive dataset of *precisely geolocalised* and *randomly allocated* LSLAs. However, these conditions are impossible to achieve: *local land contracts* are often unobserved, and firms do not acquire land randomly. In addressing the research questions at hand, the absence of randomization is a particularly challenging problem since LSLA areas are *chosen*—invalidating any comparison of inside/outside areas after the contract—and locals decide *when* to sign contracts—creating bias in simple pre/post comparisons within areas of interest.

We proceed in three steps. In Section 4.1, we document an exogenous increase in LSLA contracts, through changes in deforestation. Given this increase in LSLA contracts, in Section 4.2, we study how this has changed production in the palm oil sector. To conclude, in Section 4.3, we explore the effects on the environment and the local economy.

4.1 Large-scale land acquisitions

In the first part of the paper, we document an exogenous increase in LSLA contracts, through changes in deforestation, following the Ebola outbreak.

Measuring LSLA To the best of our knowledge, a comprehensive dataset of local land contracts with detailed information about their locations does not exist.[18] To address this constraint, we use changes in deforestation—observable at a very granular level from satellite images—to detect variation in large-scale land acquisitions. In the palm oil sector, deforestation is the initial fundamental step of production. Moreover, only palm oil companies are allowed to operate on a large scale in these concessions. Therefore, a large increase in deforestation within palm oil areas indicates an increase in companies' activities. Given the bureaucratic process described in Section 2, in the Liberian context, an increase in operations implies the signing of *new* LSLA contracts. Indeed, companies cannot expand cultivations without signing *new* contracts with local communities. Therefore, we can conclude that an increase in deforestation within the

[18] The only existing land deals dataset is Land Matrix, which records some land deals worldwide as well as some of their characteristics. However, the recorded contracts are often not local, the spatial structure of land deals is almost always missing, and is often particularly poor.

Liberian areas of interest indicates an increase in LSLA contracts.[19]

Suggestive evidence Figure 2 displays deforestation events for one of the palm oil areas of interest in Liberia. In the first map, located at the top-left, pixels (30×30 meters) are coloured red if a deforestation event occurred between 2001 and 2010, and each successive map represents the passage of one year.[20] As shown, subsequent deforestation events were quite rare up to 2013. However, in 2014 and 2015, during the Ebola outbreak, there was a significant increase in deforestation.[21] Anecdotal evidence also supports this connection between Ebola and LSLA contracts. During the years from 2010 to 2014, one leading palm oil company signed agreements for a total area of approximately 298 km^2. In the three months between August and October 2014, i.e. just after the epidemic's outbreak, the number of agreements increased by 45% (Global Witness, 2015).

Methodology By leveraging the relationship between LSLA contracts and deforestation, we use a staggered local (up to 10km from the border) difference-in-difference to document an exogenous shift in LSLAs within the areas of interest following the Ebola epidemic. Figure A2 in Appendix A presents a map of the design.[22] We compare areas just outside and just inside the areas of interest before and after the outbreak of the health crisis. The identification assumption is that Ebola has no differential impact *locally*, outside and inside areas *designated for LSLA*, other than LSLAs itself. The reduced form model is:

$$P_{krt} = \alpha + \sum_{t=2010}^{2018} \beta_t \, T_t \times A_{kr} + \mu_k + \mu_{rt} + u_{krt} \tag{1}$$

where (*k,r,t*) stand for cell, region, and year, respectively; P_{krt} indicates the percentage of tree cover; T_t are year dummies (2013 is used as reference year); and A_{kr} is a dummy variable equal to one for cells belonging to areas of interest. Cell (μ_k) and region-year (μ_{rt}) fixed effects are included, and standard errors are clustered at the cell level in all specifications.

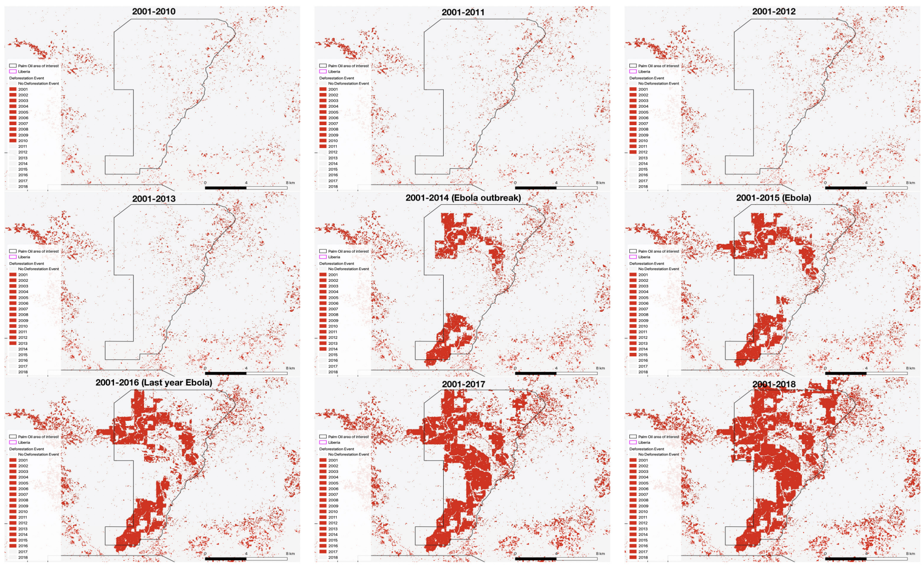
[19] This is true under the assumption that companies acquire the land and begin production in the same year. We believe this is a reasonable assumption for two main reasons. First, leaving land uncultivated is a second-best choice for a profit-maximizing firm. Second, these are large companies, thus unlikely to face production constraints, having been present in Liberia well before the period of study. Under this assumption, in Liberia, within palm oil areas of interest, deforestation is a necessary and sufficient condition for the signing of new LSLAs. Necessary because, assuming LSLA contracts had been signed, then companies would start production in the same year and, therefore, we would observe deforestation. Sufficient because, assuming large deforestation within palm oil areas of interest had occurred since only palm oil companies were allowed to operate at this scale within the concessions, then LSLA contracts must have been signed.

[20] To easily visualize tree cover loss, we use data at approximately 30×30-meter resolution (M. C. Hansen et al., 2013).

[21] Anecdotal evidence suggests that this may be attributed to a diversion of attention of NGOs (Global Witness, 2015; Roundtable on Sustainable Palm Oil Complaint Portal; Forest Peoples Programme, 2015), which may have constrained companies' acquisitions before the health crisis. Although our results are not reliant on this mechanism, we present several evidence supporting it in Section E. An alternative explanation might be an increase in the price of palm oil, however, this is not supported by the data, as shown in Figure A1 in Appendix A. Other potential mechanisms are explored in Section E, together with their potential implications for the identification assumption.

[22] The distance from cells to boundaries is computed as the (shortest) path from the centroid of each cell to the area's boundary, and 10 km is the maximum distance from a cell to the boundary of the area of interest. Hence, by restricting the sample to cells within 10 km of the boundary we are guaranteed that the sample will include all cells within the *treatment* group.

Figure 2: Ebola and deforestation



Notes: The figure presents the deforestation process within one palm oil area of interest in Liberia. In particular, in the top-left map, pixels (30×30 meters) are coloured red if a deforestation event occurred between 2001 and 2010. Each successive map represents the passage of one additional year. As can be seen, deforestation events were quite rare within the area of interest up to 2013, but in 2014 and 2015 there was a quantum leap.

Results Figure 3 presents the results. There does not appear to be any significant pre-trend in deforestation: near the boundaries, there is no notable difference in tree cover during the years preceding the Ebola outbreak. However, beginning in 2014, there was a marked decrease in the percentage of tree cover within the areas of interest.[23]

To calculate the magnitude of these results, we perform a simple local difference-in-difference, comparing cells located just within and just outside (up to 10km) the areas of interest before and after the Ebola outbreak. The results (detailed in Table A2 in Appendix B) confirm a decrease in the percentage of evergreen broadleaf cover of approximately 3% across all specifications.[24] To put this into perspective, this corresponds to a loss of over 100 million trees from 2014 to 2018.[25]

[23] Figure A6 in Appendix A examines the sensitivity of the results to the sample choice of 10 km. Specifically, we change this number from 5 km to 20 km, with steps of 1 km. Results are consistent across all specifications.

[24] These results hold with cell and year fixed effects (column 1 of Table A2 in Appendix B), similar to a standard two-way fixed effects approach, controlling for rainfall and population in the cell (column 2), and with the more demanding (and favourite) specification with region $\times$ year fixed effects (column 3). Table A3 in Appendix B assesses the sensitivity of the results. The conclusions remain unchanged with robust standard errors and when accounting for their spatial and temporal correlation, as elaborated by Colella et al. (2019), based on the work of Conley (1999). The results are robust to different sets of weather controls (lagged rainfall, SPEI, no controls), cell characteristics (nightlights), and different sets of fixed effects (such as omitting cell fixed effects, applying cell-year fixed effects, or using only cell fixed effects).

[25] 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 (25 km^2), approximately $285{,}600 \times 25 \times 0.03 \approx 214{,}200$ trees were cut down per cell. Multiplying this by the total number of cells within areas of interest (≈ 500), we obtain a tree loss of approximately 107 million trees.

Figure 3: Deforestation - Event study

Notes: This figure presents the event-study results from equation (1), with 2013 as reference category. Standard errors are clustered at the cell level, with 95% confidence intervals shown. The coefficient reflects the change in tree cover for cells within the areas of interest, with respect to the control group (10km outside the boundaries), controlling for cell and region-year fixed effects. We measure tree cover as percentage of Evergreen Broadleaf Forests MODIS land cover category, as this is the category associated with forests in Liberia.

In conclusion, the onset of the Ebola epidemic appears to have stimulated deforestation within areas of interest. Under the assumptions outlined at the beginning of this section, this indicates an increase in LSLA contracts. In section 4.3.2, as a check for this conclusion, we show a reduction in the probability of owning any land with individual-level data. Substantial anecdotal evidence suggests that the mechanism behind the relationship between the Ebola epidemic and LSLAs may be due to a diversion of attention among local and international NGOs (Global Witness, 2015; RSPO complain; Forest Peoples Programme, 2015) which were, before the health crisis, limiting the acquisitions. Appendix E provides detailed suggestive evidence in favor of this mechanism.

4.2 Palm oil production

In this section, we examine the effects of this increase in LSLAs on palm oil production. We focus on two main inputs: land and capital. For land, we explore how land cover and area cultivated for different crops have changed within areas of interest after the Ebola outbreak, using the same methodology as in the previous section (staggered local difference-in-difference). For capital, we examine changes in capital utilization in the sectors by studying changes in imports of different inputs for the palm oil production process. Here, we compare the imports of palm oil production inputs with other imports before and after the health crisis. Given the non-local nature of this last step, identification of causal effects is understood to be significantly weaker than in the previous steps, where we exploited differences across borders of areas designated for LSLAs specifically.

4.2.1 Land

Land cover We investigate whether land allocated to palm oil production increased following LSLAs. The MODIS data, as presented in Section 3, offers a direct opportunity to examine this by tracking palm oil cultivations as changes in "Woody Savannas" land cover.[26] Figure 4 presents the staggered local difference-in-difference analysis for the percentage of the cell of the 10 MODIS most relevant categories in the country, i.e. using them as P_{krt} in equation (1).[27] The graph shows a steady decrease in the presence of Evergreen Broadleaf Forests, as shown in Figure 3, together with a corresponding increase in Woody Savannas, the category 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, as expected.

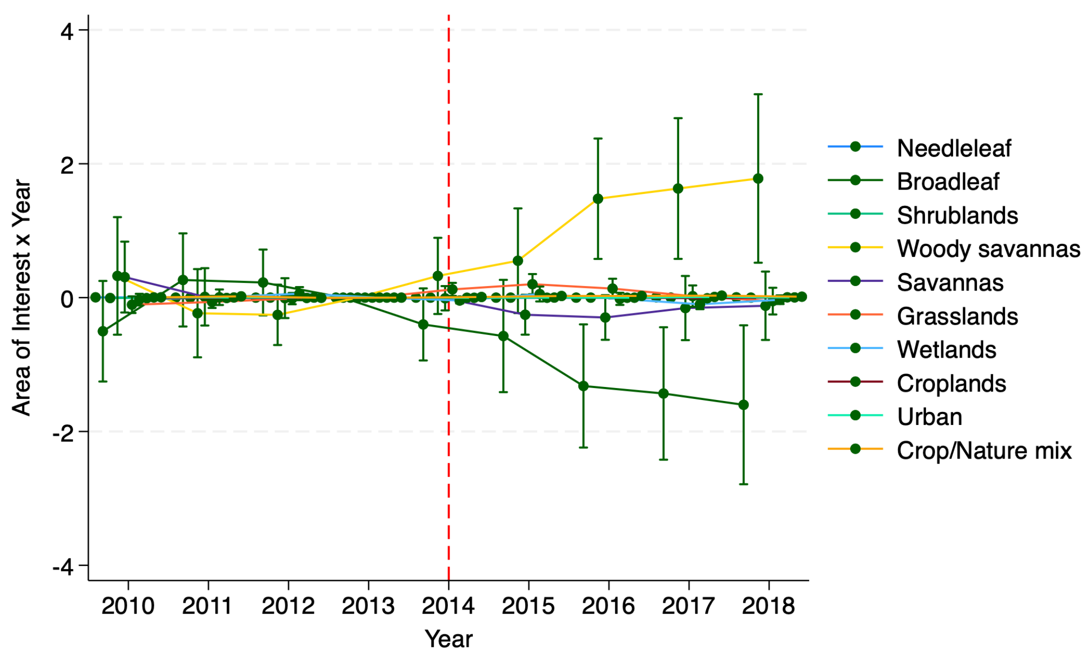
Crops To further investigate the robustness of our results, we look at crop distribution using a different source of data, i.e. the SPAM database (see Appendix F for additional details). This contains estimated global gridded maps of agricultural production. Given its nature and the substantial uncertainty in its spatial allocation methodology, results using these data have to be taken with a grain of salt, particularly regarding the actual geographic distribution of crops and crop production/productivity. Hence, we discuss only the area cultivated for different crops. Table A4 in Appendix B presents the average values of area cultivated, both before (2010) and after (2020) the Ebola outbreak, in areas outside and inside the areas of interest. A few things are worth mentioning. First, palm oil, as well as other agricultural products, were already being produced before the Ebola outbreak within areas of interest—likely by locals or companies with pre-existing LSLA agreements. Second, the production equilibrium was very similar within and outside the areas of interest before the Ebola outbreak. In both areas, land was used to produce mostly cereals, palm oil, and roots—in order of importance—followed by fruits, pulses, and other products. Third, in line with the previous evidence, there is a substantial increase in the area dedicated to palm oil cultivation after the Ebola outbreak within areas of interest. This is true both in the raw data (Table A4 in Appendix B) and when using the local (10km) difference-in-difference approach (Table A5 in Appendix B). While the precise spatial distribution of crop production may be poorly captured due to SPAM's allocation methodology, these results suggest a diverse production before the Ebola outbreak in areas of interest, and a substantial increase in the amount of land dedicated to palm oil following this shock.

Consequently, in areas with a diverse crop cultivation, including palm oil, LSLAs have expanded palm oil production by converting forests into agricultural land.

[26] Specifically, this dataset not only records the percentage cover of Evergreen Broadleaf Forests (referred to as tree cover in the previous analysis, as it is the most prevalent type in Liberia) but also includes data on 16 other mutually exclusive and precisely defined land cover classes. Appendix C provides the reason why we classify palm oil plantations as "Woody Savannas".

[27] We exclude water, permanent ice, barren land, mixed forests, deciduous needleleaf forests, and deciduous broadleaf forests, and we merge the two types of shrublands.

Figure 4: Increase in Palm Oil land cover - Event study



Notes: This figure presents the event-study results from equation (1), with 2013 as reference category. Standard errors are clustered at the cell level, with 95% confidence intervals shown. The coefficient reflects the change in in different MODIS land cover categories for cells within the areas of interest, with respect to the control group (10km outside the boundaries), controlling for cell and region-year fixed effects. We exclude Water, Permanent Ice, Barren Land, Mixed Forests, Deciduous Needleleaf Forests, and Deciduous Broadleaf Forests, and we merge the two types of Shrublands. Evergreen Broadleaf Forests is the category associated with forests in Liberia. Woody Savannas is the category associated with palm oil cultivation, details in Appendix C.

4.2.2 Fertilizers, harvesting tools, and extractive machines

Methodology The anecdotal evidence presented in Section 2 suggests that LSLAs were associated with a shift from traditional production systems toward *industrial* ones. This shift is characterized by higher capital intensity, represented by the use of chemical inputs (fertilizers) and more efficient tools for harvesting and processing. Unfortunately, given the absence of production data from individual plantations, we cannot directly measure change in the use of these inputs. To indirectly provide evidence of a shift in production equilibrium (alongside the previously presented evidence on labor), we focus on imports. The idea stems from the fact that these inputs are not commonly domestically produced. Therefore, if these companies want to use them in production, they need to import them. Moreover, it is unlikely that locals would import these inputs autonomously. To conclude, the availability of these data over time, together with the detailed granularity of import records, allows us to measure changes in the presence of palm oil inputs in the country around the health crisis.

We compare imports of palm oil inputs with other imports before and after the health crisis. The identification assumption is a standard parallel trends assumption, with palm oil input imports following the same trend as all other Liberian imports in the absence of the health crisis. Given the aggregate nature of this exercise, identification in this step is significantly weaker. However, the detailed granularity of import data and the consequent ability to target palm oil inputs specifically, is reassuring about our ability to identify key correlations in the data.

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, enabling 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 A6 in Appendix B. Firstly, given that palm oil is indigenous to Liberia, we do not consider seed imports and the associated equipment. Moreover, inputs related to the first phase have already been addressed in our discussion on deforestation and land allocation for palm oil cultivation.

For the second phase, based on the anecdotal evidence presented in Section 2 and the characteristics of agricultural production, 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).[28] In addition,

[28] 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). It is important to under-

we include hand tools used for harvesting (HS: 846722 to 846791) as saws or chain saws, while excluding unrelated equipment such as drills or polishers.

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, homogenising, emulsifying or stirring" (HS: 846982). Thus, in this category, we can target palm oil-specific machinery with greater precision than in previous classifications. 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.

Results Figure 5 presents the quantities imported for three aggregate product categories (nitrogenous/potassic fertilizers, harvesting tools, and extraction machines) over time. Table A6 in Appendix B presents the 6-digit products in each category. Imports of these key palm oil inputs were very low before the Ebola outbreak, but starting in 2014, there was a substantial increase in imports across all these product categories. The growth rates of imported quantities between the selected years were 495% for nitrogenous and potassic products (2013–2020), 401% for harvesting tools (2013–2019) and 178% for extracting machines (2013–2016). Moreover, the timing of the increase in fertilizers and harvesting tools is consistent with the palm oil production process: an increase in fertilizers first, and, three to four years after the health crisis—the time required for a palm oil tree to be productive—the increase in harvesting tools.[29] Table A7 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 Ebola outbreak, consistent with increased investment and capital intensity in the sector.

Table A8 in Appendix B presents difference-in-differences estimates for placebo products. Panel A focuses on non-agricultural products (drills, cosmetic, telecommunications, office equipments, and musical instruments). Panel B examines products used in agriculture but not in the palm oil sector (fungicides, farm equipment, milling machines, poultry farming machines, and soil preparation machines).[30] The interaction coefficient is small and not statistically different from zero for all these products.

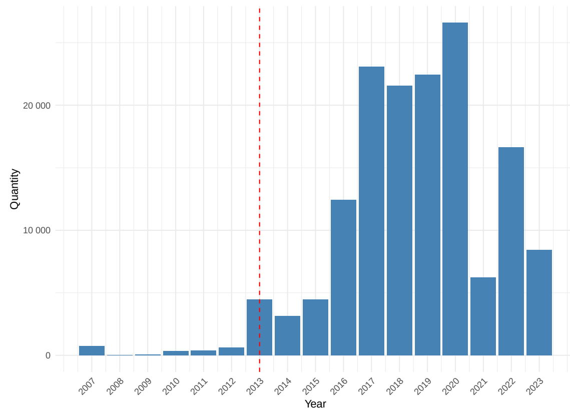
Table A9 in Appendix B replicates the analysis for all 6-digit products within the relevant 4-digit categories (fertilizers, hand tools, and extraction machines). The results show that increases are present almost

line that characterizing fertilizers as palm oil-specific or not is challenging, and it is possible that other fertilizers are also used in this cultivation.

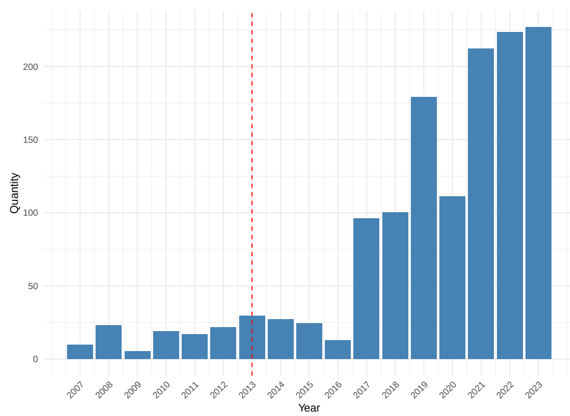
[29] Extractive machines are, instead, imported almost immediately. This could be due to expected technical time for their transportation and installation.

[30] "Farm equipment" refers to a broad range of agricultural machinery used in harvesting and primary processing activities on the farm. This includes equipment for haymaking, baling, threshing (including combine harvesters), as well as machines for root crop harvesting and for cleaning or sorting agricultural produce. Relevant spare parts are also included under this term.

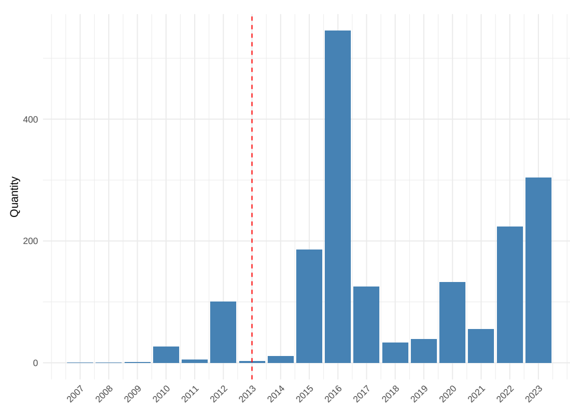
Figure 5: Palm oil inputs imports



Fertilizers - Nitrogenous/Potassic



Harvesting tools



Extracting machines

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: 846722 to 846791), and extracting machines (HS: 846920 and HS: 846982).

exclusively in products related to the palm oil industry, while changes in imports for other similar products are, on average, very small and not statistically different from zero. In categories where distinguishing between non-palm oil and palm oil inputs is challenging (fertilizers), we also observe increases in products not specifically characterized as palm oil-related. However, this is not true for product categories where classification is more straightforward: harvesting tools and extraction machines. For harvesting tools, we observe no increase in other tools (e.g., drills, HS: 846721). For extraction machines, there is no increase even in similar products used in agriculture, but not in the palm oil sector, such as presses for wood processing (HS: 847930). This provides strong evidence of the specific connection between imports in the palm oil sector and the health crisis, reinforcing confidence in our identification assumption and the actual connection between LSLAs and the imports of these inputs.

These results point toward a change in the palm oil production system from a traditional labor-intensive approach to an industrial one characterized by the use of chemical inputs and machinery. Consistent with this transition, in Section 4.3.2 we document a lower probability of working in agriculture for people living near the plantations.

4.2.3 Palm oil exports

Considering all the results from this section together, the increase in LSLAs detected in section 4.1 has led to a substantial expansion in land allocated to palm oil cultivation and an increase in imports of palm oil production inputs (fertilizers, harvesting, extraction, and milling machines), suggesting a transition from a traditional production system to a more industrial one. These changes are accompanied—approximately three to four years after the onset of the epidemic (i.e., the time required for a plantation to become productive)—by a 1064% increase in palm oil quantity exported by Liberia relative to the pre-Ebola period (Figure 1). This aligns with the anecdotal evidence presented in Section 2, suggesting a redirection of palm oil production toward the international market.

4.3 Effects on environment and local economy

In this section, we explore the effects of the increase in LSLA on the environment and the local economy. To do so, we compare cells (villages) located just outside and just inside areas of interest, before and after the Ebola outbreak. The identification assumption is the one previously presented in Section 4.1: Ebola has no differential impact *locally*, outside and inside areas *designated for LSLA*, other than LSLA itself.

It is important to mention that, given the identification strategy and the nature of the data, here we will identify and estimate local impacts of an aggregate shock, similarly to Autor et al. (2016). In other words, we will explore how outcomes change with the equilibrium shift, without focusing on identifying the "treatment" effect per se. This means that the effects described herein will represent the sum of all the changes generated by LSLAs, including both direct and indirect (e.g., the effects of LSLAs' pollution on health).

A second important point to discuss before results is that we present the effects of LSLA stimulated by the health crisis. This type of LSLA may differ from others, as in a Local Average Treatment Effect framework. In other words, the effects presented here are those of the "complier" group, those of the LSLA contracts prompted by the Ebola outbreak. However, we believe there is no inherent reason to presume that these are systematically different from others, as further discussed in Section 5.

4.3.1 Environmental effects

Outcomes Previous research has highlighted potential adverse consequences of LSLAs on the environment (e.g., Nepstad et al., 1999 on deforestation and fires, Probst et al., 2020 on deforestation, and European Economic and Social Committee, 2015 on potential soil degradation). We already discussed deforestation in Section 4.1, where we exploited this well-known adverse environmental consequence to detect the change in LSLA contracts. In the following analysis, we focus on air quality indicators (CO2, N2O, PM2.5, and fire incidence) due to data availability and the nature of the industry (for illustrative purposes, Figure A7 in Appendix A illustrates the pre-epidemic CO2 emissions, i.e. in 2010). Indeed, palm oil production is typically associated with significant air pollution. For instance, in Indonesia, palm oil production emitted an annual average of 220 million tonnes of carbon dioxide equivalent between 2015 and 2022–this accounts for nearly one-fifth of Indonesia's total annual emissions of 1.23 gigatonnes in 2022 (SEI, 2024).

Results Table 1 presents the results from the local difference-in-difference analysis. Consistent with expectations, we observe an increase in air pollution. The magnitude of these effects varies significantly: an increase of 1% for PM2.5, 12% for CO2, and null for N2O. Therefore, as in the Indonesian context, the expansion of palm oil cultivation is associated with a substantial increase in carbon dioxide emissions. In column 4, we evaluate the effects on the probability of fire events. Due to the inevitable spillover of fires, especially those occurring at the boundary of areas of interest, we expanded the control sample to include cells up to 20km from the boundary, rather than the usual 10km. We found a 37% increase in the probability of fire, which aligns with the observed increase in PM2.5. Indeed, these two factors are often linked, as highlighted in the related literature (see e.g. Burke et al., 2023). Table A10 in Appendix B assesses the sensitivity of this result to different model choices and thresholds. As shown in the table, when using the benchmark specification (10km buffer), the coefficient remains substantial—approximately a 10% increase in the incidence of fire events—but it is no longer statistically different from zero. This increase in estimation noise is clearly explained by the spillover of fires beyond the boundaries of the areas of interest. When considering logit models rather than OLS, the effect is positive and statistically significant across all specifications.

Table 1: Environmental outcomes - Local difference in difference

	(1)	(2)	(3)	(4)
Dep. Variable	PM25	CO2	N2O	Fire event
Ebola × Area of Interest	0.363***	124.8**	-0.000822	0.0244*
	(0.0817)	(63.37)	(0.0165)	(0.0133)
Observations	7,002	7,002	7,002	10,692
R-squared	0.834	0.976	0.989	0.178
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rain, Population	Yes	Yes	Yes	Yes
Sample	10km	10km	10km	20km
Mean Dep. Var. | Ebola = 0 & Area = 0	30.956	1008.29	1.469	0.054

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within the km in the sample row from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level models 1 to 4. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. PM25 is the average PM25 emission in the year-cell (ACAG B6GL01 data); CO2 is the average CO2 emission in the year-cell (EDGAR v8.0 data); N20 is the average N20 emission in the year-cell (EDGAR v8.0 data); fire event is a dummy variable indicating a fire event in the year-cell (USGS - MDC64A1 data).

4.3.2 Effects on local communities

Methodology In this section, we examine the impact of LSLA agreements on the local economy.[31] To do so, we turn to survey data. As mentioned in Section 3, we use DHS and MIS surveys (henceforth referred to as DHS) from the waves conducted in 2007, 2009, 2011, 2013, 2016, and 2019. Figure A4 in Appendix A illustrates the geographical distribution of DHS villages. Employing the pixel-based design with this data is not particularly useful. The local difference-in-difference method, when applied to this data, involves comparing individuals residing in villages just outside and just inside areas of interest, before and after the Ebola outbreak. However, different areas of interest may be quite distant from one another. Thus, using all villages outside as a control group for all villages inside may not be the appropriate approach.

With individual-level data, we can enhance our analysis by incorporating an area of interest fixed effect, given the increased statistical power due to the large number of individuals. By doing so, we compare individuals living in villages just outside and just inside the *same* area of interest, before and after the Ebola outbreak. Figure A5 in Appendix A presents an example of the variation being used in this estimation. The reduced-form linear model we utilize for this analysis is as follows:

$$Y_{iaw} = \alpha + \beta_1 W_i + \beta_2 E_w \times W_i + \mu_{aw} + u_{iaw} \tag{2}$$

[31] Remember that, as mentioned at the beginning of this section, we cannot differentiate between the direct effects (e.g., changes in the production structure) and the various possible indirect effects (e.g., negative health consequences stemming from environmental outcomes, migration) of LSLAs. Moreover, these effects should be interpreted in a "LATE" framework as those of the LSLAs stimulated by the health crisis.

where Y_{iaw} denotes the outcome of individual i, residing in a village within or outside the area of interest a, during wave w; W_i is a dummy variable indicating whether the village is located within the area of interest; E_w is a dummy variable equal to one after 2013; and μ_{aw} represents area-by-wave fixed effects. It is important to note that we do not include a "within" fixed effect in this model. This is because the inclusion of W_i not only controls for time-invariant unobservable differences between villages inside and outside areas of interest, but the coefficient itself is of interest. Specifically, it indicates the pre-Ebola differences in outcomes between individuals living in the two types of villages, thereby serving as a "balance check" prior to the occurrence of the exogenous shock. The identification assumption is similar to the previous ones: Ebola has no differential impact *locally*, on individuals living in villages just outside and just inside areas *designated for LSLA*, other than LSLAs itself.[32]

Placebo To assess the strength of our identification assumption, Table A12 in Appendix B summarizes the results for five placebo outcomes: age, a dummy variable indicating whether the village is classified as a town or a rural area, a dummy variable indicating whether the head of the household is male, a dummy variable indicating whether the individual is Christian, and a dummy variable indicating belonging to the Gola ethnicity (one of the most common ethnic groups in Liberia). All these outcomes are unlikely to be influenced by LSLAs—at least within the 6 to 7-year period of our sample—thus serving as a check for the identification assumption. The differences observed before the Ebola outbreak are minimal (respectively, 0.2%, 4%, 3%, 1%, and 8%) and not statistically different from zero. This indicates that these characteristics are balanced between villages just outside and just inside the same area of interest prior to the health crisis. The results remain consistent when considering the period following the Ebola outbreak, with all coefficients being very small and not statistically different from zero at any conventional significance level. While these results do not constitute a direct test, they provide reassurance regarding the strength of the proposed identification strategy. Figure A15 in Appendix A presents the coefficients plotted individually, and Figure A16 in Appendix A presents the difference coefficient over time.[33] This exercise is useful for understanding potential time trends. All coefficients are very small, with most being statistically indistinguishable from zero or lacking any discernible time trend.[34] Therefore, we can confidently exclude any pre-Ebola, post-Ebola, or time-trend differences in these placebo outcomes for individuals residing in villages just inside and just outside the same area of interest.

[32] The pixel-based local difference-in-difference methodology can be applied one last time to study the potential effects of LSLAs on population dynamics (for additional information on this data, please refer to Appendix F) and nightlights using remotely sensed data. The results (Table A11 in Appendix B) show a positive (albeit small, 0.07 standard deviations) effect on the population and a very limited (negative) impact on nightlights. Neither of the two results is statistically different from zero. 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).

[33] This is done with a staggered local difference-in-difference analysis, obtained by running the following linear model separately for each wave: $Y_{iaw} = \alpha + \beta W_i + \mu_{aw} + u_{iaw} \quad w = 2007, 2009, 2011, 2013, 2016, 2019$. We opted not to include a reference category and instead ran the entire model in a single regression—as done previously, in accordance with an event-study design—due to the limited number of time periods.

[34] Some coefficients are exactly zero; this occurs when the question was not included in that wave, or when the number of non-missing observations is insufficient to estimate the model.

Land ownership As a sanity check on the expansion of large-scale land acquisitions, Table A13 in Appendix B presents estimation results on a dummy variable indicating whether the DHS respondent owns any land. In column 1, we show the model without controls, and in column 2, with controls. Individuals in villages within areas of interest appear to have a lower probability of owning land prior to the Ebola outbreak, although this difference is not statistically significant at any conventional level. This observation aligns with the fact that some LSLA contracts had already been signed before the health crisis. However, this difference widens significantly following the Ebola outbreak, with approximately a statistically significant 10% reduction. This finding supports the deforestation measurement of LSLAs discussed in Section 4.1: within areas of interest, after the Ebola outbreak, individuals have a lower probability of owning land, in line with an increase in LSLA contracts being signed. Figure A8 in Appendix A presents the time trend for the probability of land ownership. Unfortunately, we only have non-missing observations for this question across two waves (one before, i.e. 2011, and one after, 2016). As indicated in the regression specification, we observe a statistically insignificant negative difference before the health crisis, followed by a substantial negative difference, statistically different from zero, after the Ebola outbreak. Figure A9 in Appendix A presents sensitivity to the 10km threshold of the local difference-in-difference.

Wealth, Education, Health Table 2 presents the results for wealth and health indicators: (1) the DHS-constructed wealth index; (2) the maximum level of education achieved by the individual (ranging from 0–no education–to 3–secondary education); (3) weight over height, a commonly used health measure computed by DHS, standardized by categories of individuals; and (4) average child weight-for-height, a widely recognized measure of maternal health.[35] We control for age, gender of the household head and the religion of the respondent.

We find no differences in wealth between individuals living in villages just inside and just outside the areas of interest before the Ebola outbreak. Following the outbreak, we observe a positive effect on wealth, although very limited, estimated at 0.34 standard deviations, e.g. the corresponding of owning an additional cupboard.[36] Similarly, we note a positive effect on the maximum level of education achieved, with

[35] The wealth index is a composite measure of a household's overall living standard. It is calculated using data on a household's ownership of selected assets, such as televisions and bicycles; materials used for housing construction; and types of water access and sanitation facilities. Each asset for which information is collected is assigned a weight or factor score derived through principal components analysis (for details, see DHS Wealth Index website). The resulting asset scores are standardized using country/wave means and standard deviations. Each household receives a standardized score for each asset, which varies depending on ownership (or, in the case of sleeping arrangements, the number of people per room). These scores are summed for each household, and individuals are ranked based on the total score of their household. The sample is then divided into quintiles. The final Wealth Index is a number indicating the number of standard deviations from the national mean. For example, a 100000 indicates a 1.00000 standard deviation higher wealth with respect to the country's mean.

[36] This corresponds to a standard deviation 0.17 standard deviations increase with respect to the country average. To put things into perspective, we use the asset scores provided by the DHS (DHS Wealth Index website). This increase is comparable to individuals living within the areas of interest, after the Ebola outbreak, owning an additional bicycle (i.e., owning a bicycle increases the wealth score by 0.172 standard deviations).

Table 2: Wealth and Health - Local difference in difference

	(1)	(2)	(3)	(4)
Dep. Variable	Wealth Index	Max education	Weight/Height	Child W/H
Within	0.00372	0.0389*	0.000509	-0.0145
	(0.0282)	(0.0221)	(0.0434)	(0.0637)
Ebola × Within	0.340***	0.0977***	0.172**	-0.0156
	(0.0440)	(0.0357)	(0.0823)	(0.112)
Observations	11,155	11,153	4,488	2,423
R-squared	0.261	0.205	0.051	0.013
Mean Dep. Var.	std	0.908	std	std

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Wealth Index is a comprehensive score of wealth computed by DHS. Max education ranges from 0 (no education) to 3 (secondary education). Weight/Height is a standardized (by categories of individuals) measure of this ratio computed by DHS. Controls are age, male head and religion.

an increase of 10%, which is equivalent to approximately a month increase in schooling.[37] The findings related to health indicate similar trends: no differences were noted before the Ebola outbreak, while a positive but modest improvement is observed in weight over height (0.172 standard deviations). In contrast, we find no significant differences in average children's weight over height, either before or after the health crisis.

Overall, the results indicate a modest improvement in the wealth and health of individuals residing in villages within areas of interest. These conclusions are robust to different specifications. Table A14 in Appendix B replicates the results presented in Table 2 without the controls. Figure A10 in Appendix A illustrates the plotted time differences. Once again, we observe almost no differences before the health crisis, alongside a small but positive and statistically significant difference following the Ebola outbreak in nearly all outcomes. Figure A11 in Appendix A presents the time trends for the other wealth outcomes. Remarkably, in nearly all measures, there is no visible pre-trend: almost all differences are not statistically different from zero before the outbreak. They become positive and statistically significant afterwards, except for average child weight over height. Given the local nature of the identification strategy, a concern about the validity of SUTVA may arise in the presence of spillovers across areas of interest (and/or migration). To deal with this, we perform two sensitivity exercises. First, Table A15 in Appendix B replicates the result on the subsample of individuals who had lived in the village for at least 6 years—which is the minimum time distance between the last year of our sample (2018) and the Ebola outbreak (2013). The results are quantitatively and qualitatively similar across all specifications. Second, Figure A12 in Appendix A replicates results by gradually restricting the control sample. In particular, we replicate the lo-

[37] Assuming 8 years of education to progress from 0 (no education) to 3 (secondary education) and 160 school days in a solar year, the coefficient can be transformed into the number of days as follows: $(0.13 * 8)/4 \times 160 \approx 32$ days.

cal difference in difference regression for the main outcomes by gradually restricting the control sample (in the spirit of Michalopoulos & Papaioannou, 2014). Starting with the initial control group of villages within the distance range of [0km, 10km], we systematically modify the lower bound by adding 1km in each specification—creating samples of [1km, 10km], [2km, 10km], and so on—while maintaining the same upper distance limit. It is important to mention that in the last specifications, the sample size is significantly reduced. Results on the wealth index are robust. The education result is robust in the majority of the specifications, losing statistical significance from 5km onward. Figure A13 in Appendix A replicates this robustness for the probability of owning land. Figure A14 in Appendix A presents sensitivity to the 10km threshold of the local difference-in-difference.

Employment Table 3 presents the results of the local difference-in-difference analysis for the following outcomes (dummy variables): (1) unemployment status; (2) a dummy variable indicating whether individuals work in sales; (3) in agriculture; (4) in services; or (5) in manual jobs. Two panels of results are included: Panel (A) for wives and Panel (B) for husbands. We control for age, gender of the household head, and the religion of the respondent. We find no significant difference in the probability of being unemployed either before or after the health crisis.[38] This absence of significant effects conceals considerable mobility between employment sectors. For both husbands and wives, there is no ex-ante difference in the probability of working in agriculture—consistent with the comparability of villages just outside and just inside areas of interest before the Ebola outbreak. However, this situation changes after the health crisis, with a 29% reduction for wives and a 22% reduction for husbands in the probability of working in this sector within the areas of interest. In other words, following LSLAs, individuals are moving away from agriculture. Then, we study where these individuals transition to. Wives appear to transition to jobs in sales and services, reflecting an average increase of 35%, whereas husbands are moving into manual jobs, with a 31% increase observed.

Table A16 in Appendix B replicates Table 3 omitting the controls for age, the gender of the household head, and religion. Figure A17 in Appendix A illustrates the differences in outcomes for wives and husbands residing in villages just outside and just inside the areas of interest, both before and after the Ebola outbreak. Figure A18 in Appendix A presents the time trends associated with these outcomes. Unfortunately, we have sufficient information regarding occupation only in the DHS waves conducted in 2009, 2013, and 2019. Consequently, information regarding pre-trends is limited to the two pre-outbreak waves. That being said, also in this case, there is no visible pre-trend in outcomes, with almost all the differences being small and not statistically different from zero prior to the outbreak. Moreover, it is evident that there has been a decline in the probability of working in agriculture, accompanied by a corresponding increase in employment in sales and services for wives, as well as manual jobs for husbands. Table A18 in Appendix B presents sensitivity using logit rather than OLS. Table A17 in Appendix B replicates the result on the

[38] It should be noted that the number of husbands declaring unemployment within these villages is very low, limiting the linear model's power to identify any differences.

Table 3: Occupation - Local difference in difference

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Unemployed	Sales	Agricultural	Services	Manual
Panel A: Wife					
Within	0.0280*	-0.0428**	-0.00112	0.000752	0.00963*
	(0.0168)	(0.0166)	(0.0186)	(0.00346)	(0.00562)
Ebola × Within	0.00765	0.0477*	-0.104***	0.0450***	-0.00570
	(0.0262)	(0.0254)	(0.0294)	(0.0155)	(0.00682)
Observations	6,617	6,617	6,617	6,617	6,617
R-squared	0.254	0.089	0.248	0.075	0.011
Mean Dep. Var.	0.333	0.219	0.356	0.050	0.018
Panel B: Husband					
Within	0.000267	-0.0147	0.00111	0.00560	-0.0101
	(0.000242)	(0.0116)	(0.0220)	(0.00866)	(0.0181)
Ebola × Within	0.00973	-0.00492	-0.114***	0.00530	0.0658**
	(0.0140)	(0.0156)	(0.0369)	(0.0187)	(0.0292)
Observations	4,862	4,862	4,862	4,862	4,862
R-squared	0.072	0.021	0.102	0.050	0.084
Mean Dep. Var.	0.018	0.059	0.524	0.060	0.211

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Unemployed is a dummy variable equal to 1 when the wife - panel A - or the husband - panel B - declares to be unemployed. Similarly, sales, agricultural, services, manual, are all dummy variables indicating employment in these macro sectors. "Other" category omitted. Controls are age, male head, and religion.

subsample of individuals who had lived in the village for at least 6 years. The results are quantitatively and qualitatively similar across all specifications. Figure A19 in Appendix A replicates results by gradually restricting the control sample. Results are unchanged in the majority of the specifications. Figure A20 in Appendix A presents sensitivity to the 10km threshold of the local difference-in-difference.

5 Discussion

Summary Palm oil is a traditional crop in Liberia and was cultivated alongside other crops. In this context, LSLAs appear to have reallocated land from forests to palm oil plantations and changed the production equilibrium, from a traditional, labor-intensive approach to a more industrial, capital-intensive one. The capital requirements of large palm oil plantations, combined with the technical and logistical constraints of accessing international markets, likely prevented large-scale palm oil cultivation before the acquisitions. This transformation process—characterized by the expansion of cultivated land, changes in production inputs, and reorientation of existing production toward international markets—resulted in a substantial increase in the quantity exported of Liberian palm oil.

The expansion of this tradable industry has yielded limited but positive effects on the local economy, manifesting as modest improvements in wealth, health, and education among individuals residing in villages within the affected areas. In addition, it appears to have spurred a process of structural transformation, with increased capital intensity in agriculture associated with decreased employment in this sector and a transition to other industries, such as services, sales, and manual labor. However, this economic development came at a significant environmental cost, including increased deforestation, forest fires, CO2, and PM25 emissions.

Back-of-the-Envelope Calculation Comparing the costs and benefits of LSLAs is inherently complex, as these issues span different areas of the economy and social environment. In this paragraph, our aim is to provide a rough, highly approximated, and necessarily limited, back-of-the-envelope calculation, converting the benefits and costs of this phenomenon into monetary equivalents. Therefore, the results presented here should be taken with caution and seen as highly indicative.

We estimated a 12% increase in CO2 emissions within the areas of interest. The average CO2 emissions per cell in the control group — i.e., cells outside concessions before the Ebola epidemic — are 1008.29 tons per year. There are 467 cells within the areas of interest, and the estimated price for 1 ton of CO2 emissions is 12.83 US$. Based on these figures, the estimated cost of the increase in CO2 emissions is 0.72 million US$ ($1008.29 \times 467 \times 12.83 \times 0.12$).[39] We proceed in a similar way for PM25 emissions, finding an estimated approximate cost of 15.9 millions US $.[40] Since costs related to forest fires and deforestation are often linked with CO2 and PM25 emissions, we consider only these categories in our analysis.

Assessing the overall benefits of LSLAs on wealth and education is even more complex. First, using LandScan data and the average number of family members in Liberia, we estimate approximately 100k families living in villages within the areas of interest. Based on this figure, and considering the increase in wealth (equivalent to one additional bicycle per family) and the average cost of a bicycle (assumed to be $30 USD), we estimate a total increase in wealth of roughly $3 million USD. Regarding educational benefits, we estimate an increase of approximately $\frac{32}{160}$ on school days. Using an estimated 10% return on average annual income from one additional year of schooling (Jones, Sohnesen, & Trifkovic, 2023), an average income of $710 USD (source: https://www.worlddata.info/africa/liberia/index.php), and three children per family, the total benefits from increased education amount to about $1.45 million USD.

Finally, the simplest benefit to quantify is from increased palm oil exports. For comparison with the other estimates, we consider exports up to 2020. The approximate increase of 110k metric tons in export volume during 2017–2020, multiplied by the average price per metric ton (500 US $, source:

[39] The nature-based carbon offset cost is set at $14.40 per tonne of carbon (source: https://www.ft.com/content/29565f44-ba71-4a44-8e84-d1e421ddb958). Given that 1ton is 907.185kg, 1ton of CO2 costs $12.83.

[40] Specifically, 30.956 (base mean of cells outside concessions before the epidemic) $\times$ 467 $\times$ 110000 (estimated cost for PM25 emissions from agricultural sources Wolfe et al., 2019) $\times$ 0.01 (the estimated increase).

https://fred.stlouisfed.org/series/PPOILUSDM), results in an estimated increase of $55 million USD in export value.

In summary, summing the estimated costs and benefits suggests that LSLAs have a positive effect on the economy, primarily driven by increased export revenue. However, as emphasized earlier, these are rough calculations that should be interpreted with caution.

External Validity The generalizability of these results to other large-scale land acquisitions, and more in general FDI in the agricultural sector, ultimately depends on the mechanisms identified and the specific characteristics of the LSLA examined. The first step in evaluating the external validity of the findings is to determine whether the land acquisitions prompted by the health crisis differ fundamentally from other LSLAs. As in a Local Average Treatment Effect framework, we present results for the "complier" acquisitions, i.e. those stimulated by the Ebola outbreak. If this group is significantly different from other LSLA groups, the findings may not extend entirely to these. However, we believe there is little evidence to suggest that these LSLAs are systematically different from other acquisitions, especially within a developing country context. A second key aspect of this study is its specific focus on Liberia. This is a low-income country with weak institutions, leading to at least two significant consequences. First, its poor institutions could have determined the acquisition constraint which was relaxed by the health crisis, as we explore in Appendix E. Second, the low percentage of land dedicated to agriculture prior to the acquisitions. Results may differ significantly in a developed country context, where land availability is near saturation. In such scenarios, LSLAs could lead to the substitution of existing crops rather than the expansion of cultivated areas. A third aspect to consider is that this study focuses on *palm oil* land acquisitions. Large-scale palm oil is known to be an extensive, monoculture, and capital-intensive woody crop. These characteristics could have possibly influenced our findings.

As a result of these three considerations, and the mechanisms highlighted, the findings presented in this paper can be extendable to LSLAs, and agricultural FDIs in general, in extensive (capital-intensive) crops within developing countries. This type of LSLA is the most common, i.e. 94% of LSLAs are located in developing countries (countries in Africa, South and Central America, South-Eastern Asia, and Eastern Europe) and 71% of LSLAs are performed for extensive (capital-intensive) monoculture crops (corn, wheat, cotton, palm oil, timber trees, rubber trees), with 15% of deals on palm oil only and 66% on monoculture crops in developing countries (author's computation from Land Matrix data).

6 Conclusions

After Liberia's second civil war, FDI surged from $100-150 million annually in 2006-2007 to about $1 billion per year by 2012-2013, largely due to significant investments in agriculture and mining by multinational corporations (WorldBank, 2015). FDIs in these sectors typically involve companies securing land concessions for the development of large-scale plantations, i.e., large-scale land acquisitions (LSLAs).

This paper examines the impact of LSLAs on agricultural production, environmental outcomes, and the local economy. We first detected an increase in LSLA contracts—through a reduction in tree coverage—prompted by the outbreak of the Ebola epidemic, leveraging the bureaucratic framework of the palm oil sector in Liberia.

We then studied the effects of this increase in LSLAs on palm oil production in two steps. First, we documented an expansion of land dedicated to palm oil production by converting forests into agricultural land. Second, we found an increase in imports of palm oil inputs (fertilizers, harvesting machines, and extraction machines), possibly linked to an increase in capital intensity in the sector. As a result, we concluded that these acquisitions both expanded the land allocated to palm oil cultivation and changed the production equilibrium from a traditional, labor-intensive system to a more industrial one.

We then examined the effects of these acquisitions on the local economy. On one hand, we find an increase in forest fires and carbon dioxide, and PM25 emissions, suggesting negative environmental consequences. On the other hand, we find a modest positive effect on the wealth and health of individuals living close to the plantations. Connected to the previous point, these acquisitions also appear to have spurred a process of structural transformation in the local economy, diverting individuals from agriculture toward other occupations, primarily in services, sales, and manual labor.

The findings presented in this paper may be extendable to LSLAs in developing countries focused on extensive monocultures (approximately 66% of all land deals).

Further research could focus on the long-term impacts of LSLAs, as they are often associated with monoculture practices and potential for soil degradation over time (European Economic and Social Committee, 2015). Moreover, the effects could change depending on different characteristics of the acquisitions, such as the availability of uncultivated land or the type of crop involved.

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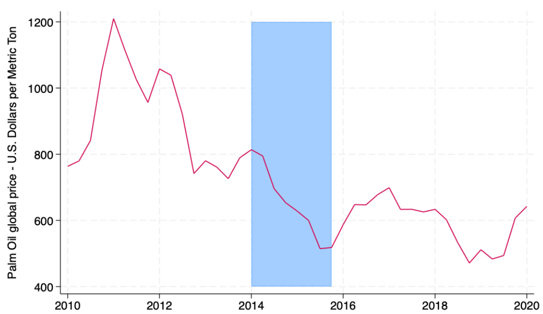
Online Appendix

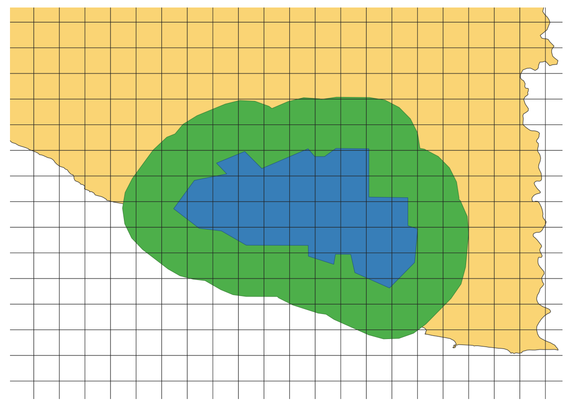
A Additional Figures

Figure A1: Palm Oil global price



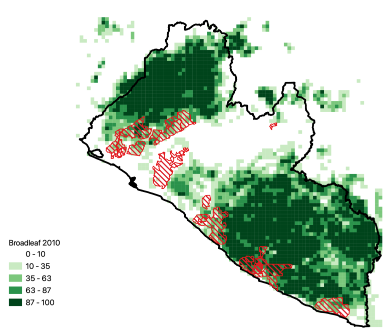
Notes: The figure presents the trend of palm oil global price (U.S. dollars per metric ton) over the period 2010-2020. Data from FRED. The blue area indicates the Ebola period as considered in this paper.

Figure A2: Map local difference-in-difference



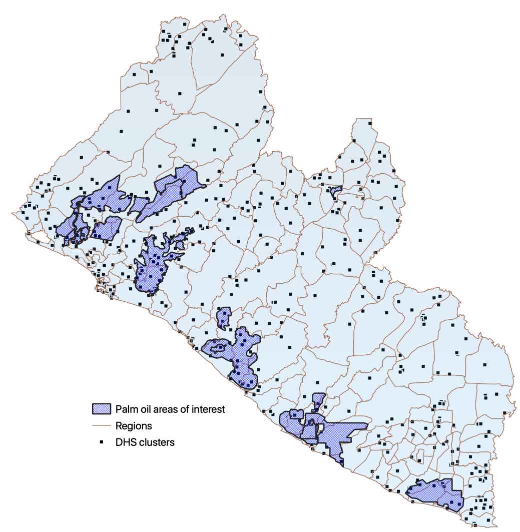
Notes: The figure presents the map of an area of interest, highlighting the sample for the local difference-in-differnece: blue for treatment, green for control.

Figure A3: Percentage tree cover Liberia 2010



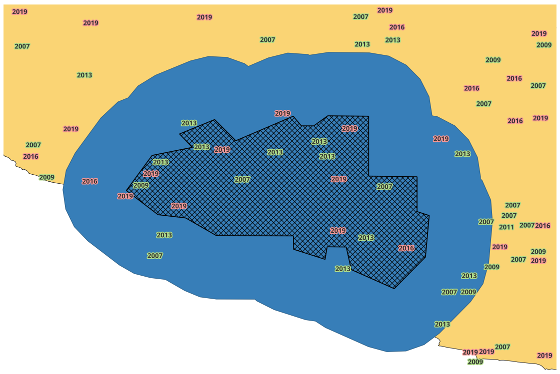
Notes: The figure presents the percentage of each cell covered by "Evergreen Broadleaf Forests" in 2010. The darker the cell, the higher the percentage. In red we have the palm oil areas of interest.

Figure A4: DHS villages



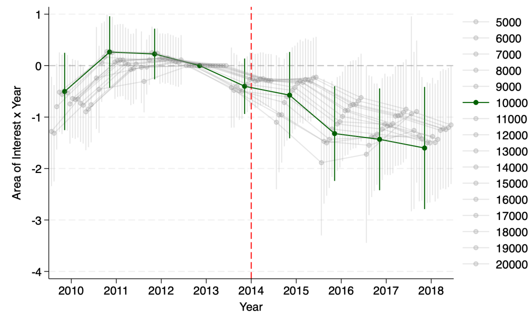
Notes: The figure presents the geographical distribution villages surveyed by the DHS (and MIS).

Figure A5: DHS map - zoom



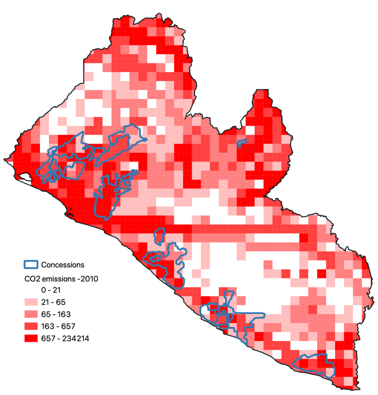
Notes: The figure presents the geographical distribution of villages surveyed by the DHS (and MIS) around an area of interest. Each dot is represented with the corresponding year of the DHS/MIS wave. In green years before the ebola outbreak, red otherwise.

Figure A6: Percentage tree cover - event study, sensitivity



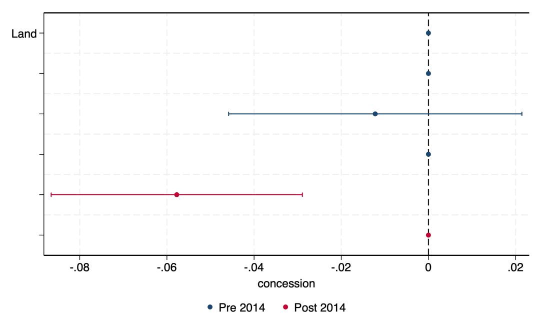
Notes: The figure presents the sensitivity of event-study graph, described in Section 4.1, equation 1, to changes in the control bandwidth from 5km to 20km. 95% confidence interval shown.

Figure A7: CO2 emissions - 2010



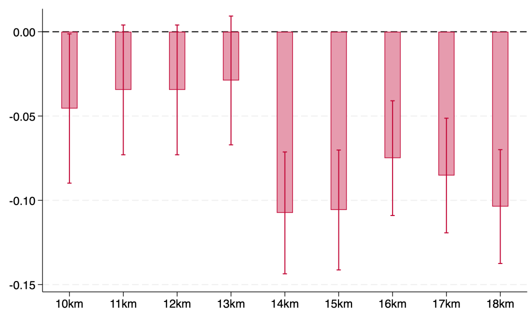
Notes: The figure presents the map of CO2 emissions in 2010, from EDGAR v8.0 data (please refer to section F). The darker the pixel, the higher emissions. In blue, palm oil areas of interest.

Figure A8: Land - trend



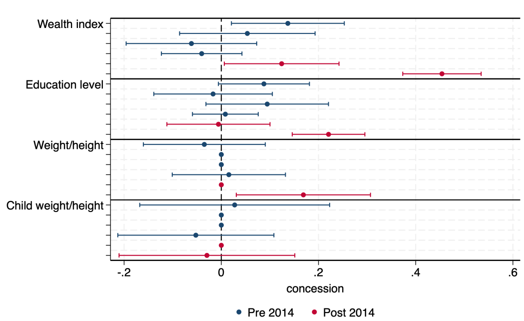
Notes: The figure presents the difference in the land ownership, between individuals living in villages just within and outside areas of interest, in all the available waves - DHS/MIS household data. When a regression was not possible - no question in the wave, or not sufficient variation - a dot at 0 is included in the graph. This is done with six simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the six waves separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Land = 1 if the household owns any agricultural land.

Figure A9: Land - sensitivity threshold



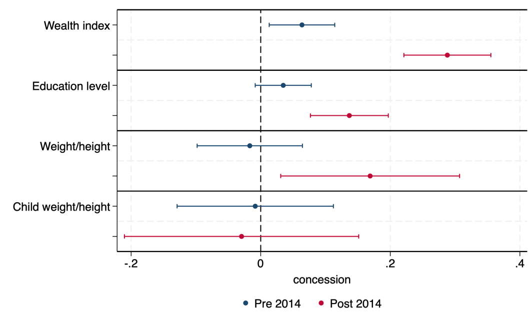
Notes: The figure presents the difference in the difference coefficients in land ownership, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 0km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown.

Figure A11: Wealth and Health - trend



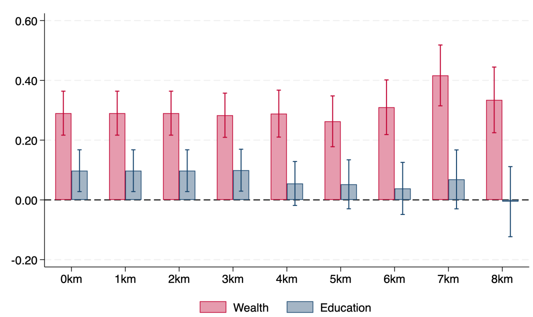
Notes: The figure presents the difference in the different wealth and health outcomes, between individuals living in villages just within and outside areas of interest, in all the available waves - DHS/MIS individual data. When a regression was not possible - no question in the wave, or not sufficient variation - a dot at 0 is included in the graph. This is done with six simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the six waves separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Land = 1 if the household owns any agricultural land. Wealth Index is a comprehensive score of wealth computed by DHS. Max education ranges from 0 (no education) to 3 (secondary education). Weight/Height is a standardized (by categories of individuals) measure of this ratio computed by DHS. Controls are age, male head and religion.

Figure A10: Wealth and Health - difference over time



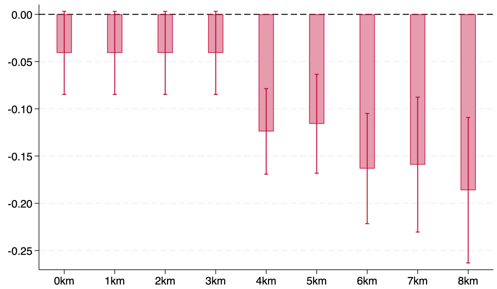
Notes: The figure presents the difference in the different wealth and health outcomes, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. This is done with two simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the two different periods separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Max education ranges from 0 (no education) to 3 (secondary education). Weight/Height is a standardized (by categories of individuals) measure of this ratio computed by DHS. Controls are age, male head and religion.

Figure A12: Wealth and Health - sensitivity buffer



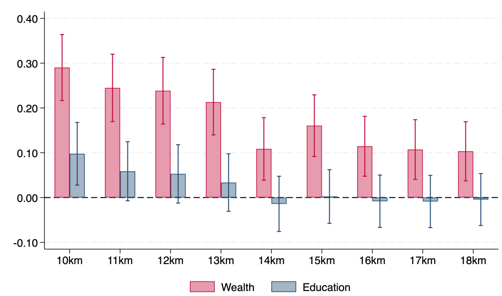
Notes: The figure presents the difference in the difference coefficients in the wealth index and the maximum education level, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 10km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown. Max education ranges from 0 (no education) to 3 (secondary education). Controls are age, male head and religion.

Figure A13: Land - sensitivity buffer



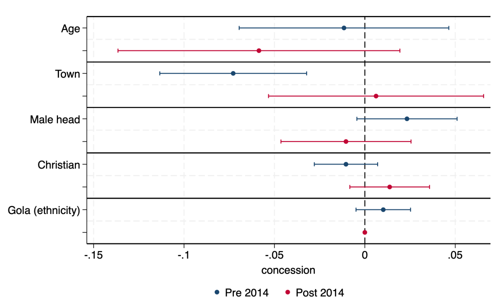
Notes: The figure presents the difference in the difference coefficients in land ownership, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 10km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown. Controls is age.

Figure A14: Wealth and Health - sensitivity threshold



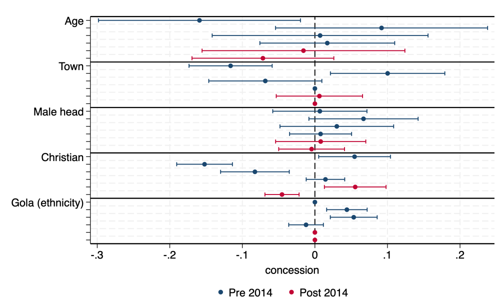
Notes: The figure presents the difference in the difference coefficients in the wealth index and the maximum education level, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 0km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown. Max education ranges from 0 (no education) to 3 (secondary education). Controls are age, male head and religion.

Figure A15: Placebo individual outcomes - difference over time



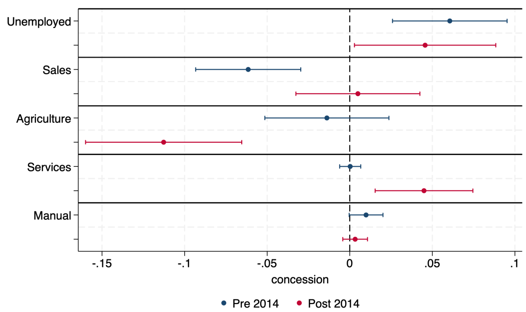
Notes: The figure presents the difference in the different placebo outcomes, between DHS respondents living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. This is done with two simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the two different periods separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Age is the age of the DHS respondent; town is a dummy variable indicating whether the DHS respondent lives in a town; male head is a dummy variable indicating whether the head of the household the DHS respondent lives in is a male; christian is a dummy variable indicating whether the DHS respondent is a christian; gola is a dummy variable indicating whether the DHS respondent belongs to the gola ethnicity.

Figure A16: Placebo individual outcomes - trend

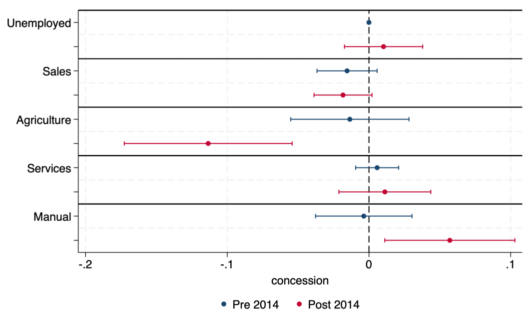


Notes: The figure presents the difference in the different placebo outcomes, between individuals living in villages just within and outside areas of interest, in all the available waves - DHS/MIS individual data. When a regression was not possible - no question in the wave, or not sufficient variation - a dot at 0 is included in the graph. This is done with six simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the six waves separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Age is the age of the DHS respondent; town is a dummy variable indicating whether the DHS respondent lives in a town; male head is a dummy variable indicating whether the head of the household the DHS respondent lives in is a male; christian is a dummy variable indicating whether the DHS respondent is a christian; gola is a dummy variable indicating whether the DHS respondent belongs to the gola ethnicity.

Figure A17: Occupation - difference over time



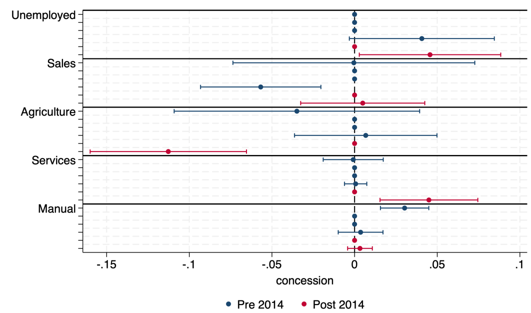
Wife



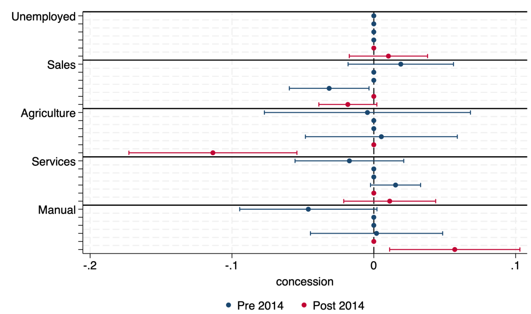
Husband

Notes: The figure presents the difference in the different occupation outcomes, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak, for wives and husbands separately - DHS/MIS individual data. This is done with two simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the two different periods separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Unemployed is a dummy variable indicating whether the DHS respondent - wide above, husband below - declares to be unemployed; sales is a dummy variable indicating whether the DHS respondent declares to work in sales; agriculture is a dummy variable indicating whether the DHS respondent declares to work in agriculture; services is a dummy variable indicating whether the DHS respondent declares to work in services; manual is a dummy variable indicating whether the DHS respondent declares to work in manual jobs.

Figure A18: Occupation - trend



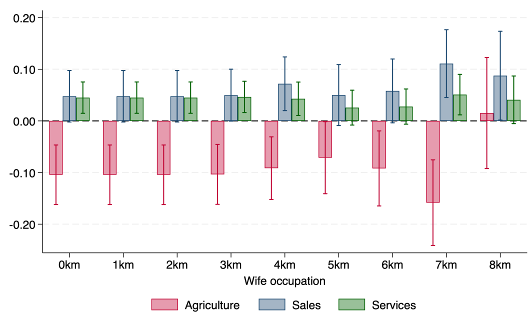
Wife



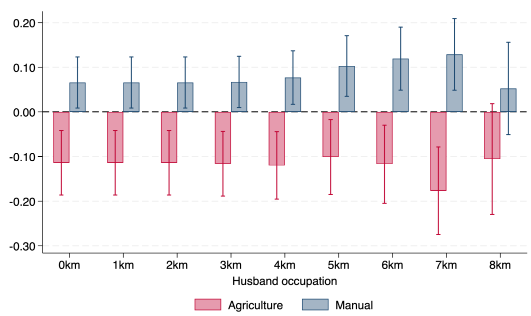
Husband

Notes: The figure presents the difference in the different occupation outcomes, between individuals living in villages just within and outside areas of interest, in all the available waves, for wives and husbands separately - DHS/MIS individual data. When a regression was not possible - no question in the wave, or not sufficient variation - a dot at 0 is included in the graph. This is done with six simple regressions of the dependent variable on a dummy variable equal to 1 for villages inside the areas of interest, for the six waves separately. Robust standard errors, area of interest fixed effect included. 95% confidence interval shown. Unemployed is a dummy variable indicating whether the DHS respondent - wide above, husband below - declares to be unemployed; sales is a dummy variable indicating whether the DHS respondent declares to work in sales; agriculture is a dummy variable indicating whether the DHS respondent declares to work in agriculture; services is a dummy variable indicating whether the DHS respondent declares to work in services; manual is a dummy variable indicating whether the DHS respondent declares to work in manual jobs.

Figure A19: Occupation - sensitivity buffer



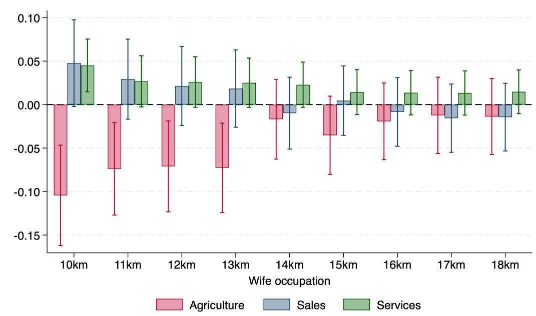
Wife



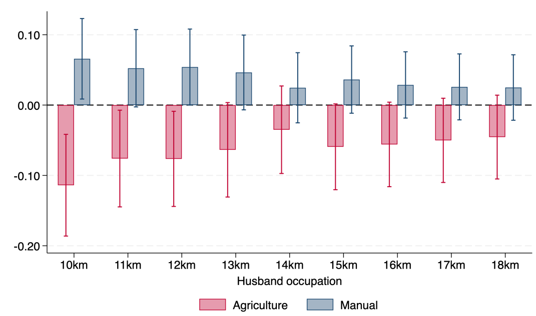
Husband

Notes: The figure presents the difference in the difference coefficients in occupation of wifes (for agriculture, services, and sales) and husbands (for agriculture and manual jobs), between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 10km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown. Max education ranges from 0 (no education) to 3 (secondary education). Controls are age, male head and religion.

Figure A20: Occupation - sensitivity threshold



Wife



Husband

Notes: The figure presents the difference in the difference coefficients in occupation of wifes (for agriculture, services, and sales) and husbands (for agriculture and manual jobs), between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. Control sample composed of villages between 0km from the border of the areas of interest and the distance shown on the x-axis. Robust standard errors, area of interest times year fixed effect included. 95% confidence interval shown. Max education ranges from 0 (no education) to 3 (secondary education). Controls are age, male head and religion.

B Additional Tables

Table A1: Descriptive Statistics

	Obs.	Mean	S.D.	Min	Max
Panel (a): All Sample					
Cell data					
% Evergreen broadleaf	30,051	46.48	38.43	0	100
% Woody Savannas	30,051	47.85	37.39	0	100
% Urban	30,051	0.216	2.993	0	88
Area of Interest	30,114	0.140	0.347	0	1
Rain	30,114	210.3	39.58	89.32	461.5
Nightlights	30,114	0.323	1.463	0	30.11
Population	30,114	1,314	7,955	0	329,609
PM25	30,114	33.18	4.496	22.31	45.58
CO2	30,114	1,477	11,852	0	380,747
N2O	30,114	1.871	4.739	0.0972	131.4
DHS individual data					
Age	37,022	29.065	9.605	15	49
Max educ. years	37,022	0.919	0.876	0	9
Wealth Index	37,022	15133.57	104088.4	-250582	477978
Male head hh	37,022	0.645	0.478	0	1
Unemployed wife	21,514	0.305	0.460	0	1
Unemployed husband	15,939	0.023	0.150	0	1
DHS household data					
Hh own land	41,412	0.400	0.490	0	1
Panel (b): Areas of Interest					
Cell data					
% Evergreen broadleaf	4,203	37.45	33.11	0	100
% Woody Savannas	4,203	53.34	32.69	0	100
% Urban	4,203	0.0738	0.749	0	10
Rain	4,203	234.2	40.68	142.9	407.6
Nightlights	4,203	0.387	1.399	0	13.58
Population	4,203	1,239	2,293	0	34,951
PM25	4,203	32.45	4.465	22.70	43.58
CO2	4,203	1,786	3,937	0	38,420
N2O	4,203	1.573	1.408	0.0979	11.64
DHS individual data					
Age	8,072	29.253	9.816	15	49
Max educ. years	8,072	0.784	0.822	0	9
Wealth Index	8,072	-4196.586	92348.93	-152040	353995
Male head hh	8,072	0.665	0.472	0	1
Unemployed wife	4,781	0.351	0.477	0	1
Unemployed husband	3,488	0.018	0.135	0	1
DHS household data					
Hh own land	9,519	0.396	0.489	0	1

Notes: Wealth Index is a number indicating the number of standard deviations from the national mean. For example, a 100000 indicates a 1.00000 standard deviation higher wealth with respect to the country mean.

Table A2: Percentage tree cover - Local difference in difference

	(1)	(2)	(3)
Dep. Variable	% Evergreen Broadleaf		
Ebola × Area of Interest	-1.226**	-1.283**	-1.064**
	(0.570)	(0.570)	(0.528)
Observations	7,002	7,002	6,687
R-squared	0.974	0.974	0.984
Cell FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Region × Year FE	No	No	Yes
Rain, Population	No	Yes	Yes
Mean y | Ebola = 0 & Area = 0	40.93	40.93	41.50

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level in all models. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. Dependent variable is the percentage of evergreen broadleaf land cover (MODIS data).

Table A3: Percentage tree cover - Sensitivity

	(1)	(2)
Dep. Variable	Coefficient	Standard error
Benchmark	-1.064**	(0.528)
Robust s.e.	-1.064***	(0.274)
Conley s.e.	-1.064**	(0.513)
No cell FE	-6.577***	(1.806)
Cell Year FE	-1.283**	(0.570)
Cell FE	-6.329***	(0.403)
No controls	-0.990*	(0.530)
Nightlights	-0.996*	(0.528)
SPEI	-0.997*	(0.528)
Lag rain	-1.249**	(0.506)

Notes:MWFE estimator. HDFE Linear regression. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Column (1) shows coefficient Ebola × Area of Interest of table A2, under different specifications. Conley std. with 250km of possible spatial correlation and 100 years of time correlation.

Table A4: Descriptives - SPAM

	Area cultivated (ha)	
	Pre	Post
Panel (a): Within		
Palm Oil	26.26	50.23
Cereals	39.55	66.79
Roots	23.14	25.02
Pulses	2.64	2.58
Fruits	11.84	15.66
Other	19.76	26.63
Panel (b): Outside		
Palm Oil	20.62	31.89
Cereals	39.55	47.76
Roots	20.18	19.36
Pulses	2.72	2.03
Fruits	10.44	10.95
Other	16.07	17.61

Notes: This table presents the average area cultivated (in hectares), within (panel a) and outside (panel b) the areas of interest , before (pre - 2010) and after (post - 2020) the Ebola outbreak.

Table A5: SPAM - Local difference in difference

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Palm Oil	Cereals	Roots	Pulses	Fruits	Others
Ebola × Area of Interest	10.75***	18.14***	2.269	0.595***	3.024***	4.835**
	(3.818)	(4.153)	(1.505)	(0.142)	(0.889)	(1.953)
Observations	1,524	1,524	1,524	1,524	1,524	1,524
R-squared	0.304	0.192	0.375	0.546	0.460	0.347
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Area = 0	19.620	39.553	20.180	2.723	10.439	16.075

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level in all models. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. Dependent variable is the average SPAM area cultivated of the different categories of crops.

Table A6: BACI categories

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	✓
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 and other machinery [...]	
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 A7: Imports - difference in difference

	(1)	(2)	(3)
Dep. Variable	Fertilizers	Extracting machines	Harvesting tools
Panel A: inverse hyperbolic sine transformation			
Palm oil	-0.022	0.061	0.039
	(0.266)	(0.414)	(0.171)
Ebola	0.675***	0.675***	0.675***
	(0.017)	(0.017)	(0.017)
Palm oil × Ebola	1.536***	2.144***	1.073***
	(0.443)	(0.523)	(0.263)
Observations	77758	77758	77639
Mean y | Ebola = 0 & Palm oil = 0	1.417	1.417	1.417
Panel B: log + 1			
Palm oil	0.009	-0.001	-0.055
	(0.237)	(0.351)	(0.137)
Ebola	0.580***	0.580***	0.580***
	(0.015)	(0.015)	(0.015)
Palm oil × Ebola	1.468***	1.885***	0.931***
	(0.402)	(0.458)	(0.221)
Observations	77758	77588	77639
Mean y | Ebola = 0 & Palm oil = 0	1.206	1.206	1.206

Notes: OLS regressions. 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. *Ebola* is a dummy equal to one after 2013. *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 A6. In each regression the other treatment groups have been excluded from the sample.

Table A8: Imports - difference in difference, placebo

	(1)	(2)	(3)	(4)	(5)
Panel A: non-agriculture					
Dep. Variable	Drills	Cosmetic	Telecom.	Office equ.	Musical ins.
Product	0.573	1.992***	1.254***	-0.404	-1.409***
	(0.395)	(0.473)	(0.253)	(0.270)	(0.014)
Ebola	0.675***	0.675***	0.675***	0.675***	0.675***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Product × Ebola	0.704	0.440	0.021	-0.127	0.224
	(0.448)	(0.581)	(0.317)	(0.417)	(0.189)
Observations	77554	77554	77554	77554	77554
Mean y | Ebola = 0 & Product = 0	1.417	1.417	1.417	1.417	1.417
Panel B: agriculture					
Dep. Variable	Fungicides	Farm equ.	Milling	Poultry	Soil prep.
Product	-0.921*	-0.941***	0.974**	-0.935***	-0.198
	(0.424)	(0.143)	(0.401)	(0.239)	(0.198)
Ebola	0.675***	0.676***	0.675***	0.675***	0.675***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Product × Ebola	0.517	-0.285	0.558	0.036	0.073
	(0.438)	(0.189)	(0.512)	(0.407)	(0.268)
Observations	77554	77554	77554	77554	77554
Mean y | Ebola = 0 & Product = 0	1.417	1.417	1.417	1.417	1.417

Notes: OLS regressions. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. 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, "Drills": HS-846721; "Cosmetic": HS-3304; "Telecommunication": HS-8517; "Office equ.": HS-8472; "Musical ins.": HS-9202; "Fungicides": HS-380892; "Farm equ.": HS-843330, 843340, 843351, 843352, 843353, 843359, 843360, 843390; "Milling": HS-8437; "Poultry": HS-843621, 843629, 843691; "Soil prep.": HS-8432. Treatment products excluded from the control group, more information on these products in Table A6.

Table A9: BACI categories - difference in difference, 6-digits products

HS Code	Palm oil	DiD coef (std. error)
Fertilizers		
310100		-0.952 (1.212)
310210	✓	2.015** (0.939)
310221	✓	2.902* (1.696)
310229	✓	0.217 (0.659)
310230	✓	4.953*** (1.037)
310240	✓	1.800 (1.191)
310250	✓	0.623 (0.515)
310260	✓	0.052 (0.686)
310280	✓	-0.226 (0.410)
310290	✓	2.676*** (0.941)
310310		0.229 (1.792)
310390		5.355*** (1.085)
310420	✓	2.818*** (0.728)
310430	✓	-1.020*** (0.242)
310490	✓	1.670 (1.104)
310510		1.174 (0.996)
310520		2.101* (1.076)
310530		1.616 (1.411)
310540		-1.236 (0.933)
310551		-
310559		1.307* (0.775)
310560		0.268 (1.316)
310590		3.395** (1.307)
Harvesting tools		
846711		0.726** (0.355)
846719		0.567 (0.365)
846721		0.707 (0.448)
846722	✓	1.760*** (0.448)
846729	✓	1.757*** (0.458)
846781	✓	0.689 (0.619)
846789	✓	0.170 (0.463)
846791	✓	1.007* (0.542)
846792		-0.779* (0.422)
846799		0.430 (0.477)
Extracting machines		
847910		-0.239 (0.351)
847920	✓	2.199** (0.927)
847930		-0.595 (0.452)
847940		-0.870*** (0.319)
847950		-0.433* (0.225)
847960		0.651 (0.611)
847981		0.090 (0.274)
847982	✓	2.097*** (0.463)
847989		0.824*** (0.268)
847990		0.320 (0.417)

Notes: OLS regressions. 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 Ebola. *Ebola* is a dummy equal to one after 2013. *Treated* 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 A6. In each regression the other treatment groups have been excluded from the sample.

Table A10: Fire sensitivity - Local difference in difference

	(1)	(2)	(3)	(4)
Dep. Variable	Fire event	Fire event	Fire event	Fire event
Ebola × Area of Interest	0.00519	0.0244*	0.786***	0.774***
	(0.0164)	(0.0133)	(0.107)	(0.107)
Observations	7,002	10,692	4,518	6,363
R-squared	0.187	0.178	-	-
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rain, Population	Yes	Yes	Yes	Yes
Model	OLS	OLS	Logit	Logit
Sample	10km	20km	10km	20km
Mean Dep. Var. | Ebola = 0 & Area = 0	0.055	0.054	0.092	0.100

Notes: MWFE estimator. HDFE local linear and logit regression. Sample restricted to be within the km in row sample from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level models 1 to 4. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. Fire event is a dummy variable indicating a fire event in the year-cell (USGS - MDC64A1 data).

Table A11: Nightlights and Population - Local difference in difference

	(1)	(2)
Dep. Variable:	Nightlights	Population
Ebola × Area of Interest	-0.00806	0.0737
	(0.0592)	(0.0480)
Observations	7002	7002
R-squared	0.663	0.779
Cell FE	Yes	Yes
Year FE	Yes	Yes

Notes: MWFE estimator. HDFE local linear regression. *Area of Interest* is a dummy equal to one for cells in an area of interest. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level in all models. Both dependent variables are standardized. Nightlights is the average nightlights density in the cell-year (Harmonization of DMSP and VIIRS data); Population is the average, satellite detected, number of people living in the cell-year (Landscan data).

Table A12: Placebo individual outcomes - Local difference in difference

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Age	Town	Male head	Christian	Gola
Within	-0.0878	-0.0364*	0.0204	-0.0185*	0.0119
	(0.312)	(0.0206)	(0.0152)	(0.00976)	(0.00856)
Ebola × Within	-0.439	0.0426	-0.0209	0.00554	0
	(0.508)	(0.0366)	(0.0241)	(0.0145)	(.)
Observations	11,180	5,536	11,180	11,155	5,555
R-squared	0.007	0.334	0.033	0.232	0.421
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	29.369	0.594	0.636	0.853	0.121

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Age is the age of the DHS respondent; town is a dummy variable indicating whether the DHS respondent lives in a town; male head is a dummy variable indicating whether the head of the household the DHS respondent lives in is a male; christian is a dummy variable indicating whether the DHS respondent is a christian; gola is a dummy variable indicating whether the DHS respondent belongs to the gola ethnicity.

Table A13: Land ownership - Local difference in difference

	(1)	(2)	(4)
Dep. Variable:	No controls	Controls	Logit
Within	-0.127	-0.0261	-0.0586
	(0.0171)	(0.0171)	(0.0821)
Ebola × Within	-0.045**	-0.040*	-0.204*
	(0.0225)	(0.0224)	(0.106)
Observations	13,458	13,458	13,325
R-squared	0.111	0.124	-
Wave × Area of Interest FE	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Within = 0	0.395	0.395	0.396

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Land = 1 if the household owns any agricultural land. Controls is only age, the only control variable among placebo outcomes present in the household data.

Table A14: Wealth and Health - Local difference in difference, no controls

	(1)	(2)	(3)	(4)
Dep. Variable	Wealth Index	Max education	Weight/Height	Child W/H
Within	0.00746	0.0341	-0.00752	-0.0167
	(0.0283)	(0.0238)	(0.0436)	(0.0636)
Ebola × Within	0.341***	0.114***	0.176**	-0.0129
	(0.0442)	(0.0393)	(0.0827)	(0.112)
Observations	11180	11176	4508	2433
R-squared	0.253	0.066	0.044	0.011
Wave × Area of Interest FE	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Within = 0	std	0.756	std	std

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Wealth Index is a comprehensive score of wealth computed by DHS. Max education ranges from 0 (no education) to 3 (secondary education). Weight/Height is a standardized (by categories of individuals) measure of this ratio computed by DHS.

Table A15: Wealth and Health - Local difference in difference, stayers

	(1)	(2)	(3)	(4)
Dep. Variable	Wealth Index	Max education	Weight/Height	Child W/H
Within	0.0288	0.0353	-0.0397	0.0680
	(0.0574)	(0.0476)	(0.0771)	(0.126)
Ebola × Within	0.410***	0.184***	0.153	-0.0793
	(0.0729)	(0.0639)	(0.113)	(0.166)
Observations	3,540	3,539	1,922	1,038
R-squared	0.267	0.083	0.064	0.020
Wave × Area of Interest FE	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Within = 0	-0.171	0.615	-0.196	0.0448

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Sample restricted to individuals who had lived in the village for at least 6 years, which is the minimum time distance between the last year of our sample (2018) and the Ebola outbreak (2013). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Wealth Index is a comprehensive score of wealth computed by DHS. Max education ranges from 0 (no education) to 3 (secondary education). Weight/Height is a standardized (by categories of individuals) measure of this ratio computed by DHS.

Table A16: Occupation - Local difference in difference, no controls

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Unemployed	Sales	Agricultural	Services	Manual
Panel A: wife					
Within	0.0313*	-0.0438***	-0.00285	0.000302	0.00977*
	(0.0173)	(0.0167)	(0.0190)	(0.00340)	(0.00560)
Ebola × Within	0.0143	0.0487*	-0.110***	0.0447***	-0.00651
	(0.0278)	(0.0254)	(0.0307)	(0.0155)	(0.00677)
Observations	6,632	6,632	6,632	6,632	6,632
R-squared	0.153	0.086	0.196	0.072	0.011
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0.305	0.243	0.414	0.008	0.014
Panel B: husband					
Within	1.51e-17	-0.0161	0.00234	0.00543	-0.0127
	(.)	(0.0115)	(0.0221)	(0.00866)	(0.0182)
Ebola × Within	0.0103	-0.00221	-0.116***	0.00578	0.0698**
	(.)	(0.0155)	(0.0374)	(0.0186)	(0.0296)
Observations	4,873	4,873	4,873	4,873	4,873
R-squared	0.072	0.016	0.088	0.050	0.060
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0	0.078	0.565	0.036	0.215

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Unemployed is a dummy variable equal to 1 when the wife - panel A - or the husband - panel B - declares to be unemployed. Similarly, sales, agricultural, services, manual, are all dummy variables indicating employment in these macro sectors. "Other" category omitted.

Table A17: Occupation - Local difference in difference, stayers

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Unemployed	Sales	Agricultural	Services	Manual
Panel A: wife					
Within	-1.07e-15	-0.0926**	0.0555	0.00574	0.0207**
	(.)	(0.0441)	(0.0451)	(0.0108)	(0.00859)
Ebola × Within	0.0380	0.0944*	-0.143***	0.0270	-0.0176*
	(0.0250)	(0.0495)	(0.0532)	(0.0192)	(0.00981)
Observations	2,506	2,506	2,506	2,506	2,506
R-squared	0.133	0.116	0.224	0.033	0.001
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0	0.277	0.698	0.009	0.009
Panel B: husband					
Within	-3.46e-18	0.0108	-0.0383	0.00788	-0.0358
	(.)	(0.0222)	(0.0447)	(0.0213)	(0.0282)
Ebola × Within	0.00816	-0.0349	-0.0767	0.0251	0.0779**
	(.)	(0.0253)	(0.0562)	(0.0266)	(0.0385)
Observations	1,846	1,846	1,846	1,846	1,846
R-squared	0.046	0.029	0.104	0.055	0.031
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0	0.043	0.611	0.062	0.134

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Sample restricted to individuals who had lived in the village for at least 6 years, which is the minimum time distance between the last year of our sample (2018) and the Ebola outbreak (2013). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Unemployed is a dummy variable equal to 1 when the wife - panel A - or the husband - panel B - declares to be unemployed. Similarly, sales, agricultural, services, manual, are all dummy variables indicating employment in these macro sectors. "Other" category omitted.

Table A18: Occupation - Local difference in difference, logit

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Unemployed	Sales	Agricultural	Services	Manual
Panel A: wife					
Within	0.179*	-0.268***	-0.0155	0.0333	0.484
	(0.0988)	(0.0996)	(0.103)	(0.377)	(0.304)
Ebola × Within	0.0462	0.299*	-0.532***	0.434	-0.101
	(0.147)	(0.157)	(0.154)	(0.412)	(0.559)
Observations	5,560	6,456	6,590	5,369	5,593
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0.422	0.247	0.409	0.013	0.019
Panel B: husband					
Within	0.221	-0.229	0.0101	0.136	-0.0769
	(0.307)	(0.157)	(0.0948)	(0.222)	(0.109)
Ebola × Within	0	-0.378	-0.496***	0.0167	0.485**
	(.)	(0.355)	(0.161)	(0.320)	(0.206)
Observations	1,380	4,581	4,859	4,344	4,800
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Within = 0	0	0.083	0.565	0.048	0.225

Notes: MWFE estimator. Logit regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Sample restricted to individuals who had lived in the village for at least 6 years, which is the minimum time distance between the last year of our sample (2018) and the Ebola outbreak (2013). Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Robust standard error shown. *Ebola* is a dummy equal to one after 2013. *Within* is a dummy equal to one for individuals within an area of interest. Unemployed is a dummy variable equal to 1 when the wife - panel A - or the husband - panel B - declares to be unemployed. Similarly, sales, agricultural, services, manual, are all dummy variables indicating employment in these macro sectors. "Other" category omitted.

C Definition of palm oil

The International Geosphere-Biosphere Programme (IGBP) land cover classes are defined, on top of other things, on canopy diameter and percentage of the cell covered by trees. These characteristics often change with the age of the trees and the type of cultivation. Here, we are interested in palm oil cultivation in the first 4/5 years after plantation. Carolita et al. (2017) studies the relationship between canopy diameter and the age of palm oil trees. This helps us compute the average canopy diameter for each year of the tree since plantation. Results are summarized in Table A19. As expected, canopy diameter increases with age. Nevertheless, it is always longer than 2 meters, the threshold used by IGBP for classification. Given these data, computing the percentage of cell coverage is straightforward. First, one needs to compute the average canopy area in each year since cultivation (column 3 of Table A19). Then, given the optimal density of palm oil cultivation of 143 trees per hectare (source: FAO), the optimal average number of trees per cell is 71500. Multiplying this figure per the canopy area, and converting it into km^2, we obtain the area covered by palm oil trees in each year since plantation (column 6 of Table A19). In column 7 of the same table, we show the percentage of the cells covered by palm oil canopy each year, i.e. 47%. These figures (>2 meters canopy diameter and average 47% coverage) are consistent with one IGBP class: "Woody Savannas" (>2 meters canopy diameter and coverage between 30% and 60%). This is in line with Keil (2016), classifying palm trees in "woodland", the University of Maryland (UMD) classification corresponding to woody savannas. Moreover, palm oil plantations are often characterized as woody crops (source: SEEA; de Sousa et al., 2020 in Liberia) which aligns with the identified land cover category.

Table A19: 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	71500 t	0,94 km^2	19%
2 y	5.3 m	22.39 m^2	143 t/ha	71500 t	1.59 km^2	32%
3 y	6.4 m	31.97 m^2	143 t/ha	71500 t	2.28 km^2	46%
4 y	7.4 m	42.84 m^2	143 t/ha	71500 t	3.06 km^2	61 %
5 y	8.3 m	53.87 m^2	143 t/ha	71500 t	3.84 km^2	77 %

Notes: The table reports 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).

Finally, we examine specific cells using satellite imagery (via Google Earth) to show an example of the approach described above. Figure A21 presents pixel 4466, in the Maryland County, located within an area of interest, clearly illustrating its border in red, across three different years: 2011 (pre-Ebola), 2014, and 2020. In 2011, pixel 4466 was entirely covered by trees. Following the Ebola outbreak, a significant portion of the pixel was deforested. By 2020, palm oil trees had grown in the previously deforested area. A closer inspection of the cultivated area, shown in the fourth image, reveals the presence of palm oil trees. We then examined the MODIS category for these pixels, which confirmed the classification.

Figure A21: Pixel 4466 across different years

(a) Pixel 4466 - 2011

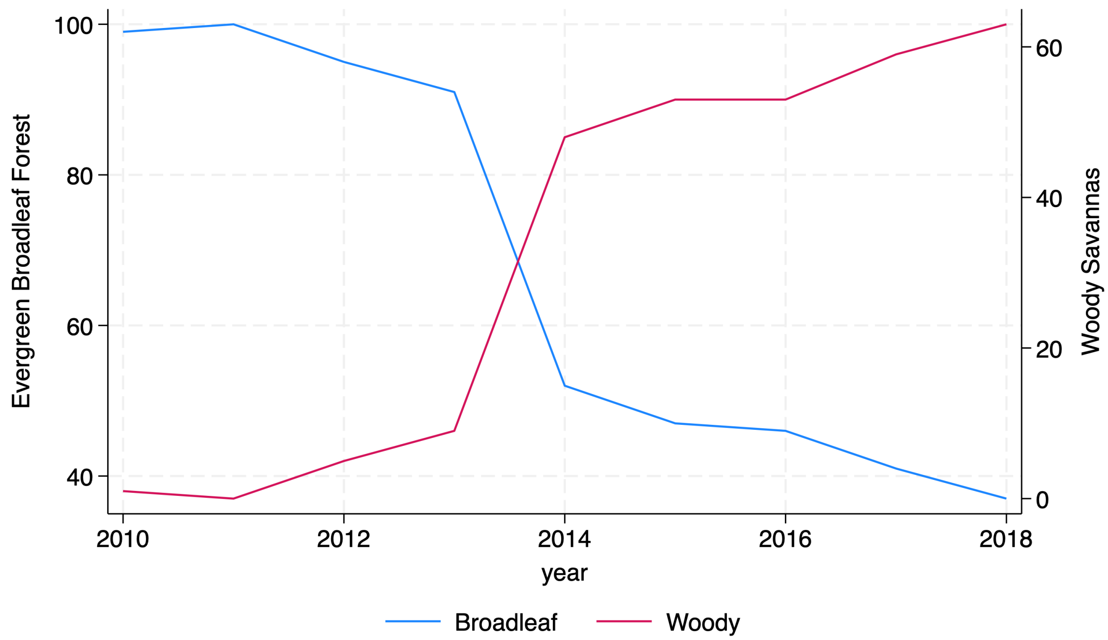
(b) Pixel 4466 - 2014

(c) Pixel 4466 - 2017

(d) Pixel 4466 - zoom

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 Ebola outbreak.

Figure A22: MODIS category 4466

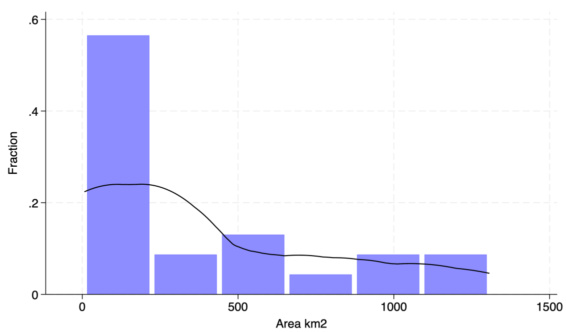


Notes: The figure presents the percentage cover for MODIS categories *Evergreen Broadleaf Forest* and *Woody Savannas* over time for cell 4466.

D Palm oil companies

In Liberia operate 7 large-scale palm oil companies, as outlined in table A20. The 23 *Areas of Interest* are not evenly distributed, with the largest company accounting for approximately 47% of them. These are quite large, with an average area of 377 km^2. Nevertheless, this means hides substantial heterogeneity, as highlighted in Figure A23. The majority of AoIs are indeed smaller than 160 km^2 (still an impressive figure). Then there is a long right tail of the area distribution, with the largest one being approximately 1300 km^2. Six out of seven companies are part of large multinational groups. In particular, the largest 3 enterprises (in terms of number of areas of interest owned) are from groups with headquarters in Malaysia (a leading country in palm oil production), the United Kingdom, and Hong Kong. As for the age of these companies, they tend to be quite old. Indeed, the average foundation year, as shown in table A20, is 1977. The youngest company was created in 2010 and the oldest one in 1926. Consistently with this feature, and the Liberian history, the majority of these companies produced rubber before converting to palm oil.

Figure A23: Distribution area AoIs



Notes: The figure shows the distribution of the area (in km^2) of the 23 Areas of Interest (AoIs) operated by large-scale palm oil companies in Liberia. The distribution is highly skewed, with most AoIs below 160 km^2 and a few much larger ones, up to about 1,300 km^2.

Table A20: Descriptives

Companies	7
Areas of Interest	23
- # AoIs 1st lagest company	11 ($\approx$ 47%)
- # AoIs 2nd lagest company	4
- # AoIs 3rd lagest company	3
Average area AoIs	377 km^2
Average foundation year	1977
Average % previously rubber	57%

Notes: The table summarizes key descriptive statistics of the 7 large-scale palm oil companies and their 23 Areas of Interest (AoIs) in Liberia. It reports the number of companies and AoIs, the concentration of AoIs among the top three companies, the average area of AoIs, the average foundation year of the companies, and the share of companies that previously produced rubber.

E One mechanism

In this paper, we exploit the exogenous increase in LSLA in the aftermath of the Ebola outbreak. But what is the mechanism behind these results? Substantial anecdotal evidence suggests that it may be due to a diversion of attention among local and international NGOs (Global Witness, 2015; RSPO complain; Forest Peoples Programme, 2015), which were, before the health crisis, limiting the acquisitions by monitoring and contesting land deals, advocating for local communities' rights, and pressuring companies and governments to comply with social and environmental standards. One example of NGO activities is the SAMFU Toolkit.

In this appendix, we provide detailed evidence in favour of this mechanism. Nevertheless, other mechanisms may be at play as well. For example, it is plausible to assume that the health crisis has had a negative impact on income, making individuals living in the areas of interest more prone to sign LSLA agreements. At the end of this section, we will discuss the consequences of the different mechanisms on the identification of our effects of interest.

Diversion of NGO attention Testing the diversion of attention mechanism requires geo-localized information on NGOs' presence before and after the Ebola outbreak, which, as one might expect, is particularly hard to obtain. We indirectly measure NGO presence using the Demographic and Health Survey (DHS), phase VI (2011), VII (2013), and VIII (2016). In particular, we assume that an NGO is present in a certain cell year if there is, in the following period, at least one DHS respondent declaring that an NGO sprayed their dwelling against mosquitoes in the previous 12 months. This measure has several limitations. First, it is not specific to NGOs working in the palm oil sector. Second, it might be particularly noisy, since it depends on a sub-question of an unrelated survey.

We document that, before Ebola, the average NGO presence was greater inside areas of interest than outside, which is consistent with the anecdotal evidence presented above. However, this is no longer true after the epidemic (Table A21).

To see how this relates to deforestation, we interact the local difference-in-difference model with the NGO measure. Specifically, we construct a dummy equal to 1 if there is a decrease in NGO presence close to or within the relevant area of interest. Hence, the linear model is:

$$T_{krt} = \alpha + \beta_1 \, E_t \times A_{kr} + \beta_2 \, E_t \times N_{kr} + \beta_3 \, E_t \times A_{kr} \times N_{kr} + \mu_k + \mu_{rt} + u_{krt}$$

In other words, we compare tree coverage (just inside and just outside areas of interest, before and after the Ebola outbreak) between areas that exhibit a decrease in NGO presence and those that do not. Results are summarized in Table A22. In Panel (A), columns 1 and 3 replicate the results presented in Table A2. In columns 2 and 4, we show results from the augmented model. The negative effect is partly captured by the interaction with the NGO measure. However, the coefficient is not statistically different from zero. This could be due to the low power and the particularly noisy NGO measure. For this reason, in Panel B of Table A22 we replicate the whole analysis with a slightly larger control group (up to 15km outside the

Table A21: NGO presence - DHS

	(1)	(2)
Dep. Variable:	NGO presence	NGO presence
Area of Interest	0.006**	0.000
	(0.003)	(0.000)
Observations	13,384	16,730
R-squared	0.008	0.001
Year FE	Yes	Yes
Sample	Before Ebola	After Ebola

Notes: MWFE estimator. HDFE local linear regression. Dependent variable is a dummy equal to 1 if, in the following year, in the cell-year there is at least one DHS respondent reporting an NGO spraying the dwelling against mosquitoes in the previous 12 months. *Area of Interest* is a dummy equal to one for cells in an area of interest. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level. In model (1) sample contains years before (and including) 2013, model (2) after.

areas of interest). In line with expectations, the interaction coefficient is negative and statistically different from zero at any conventional level. Moreover, the entire effect is captured by this interaction, which is consistent with these areas of interest being the ones targeted for deforestation due to the diversion of NGO attention. This result is robust to the inclusion of control variables (rainfall and population) in column 4.

Alternative measure of NGO In Table A23 we present results for an alternative measure of NGO, i.e. the number of non-public schools—often run by NGOs—established. As one can see, both considering the entire sample (Panel A) and the local difference-in-difference one (Panel B), we observe a decrease in the number of non-public schools established within the areas of interest, after the Ebola outbreak. This is statistically different from zero in column (1) when including only the cell fixed effects. In Panel A, results are unchanged when including the year fixed effect in column (2). When restricting to the 10km sample in Panel B, and including the region times year fixed effect in column (3), results are quantitatively similar, but the estimate is significantly noisier.

Ethnic minority Additional evidence in favour of this mechanism is presented in Table A24. Here, we interact the local difference-in-difference model with a dummy variable indicating whether an ethnic minority (defined as one politically unrepresented ethnic group, i.e. without representation in the central government) is present in the cell. If NGOs' role was to solve a problem of weak institutions, this should be especially relevant in areas characterized by these ethnic groups. In line with this line of reasoning, deforestation–and therefore LSLAs–happened exactly in these areas.

Table A22: NGO and deforestation - DHS

	(1)	(2)	(3)	(4)
Dep. Variable	% Evergreen Broadleaf			
Panel A: 10 km				
Ebola × Area of Interest	-0.990*	-0.420	-1.064**	-0.446
	(0.530)	(0.683)	(0.528)	(0.681)
Ebola × NGO		-1.310		-1.115
		(0.962)		(0.961)
Ebola × Area of Interest × NGO		-1.048		-1.110
		(1.001)		(0.996)
Observations	6,687	6,687	6,687	6,687
R-squared	0.984	0.984	0.984	0.984
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Rain, Population	No	No	Yes	Yes
Mean Dep. Var.	39.57	39.57	39.57	39.57
Panel B: 15 km				
Ebola × Area of Interest	-0.665	0.838	-0.713	0.837
	(0.517)	(0.783)	(0.517)	(0.783)
Ebola × NGO		0.813		0.995
		(1.083)		(1.085)
Ebola × Area of Interest × NGO		-2.414**		-2.477**
		(1.047)		(1.046)
Observations	8,478	8,478	8,478	8,478
R-squared	0.985	0.985	0.985	0.985
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Rain, Population	No	No	Yes	Yes
Mean Dep. Var.	41.43	41.43	41.43	41.43

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. *NGO* is a dummy equal to one if the number of NGOs close to the AoI before the Ebola outbreak is higher than the one after it. Dependent variable is the percentage of evergreen broadleaf land cover (MODIS data).

Table A23: Alternative NGO measure - Non public schools

	(1)	(2)	(3)
Dep. Variable	Pr non-public school funded		
Panel A: all sample			
Ebola × Area of Interest	-0.0227***	-0.0119**	-0.0107
	(0.00507)	(0.00527)	(0.00746)
Observations	30,114	30,114	28,188
R-squared	0.322	0.327	0.362
Cell FE	Yes	Yes	Yes
Year FE	No	Yes	No
Region × Year FE	No	No	Yes
Mean dependent	0.0117	0.0117	0.0117
Panel b: 10km sample			
Ebola × Area of Interest	-0.0227***	-0.00807	-0.00917
	(0.00508)	(0.00685)	(0.00872)
Observations	7,002	7,002	6,687
R-squared	0.250	0.254	0.251
Cell FE	Yes	Yes	Yes
Year FE	No	Yes	No
Region × Year FE	No	No	Yes
Mean dependent	0.0164	0.0164	0.0164

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. Dependent variable is a dummy equal to one if a non-public school was funded in the cell in that year.

Table A24: Ethnic minorities and deforestation

	(1)	(2)	(3)
Dep. Variable	% Evergreen Broadleaf		
Ebola × Area of Interest	1.538**	1.432*	1.796**
	(0.734)	(0.781)	(0.896)
Ebola × Area of Interest × Ethnic minority	-2.859***	-2.796***	-3.025***
	(0.952)	(0.989)	(1.054)
Observations	7,002	7,002	6,687
R-squared	0.974	0.974	0.984
Cell FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Region × Year FE	No	No	Yes
Rain, Population	No	Yes	Yes
Mean dependent	38.36	38.36	39.57

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level in all models. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. *Ethnic Minority* is dummy equal one if in a cell there is at least one politically unrepresented ethnic group, i.e. without representation in the central government. Dependent variable is the percentage of evergreen broadleaf land cover (MODIS data).

Conflict To conclude, in Table A25 we explore the effects on conflict events. If the exogenous increase in LSLA agreements is truly driven by a diversion of NGOs' attention, we could expect the outbreak of some conflict events within the areas of interest, after the Ebola outbreak. This is exactly what we find in column 1. In columns 2 to 5, we differentiate between the types of violent events generated. The only category which is associated with a positive and statistically different from zero effect is "Protests-Riots", the one we would expect in this case.

In this appendix, we presented results consistent with the diversion of NGO limited attention (Gabaix & Laibson, 2006; Chetty, Looney, & Kroft, 2009; DellaVigna, 2009) as a mechanism to explain the relationship between LSLAs and the Ebola outbreak. Alternative mechanisms may also play a role. For instance, the Ebola epidemic adversely affected villagers' incomes, making individuals more likely to accept the agreements. Also, the epidemic could have altered household preferences.

If the diversion of NGOs' attention is indeed a mechanism at play, the results regarding the effects of LSLA agreements should be interpreted as a lower bound. Indeed, it is reasonable to assume that NGOs' presence has a positive effect on the local economy, potentially leading to an underestimation of the positive effects of LSLAs. The other mechanisms mentioned are unlikely to affect the identification assumption presented in Section 4, as there is no reason to believe that Ebola had a stronger effect on income inside the areas of interest, or that it altered household preferences more or less within those areas. Nevertheless, the results presented in Section 4 should be interpreted with consideration of any potential differential effects stemming from these mechanisms.

Table A25: Conflict

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Event	Violence	Battle	Protest-Riots	Strategic
Ebola × Area of Interest	0.00503*	-0.000882	-0.000727	0.00596**	0.000672
	(0.00302)	(0.00187)	(0.000725)	(0.00291)	(0.000666)
Observations	6,687	6,687	6,687	6,687	6,687
R-squared	0.134	-0.024	-0.025	0.039	-0.040
Cell FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Rain, Population, Nightlights	Yes	Yes	Yes	Yes	Yes
Mean dependent	0.00448	0.00097	0.00015	0.0032	0.00015

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 10km from the Areas of Interest bandwidth. Standard errors in parentheses. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard errors clustered at the cell level in all models. *Ebola* is a dummy equal to one after 2013. *Area of Interest* is a dummy equal to one for cells in an area of interest. Dependent variable in model (1) is a dummy variable indicating the presence of an ACLED event in the cell-year. Dependent variables in models (2) to (5) indicate the presence of a category of ACLED events, namely: violence against civilians (2), battle (3), protests and riots (4), and strategic development (5).

F Other Data

This appendix provides additional information on some of the data used in the analysis that is not presented in Section 3.

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.

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 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.

SPAM. SPAM is an open-source cross-entropy model that generates global gridded maps of agricultural production at a 5 arc-minute spatial resolution. In particular, their model combines sub-national agricultural statistics with crop production system characteristics, satellite-derived land cover images, crop-specific agroecological suitability, irrigation, and rural population density. As a result of this process, it provides the physical area cultivated, the total amount of production, and the yield (metric tons per hectare) for 42 different crops (including palm oil) for each pixel in 2010 - before the Ebola outbreak - and 2020 - after the Ebola outbreak. This data is commonly used in scientific research in agriculture (e.g. Zapata-Caldas et al., 2009, Yu et al., 2017), climate science (e.g. Yu et al., 2018, Busch et al., 2024), and agricultural economics (e.g. Kostandini et al., 2009, Gruère et al., 2009). However, results on agricultural production and productivity should be understood and assessed as derived from data generated by this model rather than direct measurements. More information on the methodology in section G.

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).

Fire. Granular data about fire events is obtained from USGS - MCD64A1 (Version 6). It provides a global 500m record of per-pixel burned area by month. For each of these pixels and for each month, we can observe whether or not there was a fire event.

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 have imported these data, for each year, in Qgis as rasters and computed population statistics in each cell through the Qgis algorithm Zonal statistics, using this procedure for all the data since they all come as rasters, and we have to aggregate them at the cell level.

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. As usual in the literature, we join these data to our cells and then take the average rainfall each year.

SPEI. We add data on the Standardized Precipitation Evapotranspiration Index (SPEI), a multiscalar drought index that combines monthly precipitation and temperature data. These data are taken from the Global SPEI database based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia. This database offers long-term, robust information about drought conditions globally, with a 0.5 degree spatial resolution and a monthly time resolution.

NGO presence. To conclude, obtaining geo-localized measures of NGO presence is particularly difficult. We accomplish this indirectly using the Demographic and Health Survey (DHS), phase VI (2011), VII (2013), and VIII (2016). In particular, we define an NGO as being present in a specific cell-year if there is at least one DHS respondent declaring that an NGO has sprayed his dwelling in the previous year.

Schools. The data on school openings and closures were kindly shared by Romero et al. (2020). We took the raw data shared, geo-localized them using the name of the village, and merged them with our grid dataset. To conclude, we construct a dummy variable indicating whether a non-public school was founded in a given cell-year.

G SPAM methodology

In this section we provide a non-technical description of the methodology under the construction of the SPAM data we use to measure agricultural production and productivity. For a more detailed technical description we refer the reader to the methodological papers behind the datasets: You & Wood, 2006; You et al., 2009, 2014.

As described in the data section, what SPAM essentially does is to downscale sub-national crop production statistics with an approach that account for spatial variation in the biophysical conditions influencing productivity of individual crops within the cropland extent. This is done in four steps.

First, the prior. As first step of the algorithm, a prior allocation of area cultivated, bridging from the sub-national statistical reporting unit–usually a region, to the pixel is computed using the following input data:

- Global irrigation maps–Global Map of Irrigation Areas (Version 4.01), Siebert et al., 2005
- Land cover image–Ramankutty et al., 2008
- Existing crop distribution maps and experts valuations
- Rural population density–Global Rural-Urban Mapping Project (GRUMP), Alpha version, Center for International Earth Science Information Network (CIESIN) & de Agricultura Tropical (CIAT), 2005
- International crop prices
- Agro-climatic Crop suitability and potential yield by crop–Global Agro-ecological Zones (GAEZ), Fischer et al., 2021

Combining these data, they compute the pre-allocation crop area for crop j in pixel i (at input level l=high-input irrigated, rainfed-high input level, rainfed-low input level and subsistence, more information on this in You & Wood, 2006)[41]: $\bar{A}_{ijl}$. This is then normalized at the statistical reporting unit to form the priors: $\pi_{ijl} = \frac{\bar{A}_{ijl}}{\sum_i \bar{A}_{ijl}}$.

Second, spatial disaggregation of crop area. The goal of this second step is to estimate the total physical area of the statistical reporting unit of pixel i for crop j (at input level l): A_{ijl}. The main input for this allocation is the recorded sub-national physical area recorded for crop j (at input level l) $CropArea_{ij}$. In particular, defining the allocation probability as $s_{ijl} = \frac{A_{ijl}}{CropArea_{ij}}$, to estimate A_{ijl}, they solve the

[41] In our analysis we use the sum of all the input levels. Therefore, this distinction is not relevant to our results.

following minimization problem:

$$
\begin{aligned}
\min_{s_{ijl}} \quad & \sum_{ijl} lns_{ijl} - \sum_{ijl} ln\pi_{ijl} \\
\text{s.t.} \quad & \sum_{i} s_{ijl} \quad \forall j, l \\
& \sum_{jl} CropArea_{jl} \times s_{ijl} \leq Avail_i \forall i \\
& CropArea_{jl} \times s_{ijl} \leq SuitArea_{ijl} \forall i, j, l \\
& \sum_{i \in k, l} CropArea_{jl} \times s_{ijl} = SubCropArea_{jk} \forall j, k \\
& \sum_{l} CropArea_{jl} \times s_{ijl} \leq IRRArea_i \forall i
\end{aligned}
\tag{3}
$$

The objective function of the spatial allocation model is the sum of the cross entropy of area shares and their priors. The first constraint is an adding-up constraints for crop-specific areas. The second states that the sum of the production areas of all crops should not exceed the actual crop area in pixel i. The fourth constrains the area allocated to each crop not to exceed the area identified as being suitable for that crop within the pixel. The fifth, sets the sum of all allocated areas within each subnational unit with available statistical data to be equal to the corresponding subnational statistics. The sixth, states that the sum of all allocated irrigated areas in any pixel must not exceed the area equipped for irrigation as indicated in irrigated area layer. In other words, in this second step, they allocate *sub-national crop production area* from the census statistics using the previously listed data.

In the third step, they convert the estimated allocated crop areas A_{ijl} into production and yields. This is done by combining:

- Sub-national crop production statistics
- Estimated area allocations A_{ijl}
- Potential yield $PotYield_{ijl}$–Global Agro-ecological Zones (GAEZ), Fischer et al., 2021
- Crop intensity $CropIntensity_{jl}$, which in Liberia is assumed to be equal to 1: a single crop is produced in the field.

As for the productivity–yield, they first calculate the average potential yield of a statistical reporting unit $\bar{Y}_{ijl} = \frac{\sum_i PotYield_{ijl} \times A_{ijl}}{\sum_i A_{ijl}}$, and then use this value to estimate the pixel-level productivity:

$$Y_{ijl} = \frac{PotYield_{ijl} \times Yield_{jl}}{\bar{Y}_{ijl}}$$

where $Yield_{jl}$ is the yield observed in the sub-national crop production statistics. To conclude, this estimated yield is used to estimate production:

$$Prod_{ijl} = A_{ijl} \times CropIntensity_{jl} \times Y_{ijl}$$

Fourth, validation. The results obtained with this algorithm have been validated by experts consultations. In particular, they sent their maps to CGIAR (Consultative Group for International Agricultural Research) centers, ech with its own mandate crop. For example IRRI's (International Rice Research Institute) for rice. In addition, they also held their own crop validation workshop where local experts were asked to confirm or validate the crop distribution and performance. This feedback was used both for validation, and, when disagreement appeared, to re-inform the prior (hence, the experts valuations described in the input data for the first step).