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Large-scale land acquisitions: Trees, trade and structural change

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Abstract
Large-scale land acquisitions are a key component of agricultural foreign direct investment. In 2023 alone, nearly 6% of the world's arable land was acquired globally. 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 54% growth in production, primarily due to an expansion in cultivated hectares rather than large improvements in land productivity, accompanied by a significant rise in palm oil exports. Our results indicate that LSLAs have altered the equilibrium of palm oil production, fuelling the adoption of an extensive monoculture system oriented toward international markets. The expansion of this tradable industry generated modest positive effects on the local economy and spurred a process of structural transformation. Women transitioned from agriculture to service and sales jobs, while men shifted into manual labour positions. However, all of this came at a cost: increased deforestation, air pollution, and a decline in local land ownership.

Key words: large-scale land acquisitions, agricultural production, structural transformation
JEL codes: F18; F63; O13; Q15

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1 Introduction

Global foreign direct investment inflows into the primary sector experienced consistent growth 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 agricultural land, commonly referred to as large-scale land acquisitions (LSLAs). In 2023, over 80 million hectares were acquired globally through public large-scale land deals (5.8% of the world's arable land), and the number of large-scale land contracts increased by 128% over the past 13 years.[1] Since their inception, LSLAs have sparked significant debate.[2] Advocates highlight potential benefits such as increased agricultural productivity, capital inflows, and positive impacts on local economies. Critics emphasize negative environmental consequences, the absence of productivity gains, and detrimental effects on local economies.[3] Conceptualizing LSLAs as a means of reallocating land to more productive owners, they could potentially address the issue of low agricultural productivity in developing countries (Adamopoulos & Restuccia, 2014), in line with the theoretical insights presented by Lagakos and Waugh (2013) and the recent experimental evidence provided by Acampora et al. (2024). However, LSLAs differ significantly from the existing evidence on the topic across various dimensions–including the scale of land reallocation, ownership and concentration of land titles, and production function–resulting in a priori ambiguous aggregate effects on production and productivity. Consequently, the impact of land reallocation on the local economy remains uncertain, underscoring the need for further research, as suggested by Liao et al. (2016).

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 variation in land acquisitions, usually unobserved, through changes in deforestation. Our results may be extended to similar land acquisitions in developing countries characterized by extensive and relatively capital-intensive monocultures, accounting for more than 65% of all land deals recorded as of the end of 2024.[4]

Studying the consequences of LSLA is inherently complex. The ideal experiment would be possible with a comprehensive dataset of precisely geolocated and randomly allocated LSLAs. However, these

[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 the 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. Notably, 15% of LSLA deals involve palm oil exclusively.

conditions are difficult to achieve: land contracts are often unobserved, and firms do not acquire land randomly. Identification is a key challenge in our analysis since LSLA areas are selected strategically, invalidating any direct post-contract comparisons between areas inside and outside the designated zones. Additionally, the timing of contract signings is influenced by local decisions, introducing bias in simple pre/post comparisons within the concessions. Our strategy proceeds in two steps. In the first part of the paper, we document an exogenous increase in LSLA contracts, driven by the 2014 Ebola epidemic, through changes in deforestation and land use (addressing unobservability).[5] In the second part of the paper, we leverage this exogenous increase in LSLA propensity (tackling the lack of randomization) to study their effects on our outcomes of interest. To do so, we employ a local difference-in-difference design, using areas outside the concessions–up to 10 km from the border–as a control group. In summary, we compare areas just outside and just inside the LSLA-designated zones before and after the health crisis. 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.[6]

We combine geo-localized data on tree coverage, palm oil areas of interest, agricultural productivity, 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 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 areas of interest, we rely on maps provided by Global Forest Watch. For agricultural production and productivity, we utilize SPAM 2010 and 2020 data, a cross-entropy model generating global gridded maps of agricultural production at a spatial resolution of 5 arc-minute (You et al., 2014). 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.

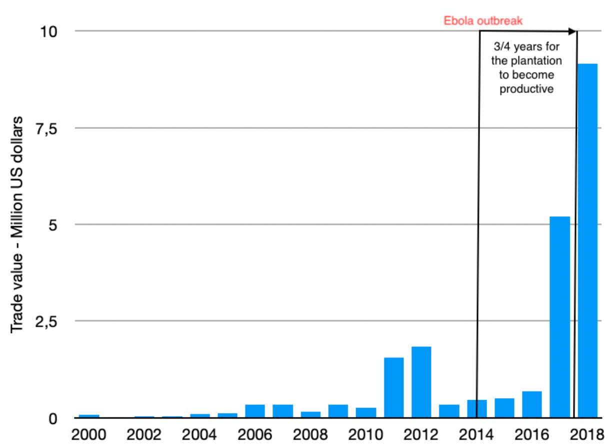
The analysis consists of two steps. First, we document an exogenous increase in deforestation following the 2014 Ebola outbreak, indicating a shock to LSLA contracts. Comparing pixels located just outside and just inside the areas of interest before and after the Ebola outbreak, we observe a 3% decrease in the percentage of evergreen broadleaf cover (approximately 107 million trees lost). The staggered local difference-in-difference analysis reveals no significant pre-trend in deforestation. Using the same methodology, we find a corresponding increase in palm oil plantations. These results indicates an increase in LSLA contracts within the areas of interest driven by the outbreak of the Ebola epidemic.

[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 3 provides a detailed explanation of this context.

[6] It is important to note that 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). This implies that the only factor discontinuous at the border is the possibility of signing large-scale land contracts.

Second, we leverage this exogenous increase to examine the consequences of these LSLAs on agricultural production, environmental outcomes, and local communities. Palm oil production increases by 54%. Productivity changes are modest, with a slight 3% (statistically insignificant) or 7% (marginally significant) rise in yield, depening on the specification. These results suggest that the positive impact of LSLA on palm oil production stems primarily from expanded cultivation rather than improved productivity. Approximately three to four years after the epidemic (the time required for plantations to mature), palm oil exports from Liberia increased by 1428% (Figure 1), indicating a shift of production towards international markets. This rise in production is associated with a 13% increase in carbon dioxide emissions, while effects on other pollutants are minimal (1% for PM2.5 and no change for N2O). We then analyze the effects on local communities by comparing individuals living just inside and outside the areas of interest before and after the Ebola outbreak. Placebo tests (e.g., age, religion, ethnicity) confirm no pre-existing differences or time trends. We find 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. Finally, we examine the occupational structure and 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%).

Figure 1: Liberian Palm Oil Exports



Notes: Value of palm oil exports 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. In particular, there is a 1428% increase in value relative to the pre-Ebola period. Export data from BACI HS6 Revision 1992 (1995 - 2018).

Overall, the findings show that LSLAs have shifted production from intensive, self-sustaining practices to extensive cultivation 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 importance of inputs within the sector. However, these developments are accompanied by increased deforestation, higher CO2 emissions, and reduced local land ownership. These findings may be extend to LSLA,and, more in general, agricultural FIDs,in extensive crops within developing countries. Notably, 94% of LSLAs occur in developing nations (including regions like 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 three related strand of literature. The primary one focuses on large-scale land acquisitions, mainly developed outside economics.[7] In economics, this question can be associated with the classical literature exploring the relationship between FDIs 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)[9], and overall a complex causal relationship between FDI and growth in developing countries (e.g., Aitken & Harrison, 1999; Chakraborty & Basu, 2002). 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. The FDI sector seems to be an important determinant too, with positive effects mainly shown to be in manufacturing, and in general capital intensive sectors,rather than agriculture or services (Wang, 2009; Chakraborty & Nunnenkamp, 2008). This paper contributes to this literature by providing evidence that large-scale land acquisitions (FDIs in the agricultural sector) may stimulate production, improve local economic conditions, and promote a process of structural trans-

[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 highlited by Herrmann, 2017).

[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).

formation by opening access to foreign markets. However, this development comes with a cost: increased deforestation, pollution and lower land ownership.

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 large 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 in general, capital-intensive agricultural FDIs. Indeed, these could change the employment equilibrium, possibly by shifting the factor intensity in the agriculture industry.

In conclusion, this paper addresses the debate on agricultural productivity in developing countries. Adamopoulos and Restuccia (2014) documents a 34-fold difference in average farm size (land per farm) between rich and poor countries, indicating productivity differences and factor misallocation, influenced by farm-level policies, as the main mechanism. Multiple studies analyzed the relationship between land misallocation and farm productivity in developing countries (e.g. Chen, 2017; Adamopoulos et al., 2022; Chen et al., 2023; Acampora et al., 2024) and looked at policies to mitigate misallocation through the rental market, such as the formalization of leasing rights (Chari et al., 2021), land certification reform (Chen et al., 2022), and the digitization of land records (Beg, 2022). We contribute to this literature by analyzing to what extent large-scale land acquisitions–foreign direct investment in agriculture–by reallocating land from locals to companies, may represent another channel to potentially address the misallocation problem.

The paper is structured as follows. Section 2 presents the background, specifying how the peculiarity of the Liberian palm oil sector represents an ideal setting for our analysis. Section 3 outlines the empirical analysis and details our identification assumptions, while Section 4 describes the data. Section 5 presents the results, and Section 6 concludes.

[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).

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 pesticides, fertilizers, and herbicides 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 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]

[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).

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

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 will discuss in Section 3. 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 Empirical strategy

In this paper, we want to study the impact of LSLAs on agricultural, environmental, and individual outcomes. The ideal experiment would be possible with a comprehensive dataset of *precisely geolocalised* and *randomly allocated* LSLAs. However, these conditions are difficult to achieve: 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 two steps. In the first part of the paper, we document an exogenous increase in LSLA contracts, through changes in deforestation and land use (addressing *unobservability*). In the second part of the paper, we leverage this exogenous increase (addressing–absence of–*randomization*) in LSLA propensity to study their effects on our outcomes of interest.

3.1 Variation in large-scale land acquisitions

In the first part of the paper, we document an exogenous increase in LSLA contracts, through changes in deforestation and land use, within the areas of interest following the Ebola outbreak.

To the best of our knowledge, a comprehensive dataset of granular land contracts with detailed information about their locations does not exist.[15] To address *unobservability*, in the first part of the paper, 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 can operate at large scale in these concessions. Therefore, a

[15] The only existing land deals dataset is Land Matrix, which records some land deals worldwide as well as some of their characteristics. However, the spatial structure of land deals is almost always missing and particularly poor in terms of spatial precision.

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 start production without signing *new* contracts with local communities. Therefore, we can conclude that an increase in deforestation within the Liberian areas of interest indicates an increase in LSLA contracts.[16]

By leveraging the relationship between LSLA contracts and deforestation, we use a local staggered difference-in-difference design to document an exogenous shift in LSLAs within the areas of interest following the Ebola epidemic. Therefore, we compare deforestation (and other land uses) just outside and just inside to the areas of interest in the years before and after the outbreak of the health crisis.

To visualize this phenomenon, 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.[17] 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.[18] In line with the connection between deforestation and LSLA contract, 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).

3.2 Effects of large-scale land acquisitions

In the second part of the paper, we leverage the exogenous increase in LSLAs' propensity described in Section 3.1 to study their effects. To do so, we use a local difference-in-difference design, with the control group consisting of areas outside the areas of interest up to 10 km from the border (Figure A2 presents a map of the design).[19] In other terms, we compare areas just outside and just inside the areas of interest

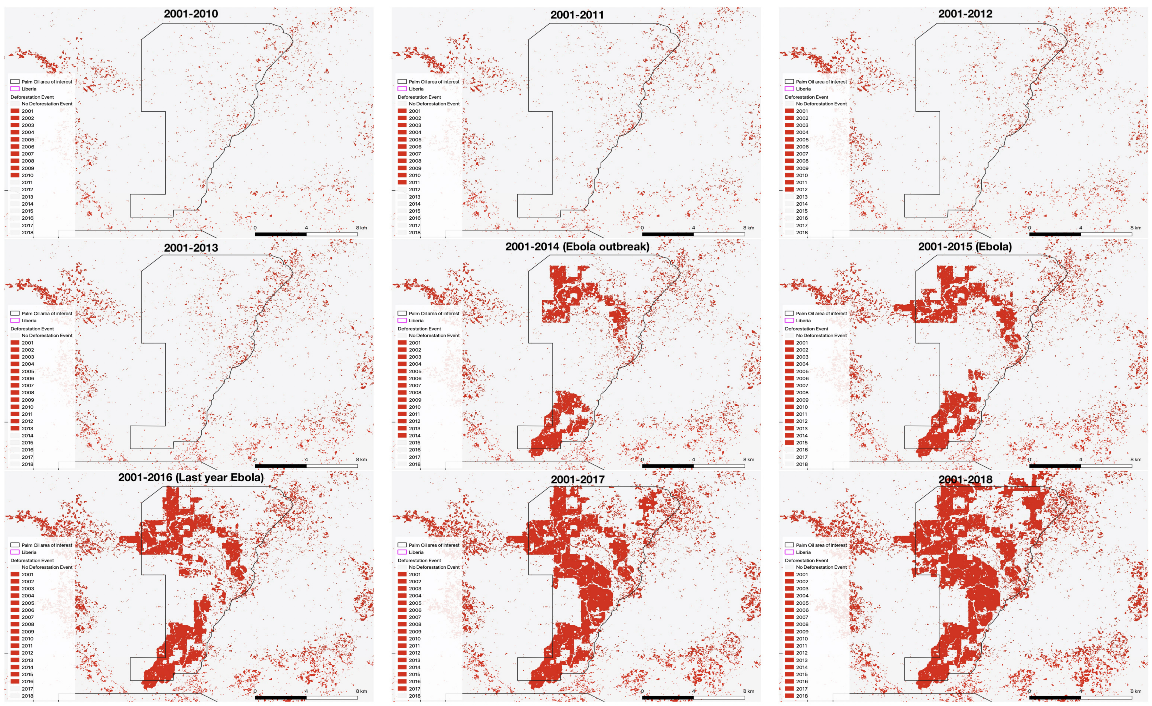
[16] This is true under the assumption that companies acquire the land and begin production in the same year. We believe this is a reasonable assumption for two main reasons. First, leaving land uncultivated is a second-best choice for a profit-maximizing firm. Second, these are large companies, thus 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.

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

[18] 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. Other potential mechanisms are explored in Section E, together with their potential implications for the identification assumption.

[19] 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.

before and after the outbreak of the health crisis. To do this, we use the following linear regression model:

$$Y_{krt} = \alpha + \beta\ E_t \times A_{kr} + \mu_k + \mu_{rt} + u_{krt} \tag{1}$$

where Y_{krt} denotes the (agricultural, environmental, or individual) outcome of interest in cell *k* in region *r* in year *t*, E_t is a dummy variable equal to one after 2013, indicating the Ebola epidemic years, and A_{kr} is a dummy variable equal to one for cells within areas of interest. The identification assumption is that Ebola has no differential impact *locally*, outside and inside areas *designated for LSLA*, other than LSLAs itself.

4 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 resulting 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 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 types, ultimately allows us to measure palm oil land cover.[20]

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.[21] 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.[22] 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.

[20] Additional details can be found in Section 5.1 and Appendix C.

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

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

Agricultural Outcomes. To measure agricultural production and productivity, we rely on the SPAM 2010 and 2020 data (You et al., 2014). SPAM is an open-source cross-entropy model that generates global gridded maps of agricultural production at a 5 arc-minute spatial resolution, combining agricultural statistics at national and subnational levels with crop production system characteristics, satellite-derived land cover images, and map layers of crop-specific agroecological suitability and irrigation.[23] 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). We merge the SPAM data with our cells (computing the average value for each dimension/crop for our geographical unit), and then aggregate them into average area cultivated (hectares), production (metric tons), and yield (metric tons per hectare) for six crop categories (palm oil, cereals, roots, pulses, fruits, and other) for each pixel in the two available years, i.e. 2010 and 2020.

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 illustrates the geographical distribution of the DHS-surveyed villages. Figure A5 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 NGOs' presence, population, and weather. See Appendix F for a detailed description of these data.

Descriptive statistics. Table A1 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

[23] Additional details about this methodology can be found on the SPAM website.

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 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 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.

5 Results

Results are presented in two steps. First, Section 5.1 documents the post-Ebola increase in deforestation and palm oil cultivation within the areas of interest. Following the argument presented in Section 3, these results indicate an increase in LSLA contracts. Second, Section 5.2 examines the effects of this exogenous increase in contracts on agricultural production and productivity, environmental outcomes, and local communities.

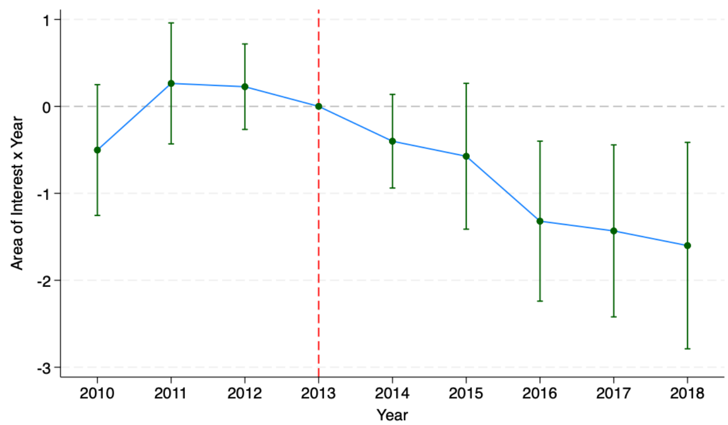
5.1 Increase in large-scale land acquisitions

Figure 2, discussed in Section 3, provides suggestive evidence of the increase in deforestation following the Ebola outbreak. In this section, we present a more rigorous analysis of this rise in deforestation and the subsequent increase in palm oil land cover within the areas of interest after the epidemic. We do so using a staggered local (up to 10km from the border) difference-in-difference approach. Panel (a) of Figure 3 presents the results of the following model:

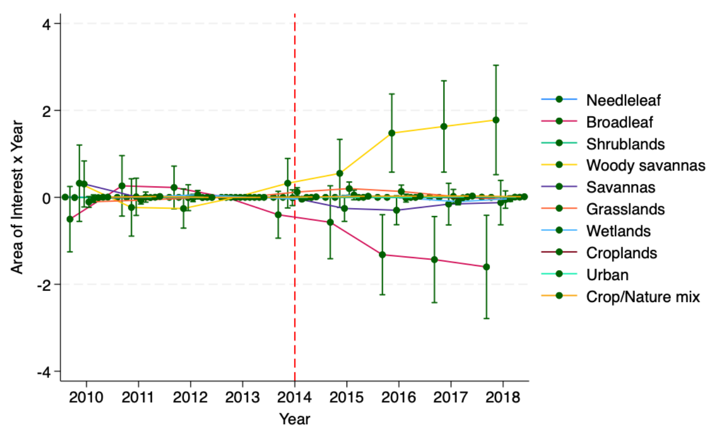
$$P_{krt} = \alpha + \sum_{t=2010}^{2018} \beta_t \, T_t \times A_{kr} + \mu_k + \mu_{rt} + u_{krt} \tag{2}$$

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. Remarkably this exercise allows us also to assess the strength of the identification assumption discussed in Section 3, i.e. that Ebola has no differential impact *locally*, outside and inside areas *designated for LSLA*, other than LSLAs itself. 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.[24]

Figure 3: Deforestation and increase in Palm Oil - Event study



(a) Percentage tree cover



(b) Land use

Notes: Panel (a) presents the event-study described in section 5.1, equation (2). Panel (b) presents the same exercisefor different categories of land cover. 95% confidence interval shown.

To calculate the effect 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) confirm a decrease in the percentage of evergreen broadleaf cover of approximately 3% across all specifications.[25] To put this into perspective, this corresponds to a

[24] Figure A6 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.

[25] These results hold with cell and year fixed effects (column 1 of Table A2), 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

loss of over 100 million trees from 2014 to 2018.[26]

In Section 3, we discussed the rationale for using deforestation to detect variation in LSLAs, highlighting its strong connection with production in the palm oil sector. This raises an important question: do we observe an increase in palm oil cultivation following deforestation within areas of interest after the Ebola outbreak? While this might appear straightforward–given that only palm oil companies are permitted to operate at such a large scale within these areas–the MODIS data, as presented in Section 4, offers a direct opportunity to investigate this, by allowing us to examine palm oil cultivations as changes in "Woody Savannas" land cover.[27] Panel (b) of Figure 3 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 (2).[28] The graph shows a steady decrease in the presence of Evergreen Broadleaf Forests, as described in Panel (a) of the same figure, 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.

In conclusion, the onset of the Ebola epidemic appears to have stimulated deforestation within areas of interest, as well as an increase in palm oil land cover. Under the assumptions outlined in Section 3, this indicates an increase in LSLA contracts. Despite being outside the scope of this work, Appendix E explores potential mechanisms.

5.2 Effects of large-scale land acquisitions

In this section, we explore the effects of the increase in LSLA on (i) agricultural production and productivity; (ii) air pollution; and (iii) the local economy.

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., migration) impacts on the local economy.

A second important point to discuss before results is that here we are presenting the effects of LSLA

with region × year fixed effects (column 3). Table A3 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).

[26] 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.

[27] 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".

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

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 5.3.

In the analysis that follows, 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 3: Ebola has no differential impact *locally*, outside and inside areas *designated for LSLA*, other than LSLA itself.

5.2.1 Agricultural production

To examine the effects on agricultural production and productivity, we exploit the SPAM data. This dataset provides information on the physical area cultivated (in hectares), total production (in metric tons), and yield (in metric tons per hectare) for 42 different crops, which we aggregate into six categories: palm oil, cereals, roots, pulses, fruits, and other. These metrics are available for each pixel in 2010, before the Ebola outbreak, and in 2020, after the Ebola outbreak. Consequently, we compare 2010 agricultural outcomes with 2020, just outside and just inside areas of interest. Figure A7 illustrates the geographical distribution of palm oil production in 2010.

Table 1 presents the average values of production, area cultivated, and yield, both before and after the Ebola outbreak, in areas outside and inside the areas of interest. A few things are worth mentioning. First, palm oil is by far the most produced commodity, both inside and outside the areas of interest, even in the 2010 data. This is reassuring regarding the quality of the data. Additionally, it demonstrates that palm oil, as well as other goods, 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. While this similarity is not essential for the identification strategy, it is nevertheless reassuring. Third, there is a substantial increase in palm oil production within areas of interest (approximately 90%). Fourth, this increase in production appears to be mostly driven by an expansion in the cultivated area (up by approximately 90%), rather than by an increase in yield, which in fact slightly decreased. Nonetheless, these trends could potentially be explained by temporal factors, environmental conditions, and other time-varying unobservables. Therefore, we turn to the local difference-in-difference approach.

Table 2 presents the results of the local difference-in-difference analysis: Panel (A) focuses on production, and Panel (B) on productivity. Consistent with the descriptive evidence, and the land cover results outlined in Section 5.1, within areas of interest, we identify a 54% increase in palm oil production post-Ebola outbreak. Additionally, we observe production spillovers on other commodities, albeit with smaller magnitudes. Regarding productivity, the observed effects are small. The yield of palm oil appears to have slightly increased by 3%–in fact decreased less with respect to areas outside–yet this effect is minor and not statistically significant from zero. Similar results for the other categories.

Table 1: Descriptives - Agricultural outcomes

	Production (mt)		Area cultivated (ha)		Yield (mt/ha)	
	Pre	Post	Pre	Post	Pre	Post
Panel (a): Within						
Palm Oil	269.26	506.85	26.26	50.23	8.876	6.907
Cereals	45.23	73.49	39.55	66.79	0.157	0.155
Roots	181.74	204.75	23.14	25.02	6.934	7.720
Pulses	1.317	1.551	2.64	2.58	0.143	0.176
Fruits	59.333	85.558	11.84	15.66	3.783	3.694
Other	46.735	65.124	19.76	26.63	1.036	0.998
Panel (b): Outside						
Palm Oil	200.75	318.88	20.62	31.89	8.015	5.758
Cereals	44.92	51.98	39.55	47.76	0.149	0.155
Roots	154.81	156.84	20.18	19.36	6.668	7.622
Pulses	1.305	1.166	2.72	2.03	0.142	0.162
Fruits	50.339	58.47	10.44	10.95	3.560	3.612
Other	39.695	45.901	16.07	17.61	0.978	0.949

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

The coarser granularity of the SPAM data could introduce some additional noise in the results. To deal with this limitation, in Table A4 we replicate Table 2 with a slightly larger control group (up to 15km rather than 10km). Conclusions on production are unchanged. As for productivity, with this larger control group, we find a slight increase in palm oil productivity, i.e. 7% increase, statistically different from zero at 10% level. Therefore, there seems to be a limited positive impact on palm oil productivity, although this is very noisy. Figure A8 presents a particularly informative exercise by plotting the difference between areas within and outside over the two time periods. This clearly illustrates the significant effect on palm oil production and the small impact on palm oil productivity.

This increase in production is 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 1428% increase in the value of palm oil exports from Liberia relative to the pre-Ebola period (Figure 1). This result is in line with the anecdotal evidence, presented in Section 2, suggesting the redirection of palm oil production towards the international market.

In summary, it appears that LSLAs have positively impacted palm oil production. However, this increase in production is mostly attributable to the expansion of the area devoted to palm oil cultivation, rather than a large improvement in the yield of existing plantations. This expansion of production contributed to a spectacular increase in palm oil exports.

5.2.2 Environmental effects

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 Eco-

Table 2: Agricultural outcomes - Local difference in difference

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Palm Oil	Cereals	Roots	Pulses	Fruits	Others
Panel A: Production (mt)						
Ebola × Area of Interest	109.9***	19.76***	17.36	0.345***	16.19***	10.91**
	(38.38)	(4.845)	(11.46)	(0.0866)	(5.255)	(4.824)
Observations	1,524	1,524	1,524	1,524	1,524	1,524
R-squared	0.308	0.152	0.398	0.493	0.418	0.388
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Area = 0	200.751	44.921	154.806	1.306	50.339	39.695
Panel B: Productivity (mt/ha)						
Ebola × Area of Interest	0.239	-0.00764***	-0.170	0.0125***	-0.158**	-0.0108
	(0.373)	(0.00291)	(0.132)	(0.00467)	(0.0735)	(0.0298)
Observations	1,524	1,524	1,524	1,524	1,524	1,524
R-squared	0.152	-0.137	0.214	0.078	-0.002	0.061
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Area = 0	8.015	0.149	6.668	0.142	3.560	0.978

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 production, panel A, or productivity, panel B, of the different categories of crops.

nomic and Social Committee, 2015 on potential soil degradation). We already discussed deforestation in Section 5.1, 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 A9 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).

Table 3 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, 13% for CO2, and null for N2O. Therefore, consistent with the Indonesian context, the expansion of palm oil cultivation is associated with a substantial increase in carbon dioxide emissions, while the effects on the other pollutants are relatively modest. With respect to fire events, although the magnitude of the coefficient indicates a significant increase of 20% in the incidence of fire events, it is not statistically different from zero. This lack of statistical significance may be attributable to the estimates being noisy, given the relatively coarse geographical resolution of our pixels with respect to the phenomenon at hand.

Table 3: 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***	-0.00503	0.00957
	(0.0817)	(26.50)	(0.0230)	(0.0249)
Observations	6,687	6,687	6,687	6,687
R-squared	0.977	0.985	0.993	0.519
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rain, Population	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Area = 0	30.956	1008.29	1.469	0.046

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. 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).

5.2.3 Effects on local communities

This section examines the overall impact of LSLA agreements on the local economy.[29] Before transitioning to the survey data, we use our pixel-based local difference-in-difference methodology 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 A5) 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).

Due to the limitations of nightlights in assessing development in rural areas and the challenges of using remote sensing data to examine individual-level dynamics, we turn to survey data. As mentioned in Section 4, 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 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

[29] Remember that, as mentioned at the beginning of the second part of Section 5.2, 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.

individuals living in villages just outside and just inside the *same* area of interest, before and after the Ebola outbreak. Figure A5 presents an example of the variation being used in this estimation. The reduced-form linear model we utilize for this analysis is as follows:

$$Y_{iaw} = \alpha + \beta_1 W_i + \beta_2 E_w \times W_i + \mu_{aw} + u_{iaw} \tag{3}$$

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.

To assess the strength of our identification assumption, Table A6 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 A10 presents the coefficients plotted individually (in a manner similar to that shown in Figure A8 for Table 2), and Figure A11 presents the difference coefficient over time.[30] This exercise is useful for understanding potential time trends. Remarkably, all coefficients are very small, with most being statistically indistinguishable from zero or lacking any discernible time trend.[31] 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.

Table 4 presents the results for wealth and health indicators: (1) a dummy variable indicating whether

[30] 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.

[31] 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.

Table 4: Wealth and Health - Local difference in difference

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Land	Wealth Index	Max education	Weight/Height	Child W/H
Within	-0.0261	0.00372	0.0389*	0.000509	-0.0145
	(0.0171)	(0.0282)	(0.0221)	(0.0434)	(0.0637)
Ebola × Within	-0.0402*	0.340***	0.0977***	0.172**	-0.0156
	(0.0224)	(0.0440)	(0.0357)	(0.0823)	(0.112)
Observations	13,458	11,155	11,153	4,488	2,423
R-squared	0.124	0.261	0.205	0.051	0.013
Mean Dep. Var.	0.395	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. 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 in columns 4-6, only age in 1 (only this control variable, among the previous ones, is present in the household data).

the household owns any land; (2) the DHS-constructed wealth index;[32] (3) the maximum level of education achieved by the individual (ranging from 0–no education–to 3–secondary education); (4) weight over height, a commonly used health measure computed by DHS, standardized by categories of individuals; and (5) average child weight-for-height, a widely recognized measure of maternal health. In column 1 we control for age, while in columns 2-6 we add controls for the gender of the household head and the religion of the respondent.[33] 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 3: within areas of interest, after the Ebola outbreak, individuals have a lower probability of owning land, consistent with an increase in LSLA contracts being signed.

As far as the wealth index is concerned, 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.[34] Similarly, we note a positive effect on the maximum

[32]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 mean.

[33]Unfortunately, in the household data needed for the analysis in column 1, only the age control variable is available.

[34]This corresponds to a standard deviation 0.17 standard deviations increase with respect to the country average. To put

level of education achieved, with an increase of 10%, which is equivalent to approximately a month increase in schooling.[35] 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, aside from the probability of land ownership, the results indicate a modest improvement in the wealth and health of individuals residing in villages within areas of interest. These results are robust to different specifications. Table A7 replicates the results presented in Table 4 without the controls. The results remain robust across all specifications. Figure A12 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 A13 presents the time trend for the probability of land ownership. Unfortunately, we only have non-missing observations for this question across two waves (likely one before, 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 A14 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.

The final set of outcomes pertains to the occupational structure in villages affected by LSLAs. Table 5 presents the results of the local difference-in-difference analysis for the following outcomes: (1) unemployment status (dummy variable); (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.[36] 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.

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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 cupboard (i.e., owning a cupboard increases the wealth score by 0.172 standard deviations).

[35] 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.

[36] 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 5: 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.

Table A8 replicates Table 5 omitting the controls for age, the gender of the household head, and religion. The results are quantitatively and qualitatively similar across all specifications. Figure A15 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 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.

5.3 Discussion

Large-scale land acquisitions in the palm oil sector in Liberia appear to have significantly increased production, primarily by expanding the cultivated area, rather than significantly improving land productivity.

This observation aligns with the characteristics of large palm oil plantations, which are often characterized by extensive, (more) capital-intensive, monocultures (Carrere, 2013). The nature of large palm oil plantations, combined with the constraints associated with accessing international markets, likely contributed to the limited palm oil cultivation before the acquisitions. In this context, these land acquisitions seem to have changed the equilibrium of palm oil agricultural production. In addition to the previous reliance on, predominantly self-sustaining, polycultures, there is now an expansion of extensive monoculture aimed at serving the international market (Republic of Liberia & International Trade Center - WTO and UN, 2014). As a result of this process, characterized by both the expansion of cultivation and the reorientation of existing production towards international markets, we observe a substantial increase in the export value of Liberian palm oil.

The expansion of this tradable industry has yielded some limited but positive effects on the local economy, manifesting as a modest increase in the wealth, health and education of individuals residing in villages within the areas of interest. Regarding the local economy, LSLAs have likely prompted two distinct responses. Possibly due to the higher capital-intensive nature of large palm oil plantations, some individuals have transitioned away from agriculture–hence fostering a process of structural transformation by changing the relative factor intensity–to other sectors, stimulated by the expansion of the tradable industry, such as sales, services, and manual labour. Others may have relocated their agricultural production, benefiting from a positive local demand shock resulting from the new economic equilibrium–hence the observed positive spillovers on production for the other crops. This economic development came with a cost: increased deforestation, CO_2 emissions, and lower local land ownership.

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 regarding agricultural production for other crops and the local economy 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 these 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 productivity, environmental outcomes, and the local economy. We first detected an increase in LSLA contracts–through a reduction in tree coverage and a corresponding increase in land cover dedicated to palm oil cultivation–prompted by the outbreak of the Ebola epidemic, leveraging the bureaucratic framework of the palm oil sector in Liberia. To assess the effects of this exogenous increase in the propensity for LSLA, we employ a local difference-in-difference design, with the control group consisting of areas located just outside the areas specifically designated for palm oil LSLA (called areas of interest).

Using satellite estimates of land production and productivity, we identify a significant increase in palm oil production. This production increase is primarily attributable to the expansion of the area devoted to palm oil cultivation, rather than any large improvement in the yield of existing plantations. This expansion in palm oil cultivation has resulted in a significant increase in carbon dioxide emissions. In terms of the local economy, within areas of interest, individuals have a reduced probability of land ownership following the Ebola outbreak. LSLA contracts appear to have also exerted a modest positive effect on the wealth and health of individuals residing in villages within these areas. Analyzing the occupational structure within these villages, we find evidence supporting the idea that LSLAs have diverted individuals away from agriculture toward other occupations, primarily in services, sales, and manual labour.

These results are consistent with LSLAs changing the equilibrium of agricultural production, with the expansion of an extensive monoculture system oriented toward international markets. The growth of this tradable industry has had modest positive effects on the local economy and stimulated a structural transformation process but, at the same time, increased deforestation, air pollution, and decreased local land ownership. Without a method to directly compare these positive and negative effects–such as balancing increased emissions against production expansion–it is challenging to definitively ascertain whether these acquisitions are welfare-improving or not. Most likely, they created winners and losers.

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 with 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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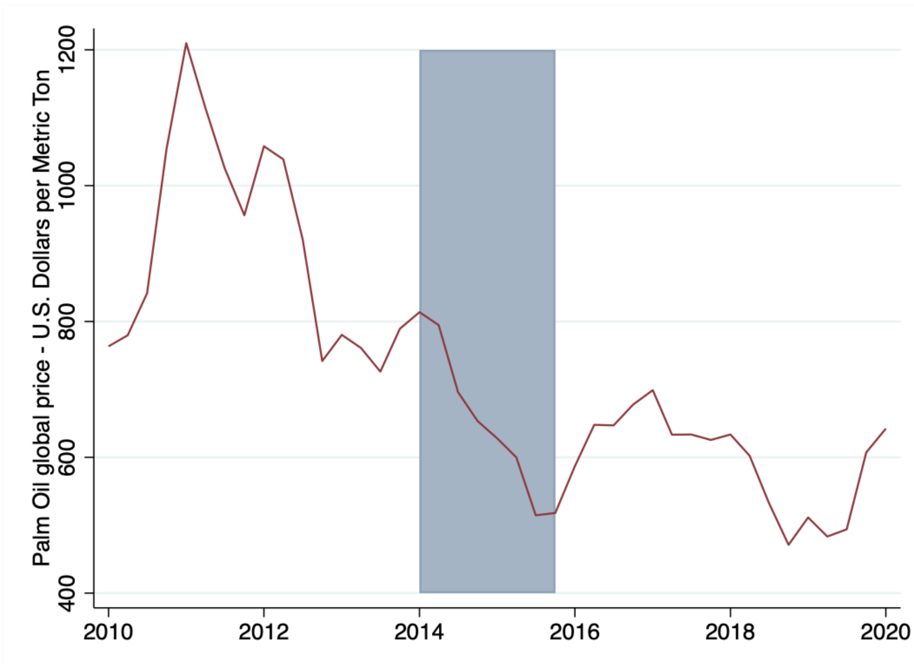
Appendix

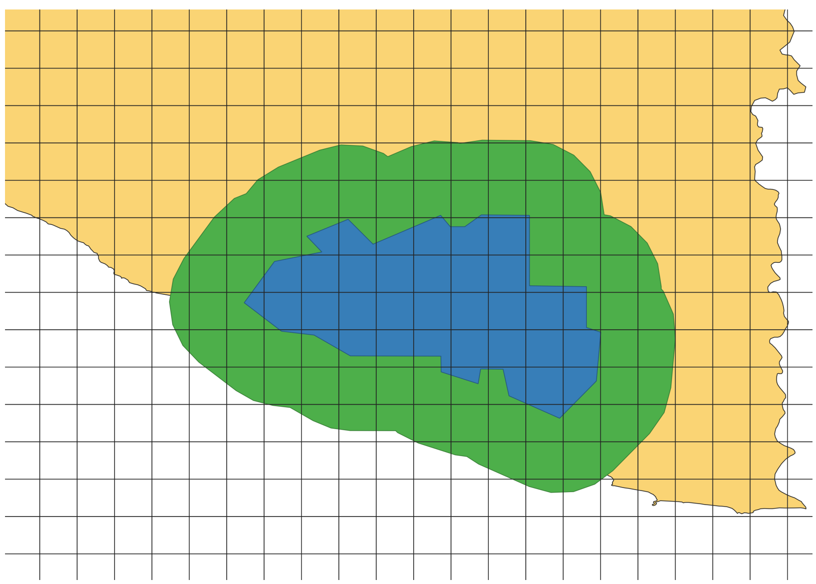
A Additional Figures

Figure A1: Palm Oil global price



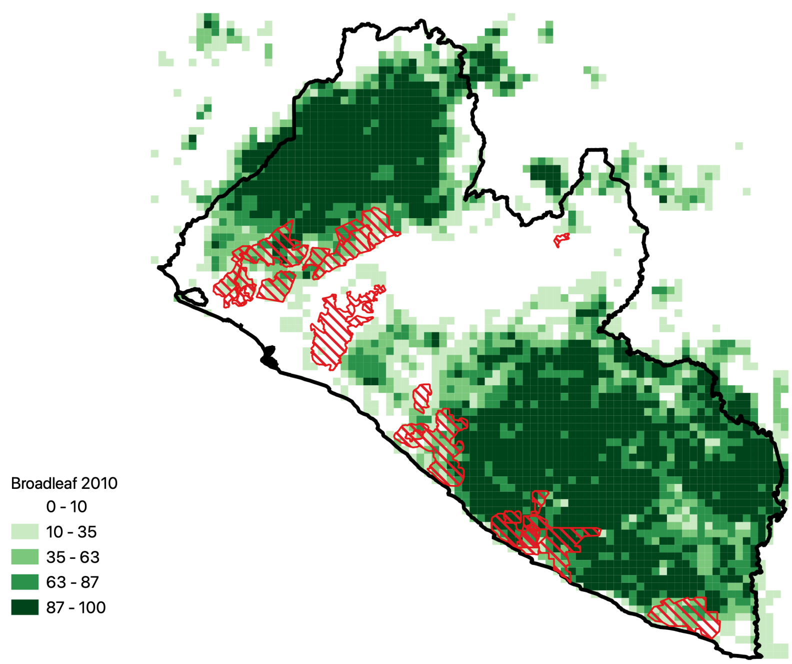
Notes: The figure presents the trend of palm oil global price (U.S. dollars per metric ton) over the period 2010-2020. Data from FRED. The blue area indicates the Ebola period as considered in this paper.

Figure A2: Map local difference-in-difference



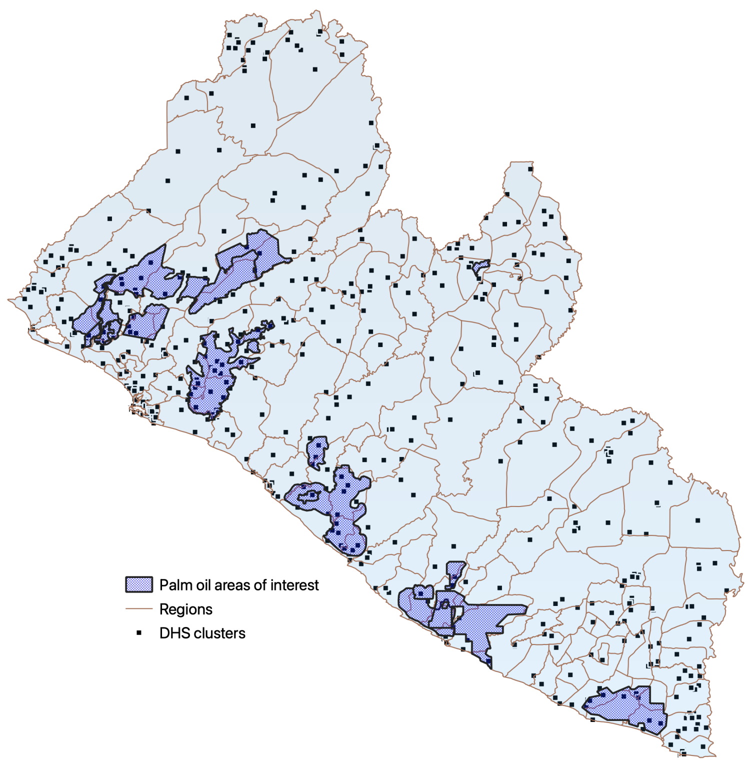
Notes: The figure presents the map of an area of interest, highlighting the sample for the local difference-in-differnece: blue for treatment, green for control.

Figure A3: Percentage tree cover Liberia 2010



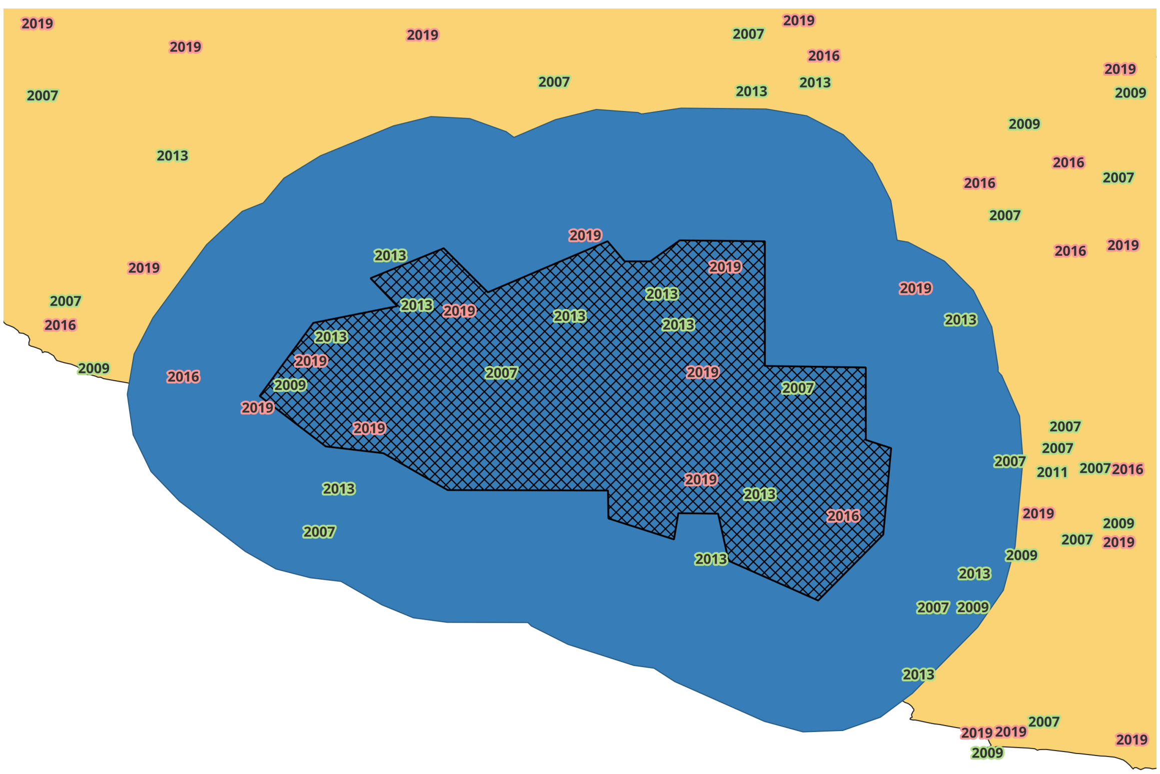
Notes: The figure presents the percentage of each cell covered by "Evergreen Broadleaf Forests" in 2010. The darker the cell, the higher the percentage. In red we have the palm oil areas of interest.

Figure A4: DHS villages



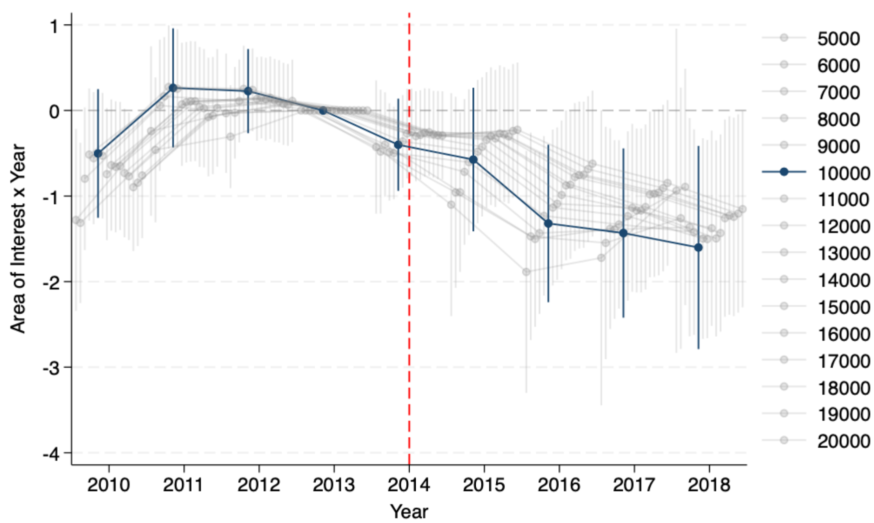
Notes: The figure presents the geographical distribution villages surveyed by the DHS (and MIS).

Figure A5: DHS map - zoom



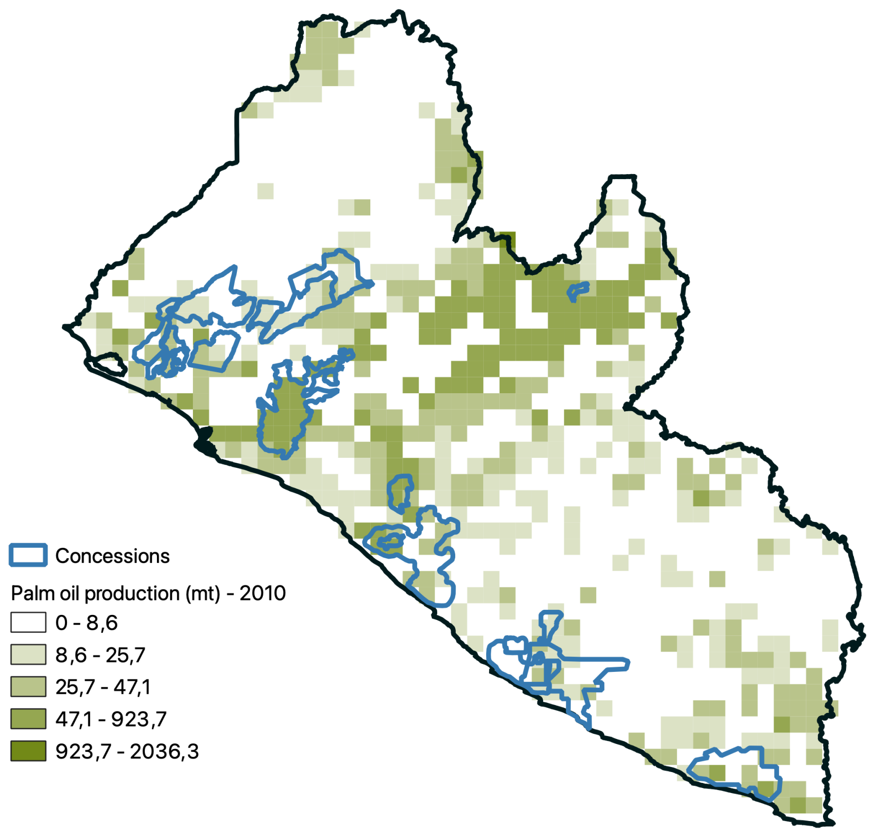
Notes: The figure presents the geographical distribution of villages surveyed by the DHS (and MIS) around an area of interest. Each dot is represented with the corresponding year of the DHS/MIS wave. In green years before the ebola outbreak, red otherwise.

Figure A6: Percentage tree cover - event study, sensitivity



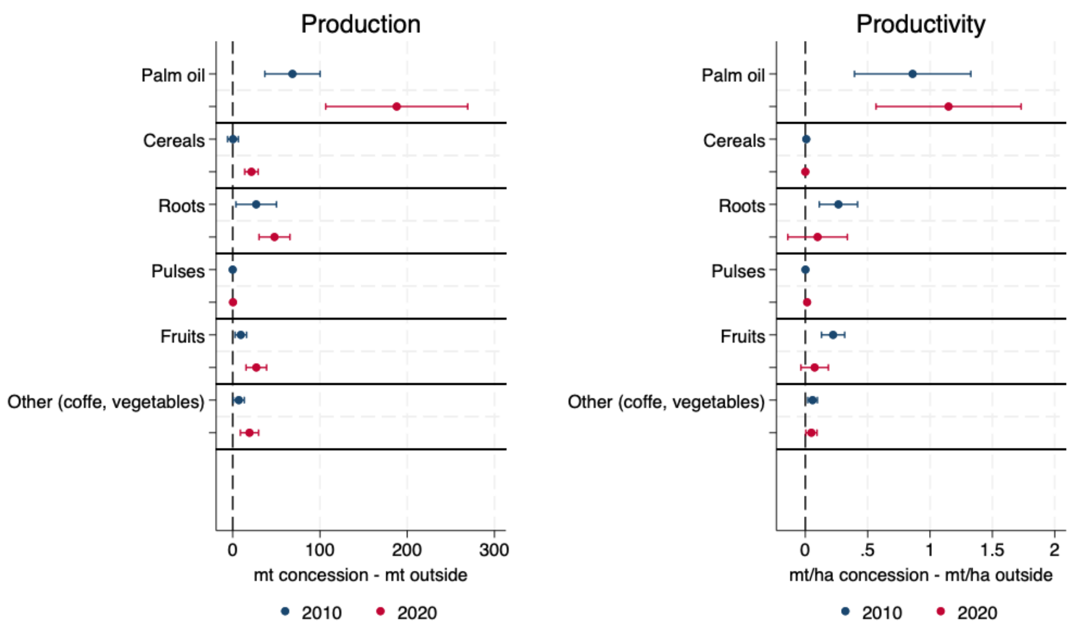
Notes: The figure presents the sensitivity of event-study graph, described in section 5.1, equation 2, to changes in the control bandwidth from 5km to 20km. 95% confidence interval shown.

Figure A7: Palm oil production (mt) 2010



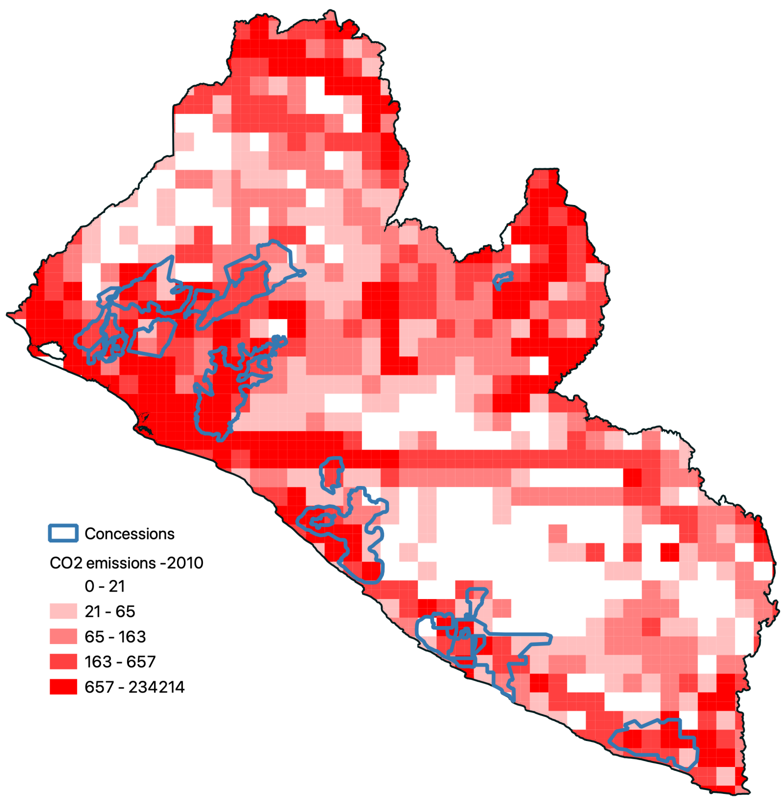
Notes: The figure presents the map of palm oil production in 2010, in metric tons, from the satellite SPAM data. The darker the pixel, the higher production. In blue, palm oil areas of interest.

Figure A8: Agricultural outcomes - Difference over time



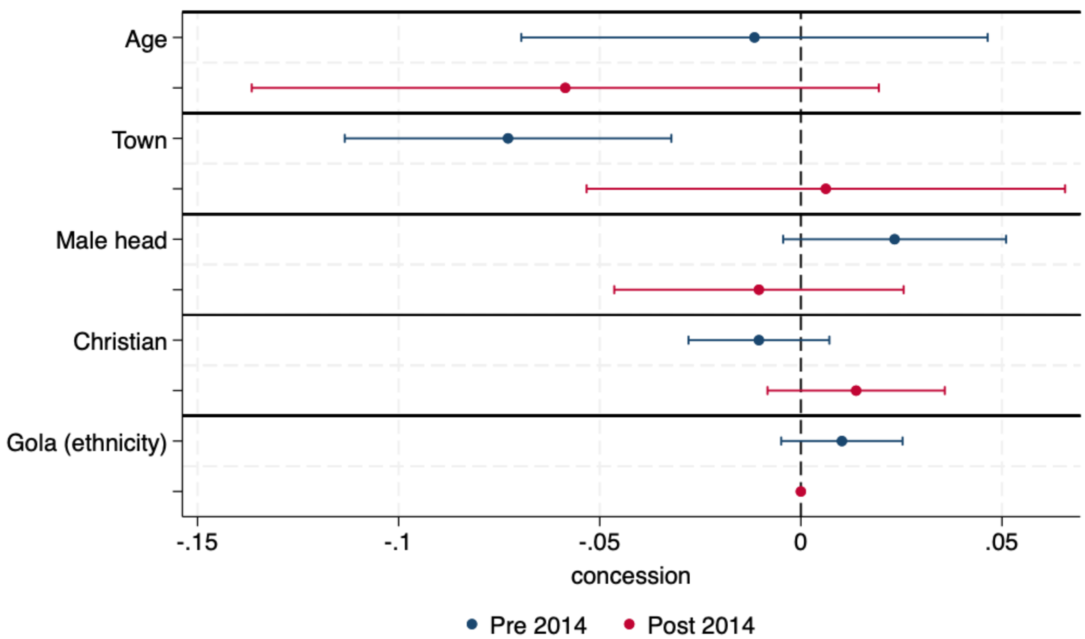
Notes: The figure presents the difference in production (mt) and productivity (mt/ha) of different crop categories, between areas within and outside areas of interest, in 2010 and 2020 - SPAM data. This is done with two simple regressions of the dependent variable on a dummy variable equal to 1 for pixels inside the areas of interest, for the two different periods separately. Standard errors clustered at the cell level. 95% confidence interval shown.

Figure A9: CO2 emissions - 2010



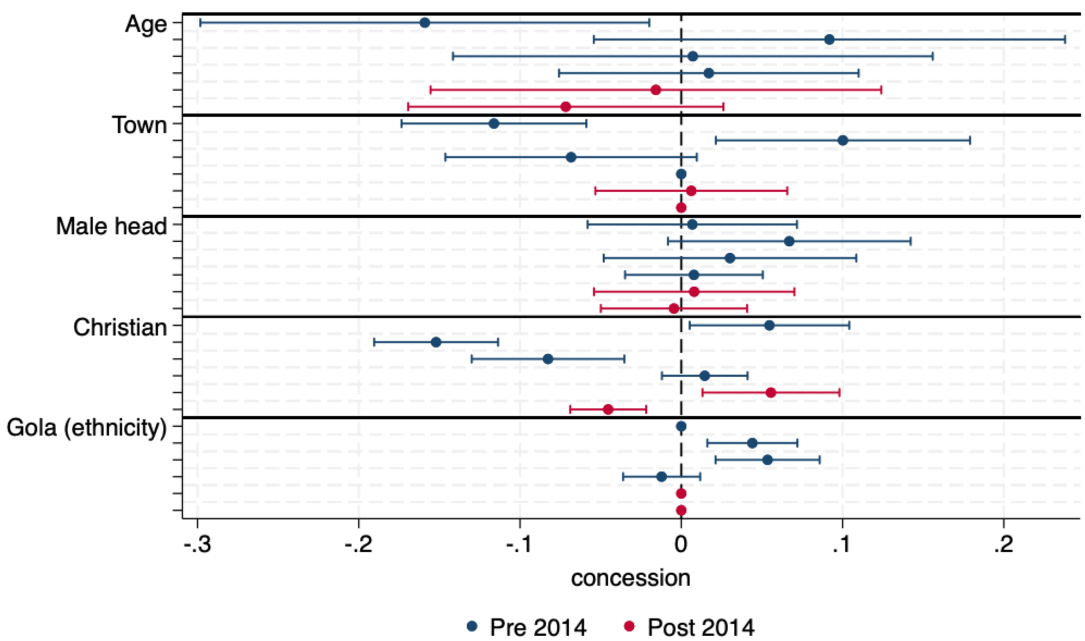
Notes: The figure presents the map of CO2 emissions in 2010, from EDGAR v8.0 data (please refer to section F). The darker the pixel, the higher emissions. In blue, palm oil areas of interest.

Figure A10: Placebo individual outcomes - difference over time



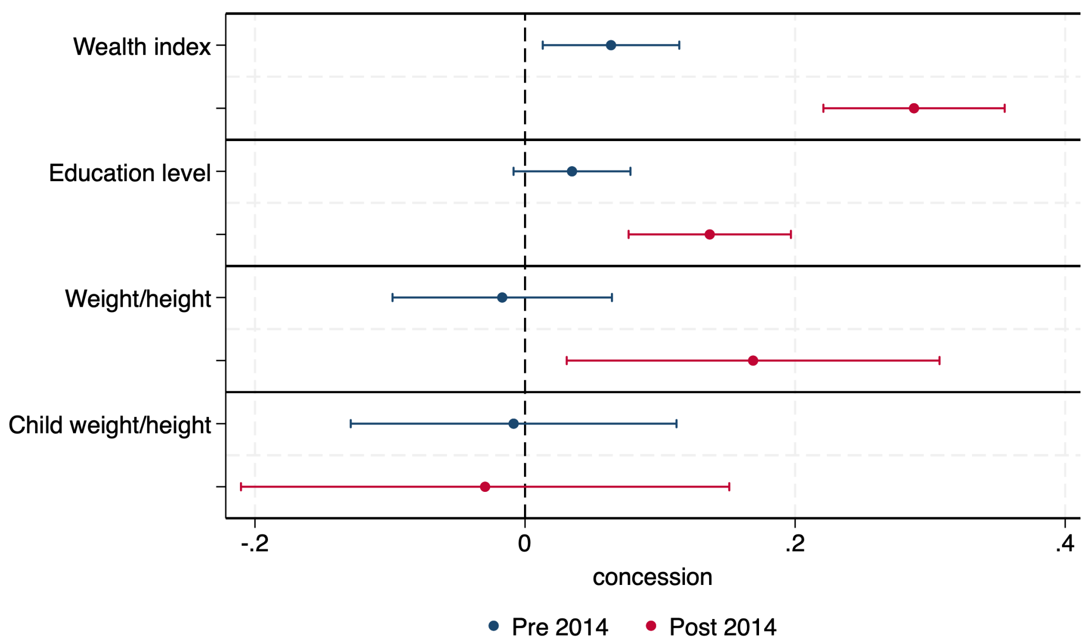
Notes: The figure presents the difference in the different placebo outcomes, between DHS respondents living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. This is done with two simple regressions of the dependent variable 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 A11: Placebo individual outcomes - trend



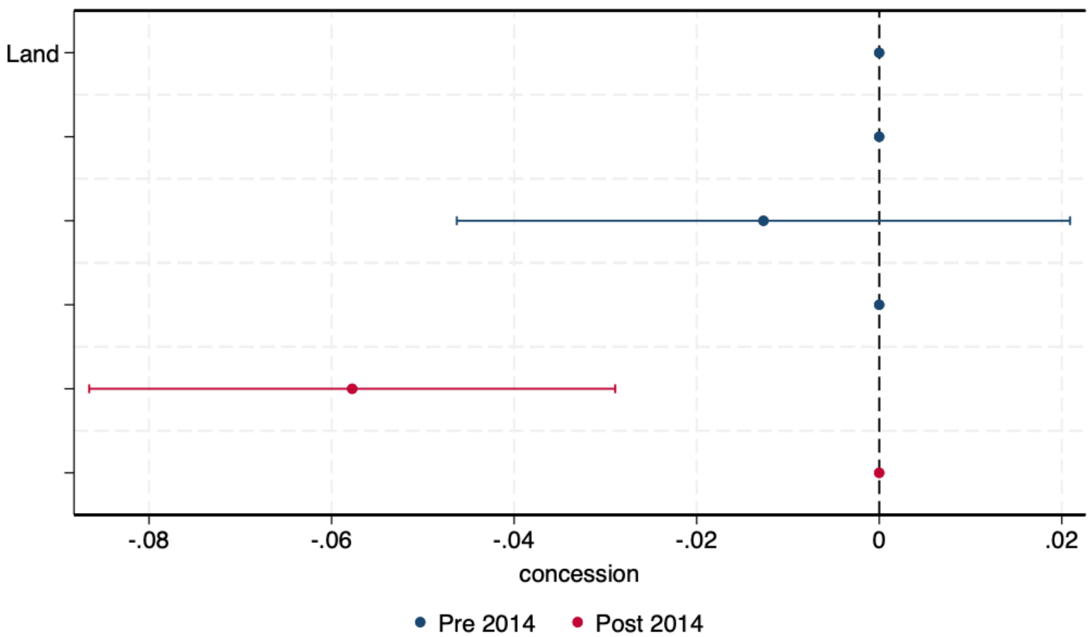
Notes: The figure presents the difference in the different placebo outcomes, between individuals living in villages just within and outside areas of interest, in all the available waves - DHS/MIS individual data. When a regression was not possible - no question in the wave, or not sufficient variation - 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 A12: Wealth and Health - difference over time



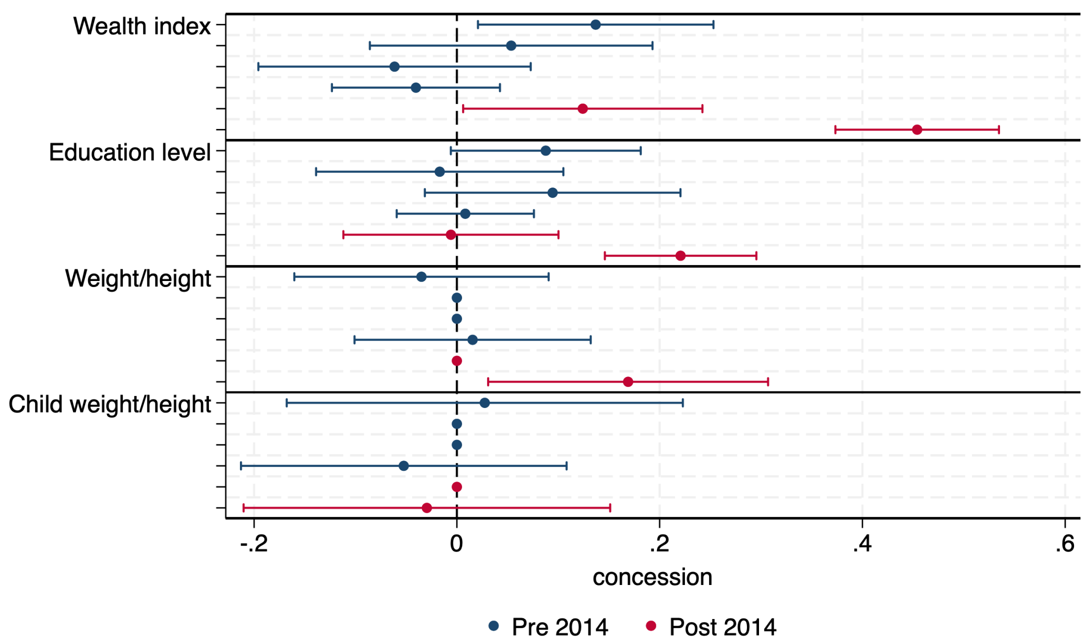
Notes: The figure presents the difference in the different wealth and health outcomes, between individuals living in villages just within and outside areas of interest, in waves before and after the Ebola outbreak - DHS/MIS individual data. This is done with two simple regressions of the dependent variable 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 in 4-6, only age in 1 (only this control variable, among the previous ones, is present in the household data).

Figure A13: 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 A14: 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 in 4-6, only age in 1 (only this control variable, among the previous ones, is present in the household data).

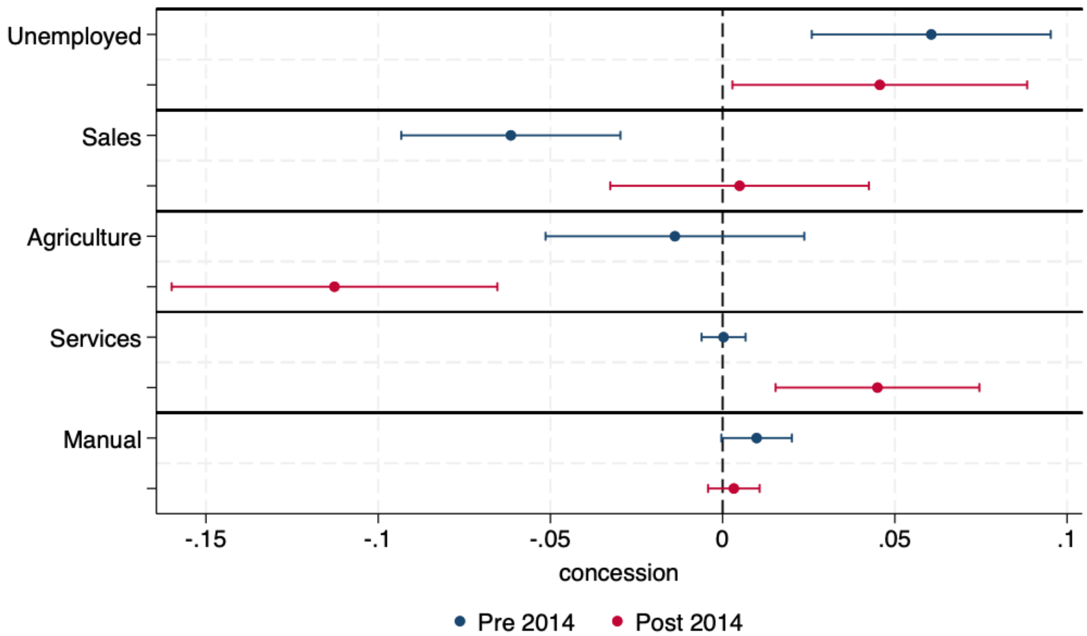


Figure A16: Wife

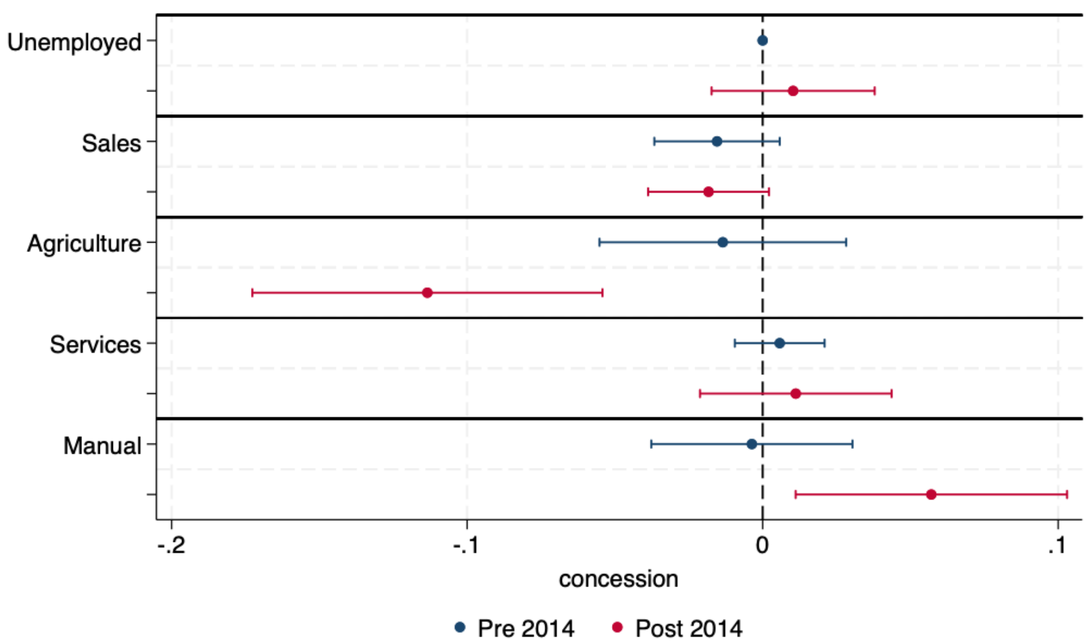


Figure A17: Husband

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.

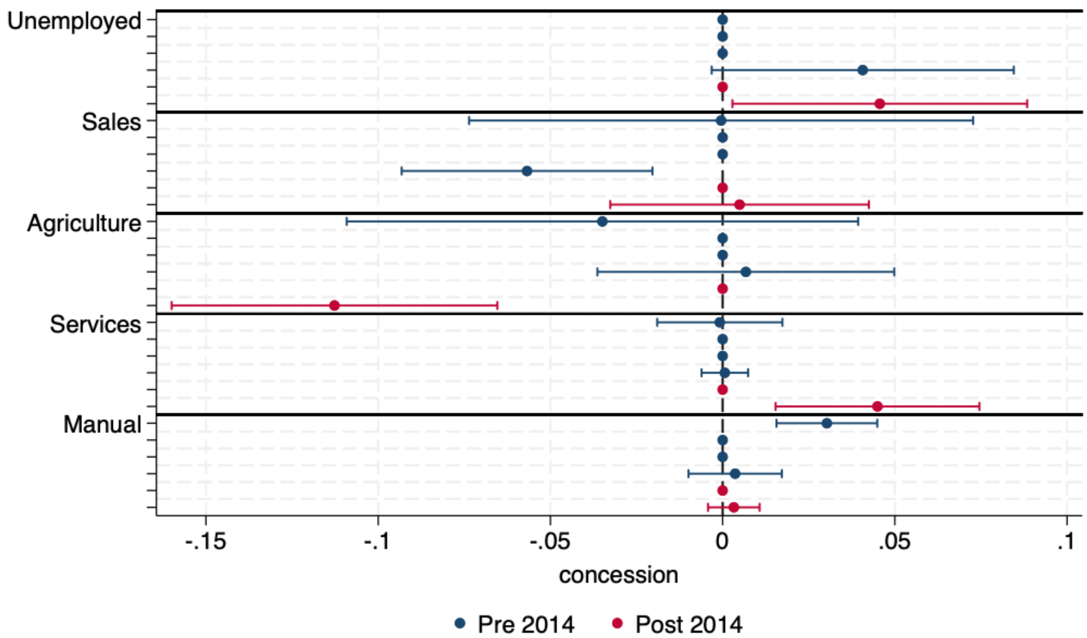


Figure A19: Wife

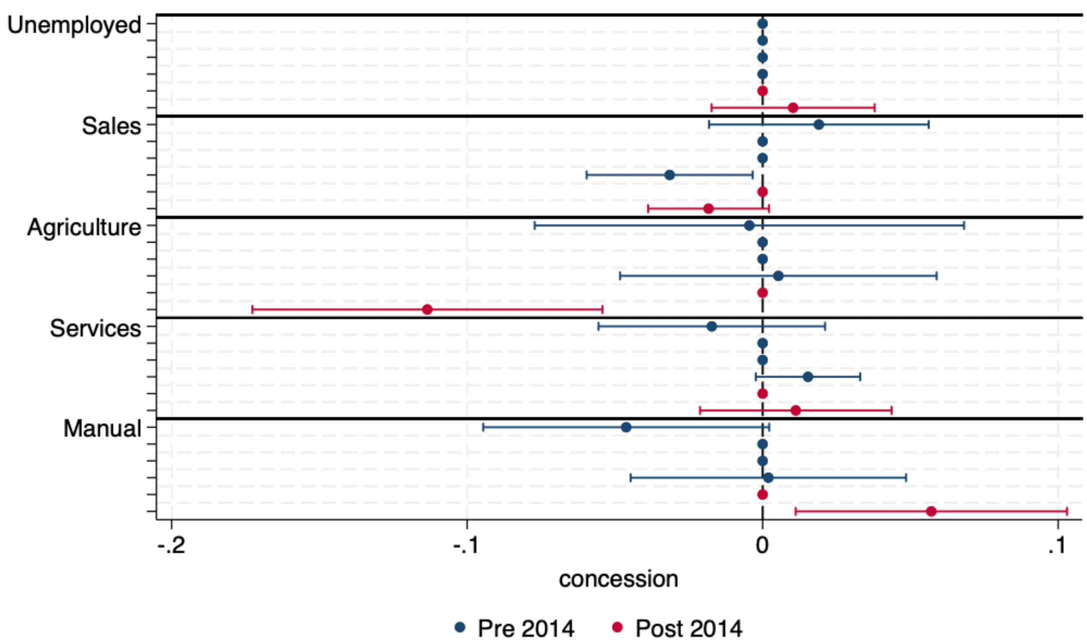


Figure A20: Husband

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.

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: Agricultural outcomes - Local difference in difference (15km)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Palm Oil	Cereals	Roots	Pulses	Fruits	Others
Panel A: Production (mt)						
Ebola × Area of Interest	157.3***	24.91***	21.20**	0.415***	22.01***	16.69***
	(34.89)	(4.168)	(10.35)	(0.0783)	(4.839)	(4.442)
Observations	1,918	1,918	1,918	1,918	1,918	1,918
R-squared	0.301	0.155	0.428	0.508	0.429	0.394
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Area = 0	196.896	44.562	148.331	1.267	49.127	38.761
Panel B: Productivity (mt/ha)						
Ebola × Area of Interest	0.568*	-0.0105***	-0.160	0.0135***	-0.144**	0.0100
	(0.320)	(0.00264)	(0.119)	(0.00411)	(0.0641)	(0.0260)
Observations	1,918	1,918	1,918	1,918	1,918	1,918
R-squared	0.162	-0.091	0.228	0.080	0.045	0.051
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean y | Ebola = 0 & Area = 0	7.936	0.147	6.658	0.142	3.542	0.975

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within 15km 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 production, panel A, or productivity, panel B, of the different categories of crops.

Table A5: 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 A6: 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 A7: Wealth and Health - Local difference in difference

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Land	Wealth Index	Max education	Weight/Height	Child W/H
Within	-0.127	0.00746	0.0341	-0.00752	-0.0167
	(0.0171)	(0.0283)	(0.0238)	(0.0436)	(0.0636)
Ebola × Within	-0.045**	0.341***	0.114***	0.176**	-0.0129
	(0.0225)	(0.0442)	(0.0393)	(0.0827)	(0.112)
Observations	13,458	11180	11176	4508	2433
R-squared	0.111	0.253	0.066	0.044	0.011
Wave × Area of Interest FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. | Ebola = 0 & Within = 0	0.395	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. 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.

Table A8: Occupation - Local difference in difference

Dep. Variable	(1) Unemployed	(2) Sales	(3) Agricultural	(4) Services	(5) 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.

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 A9. 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 A9). 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 A9). 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 A9: 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 %

Finally, we examine specific cells using satellite imagery (via Google Earth) to show an example of the approach described above. Figure A21 presents pixel 4266, 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 4266 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 4266 across different years

(a) Pixel 4266 - 2011

(b) Pixel 4266 - 2014

(c) Pixel 4266 - 2017

(d) Pixel 4266 - zoom

D Palm oil companies

In Liberia operate 7 large-scale palm oil companies, as outlined in table A10. 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 mean hides substantial heterogeneity, as highlighted in figure A22. 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), 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 A10, 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 A22: Distribution area AoIs

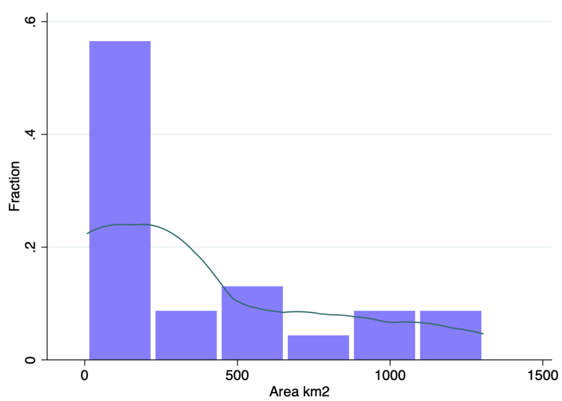


Table A10: Descriptives

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%

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. One example of NGO activities is the SAMFU Toolkit. In this appendix, we will provide some 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.

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 his 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 is very noisy, since it depends on a sub-question of an unrelated survey.

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 A11). To see how this relates to deforestation, we interact the local difference-in-difference model

Table A11: 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.

(equation 1) 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 A12. 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 A12 we replicate the whole analysis with a slightly larger control group (up to 15km outside the 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).

In Table A13 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 more noisy.

Additional evidence in favour of this mechanism is presented in Table A14. 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.

To conclude, in Table A15 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 present results consistent with the diversion of NGO limited attention (Gabaix & Laibson, 2006; Chetty, Looney, & Kroft, 2009; DellaVigna, 2009) as a mechanism to explain the re-

Table A12: 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 A13: 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 A14: 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).

lationship 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 3, 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 5 should be interpreted with consideration of any potential differential effects stemming from these mechanisms.

Table A15: 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 4.

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

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

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.

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