Centre for Economic Performance

Discussion Paper

ISSN 2042-2695

No.1833

March 2022

Epidemics and rapacity of multinational companies

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Economic and Social Research Council

Abstract
Do multinationals engage in rent-seeking behaviour in developing countries during crises? With a difference in discontinuity approach, we use the Ebola epidemic in Liberia as a natural experiment on the sharp increase in deforestation, which produced a dramatic growth in newly planted palm oil trees and a 1428% increase in palm oil exports. We show that the probability of forest fire – the fastest way to clear forests and start new production – increased by 125% in the same period. Both effects are amplified in areas populated by ethnic minorities.

Key words: epidemics, multinational enterprises, land grabbing, palm oil
JEL: C23; F23; O13

This paper was produced as part of the Centre's Trade Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We are grateful for suggestions and support to Pascal Nadembega (Ministry of Health of Burkina Faso) and Luke L. Bawo, Nelson K. Dunbar, and Mohammed Kamara (Ministry of Health of Liberia). We wish to thank the UniCredit Foundation for Modigliani Research Grant funding. For their valuable comments and suggestions let us also thank Pol Antràs, Oriana Bandiera, Andy Bernard, Francesco Caselli, Bruno Conte, Eliana La Ferrara, Bilbiie Florin, Jonas Hjorn, Annalisa Loviglio, Massimo Morelli, Imran Rasul, Alessandro Sforza, and Vincenzo Scrutinio. We are grateful for the comments of participants in seminars at the European Trade Study Group, the Online Political Economy Seminar Series, the University College London, and the University of Bologna. Michael Hall provided excellent research assistance. All errors remain our own.

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Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

This paper investigates the relationship between the Ebola epidemic, deforestation, and palm oil concessions in Liberia. Whether the activity of multinational enterprises (MNEs) fosters or diminishes economic growth in developing countries is still an open question. In particular, how MNEs behave during challenging times such as an epidemic is of fundamental importance, in view of the global Covid-19 crisis. Indeed, a health crisis may alter the short-run incentives of some MNEs, encouraging rapacity vis-à-vis natural resources and this is exactly what occured in Liberia during the Ebola epidemic in 2014-2015. During this delicate health situation, within palm oil concessions we observe a 3% increase in deforestation, which doubles in areas populated by politically unrepresented ethnic groups, together with a rise of 125% in the likelihood of observing a fire event.[1] Simultaneously, we find a 150% increase in land devoted to crop. Three to four years later – the time needed for palm oil trees to become productive – Liberia had a 1428% increase in palm oil exports with respect to the pre-Ebola period. These results suggest that the palm oil companies exploited the chaos created by Ebola to carry out land grabs, and increase their production. Our results further indicate that these effects are particularly strong in areas where minority ethnic groups live, reinforcing the evidence of collusion between these companies and local political leaders. The consequences of deforestation are multiple and pervasive, from socio-economically and environmentally, and they are often associated with large-scale land acquisitions (Davis et al., 2015, Probst et al., 2020, Nepstad et al., 1999).[2] If one adds even the severe health repercussions of controlled forest fires (Marlier et al., 2013, Johnston et al., 2021, Emmanuel, 2000, Moreira & Pe'er, 2018), the long-lasting consequences of the rapacity of these MNEs become a prime issue.

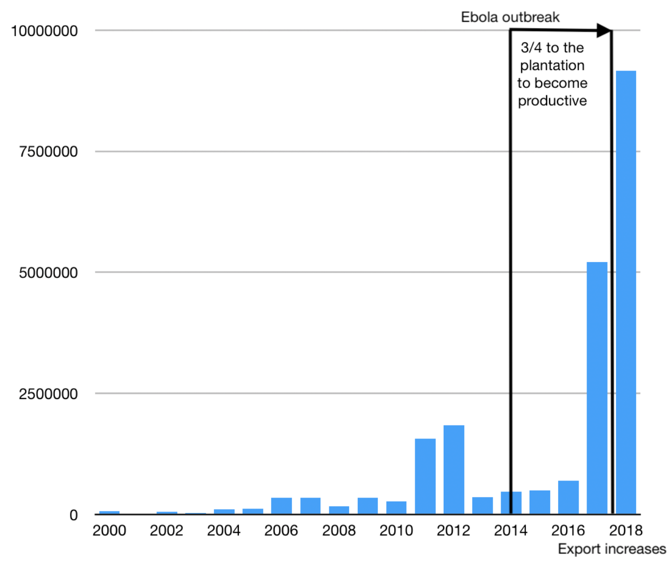
These effects are brought out through the combination of a natural experiment together with a difference-in-discontinuity approach. Once companies have gotten concessions from the central government, they need the consensus of local villages to gain access to their land and start production. This consensus was obtained by formal documents (Memoranda of Understanding). However, they were generally agreed to in a climate of fear. Accordingly, NGOs got interested and began to help local communities confront the multinationals. This equilibrium was

[1] Agricultural enterprises tend to deforest by using controlled fires to clear areas, being it the fastest and cheapest way to switch production (Marlier et al., 2013, Emmanuel, 2000) . This is extremely damaging for the environment, as a major source of carbon dioxide (Palut & Canziani, 2007). In Indonesia, another palm oil producer, the smoke and haze from these blazes induced severe health consequences (Margono et al., 2014).

[2] Some prominents examples of the literature on deforestation's consequences are Hirota et al., 2011; Franklin Jr & Pindyck, 2018; Scheffer et al., 2001; Staver et al., 2011; Lawrence & Vandecar, 2015; Fearnside, 2005; Leite-Filho et al., 2021.

distorted by the outbreak of Ebola which that redirected the NGOs efforts towards the epidemic. As a result, three or four years after the onset of the epidemic (the time needed for a plantation to become productive), we observe a 1428% increase in the value of Liberian palm oil trade with respect to the pre-Ebola period (Figure 1).[3]

Figure 1: Liberian Palm Oil Export



Notes: The figure presents palm oil export value from Liberia in the period from 2000 to 2018. Three-four years after the Ebola outbreak (2014), hence the time a plantation of palm oil need to become productive, there is a sharp increase in export of this product. In particular, there is a 1428% increase of trade value with respect to the pre-Ebola period.

This paper relates to several strands of the literature. First, the unexpected personal and environmental consequences of pandemics. Health crises may have various unexpected effects on different spheres of life. An influential body of work has studied increased violence against women and children during pandemics (among others, Peterman et al., 2020; Bradbury-Jones & Isham, 2020), increased pregnancy rates together with a drop in school-enrolment (Bandiera et al., 2019), and an increase in mistrust and economic distress (Pellecchia et al., 2015). Dhanani and Franz (2020) report a rise in discriminatory behavior toward Asian people and a decline in trust in science during the recent Covid-19 pandemic. Turning to the environmental consequences, Bonardi et al. (2021) find that domestic and international lockdowns decreased PM2.5 pollution, an effect that seems to be persistent in the medium run. On the same note, Liu et al. (2020) found a 48% decrease in tropospheric nitrogen dioxide vertical column densities. Our paper contributes

[3]Export data from BACI HS6 Revision 1992 (1995 - 2018).

to this literature by discussing one possible adverse environmental effect in a health crisis due to the rapacity of resource-intensive multinational enterprises.

Second, this paper relates to studies on the impact of MNE's in developing countries. Some recent literature has observed a connection between multinationals and local labor demand shocks. As an example, Méndez-Chacón and Van Patten (2019) find that the presence of *The United Fruit Company* in Costa Rica attracted a sizeable workforce. As a result, regions where it was present were 26% less likely to be poor than nearby regions where it was absent. In a study involving all African countries, Mendola et al. (2021) find that having an MNE in the vicinity significantly increases the probability of an individual being employed (with some heterogeneity depending on the MNE's nationality). Although MNE's may stimulate the local economies, they can also have negative consequences. As an example, their presence may stimulate conflicts (Sonno, 2020) or increase corruption (Spencer & Gomez, 2011). We contribute to this literature by highlighting another possible negative consequence for in developing countries and investigating how the latter may respond to critical periods such as health crises.

Finally, this paper contributes to the work on the phenomenon known as "land grabbing". This is particularly wide spread in Africa (Nolte et al., 2016) and it is often connected with conflict events (Rulli et al., 2013, Woodhouse, 2012, Woodhouse & Ganho, 2011). Sonno, 2020, has also shown a link between large-scale land acquisitions, MNE's, and conflict. This paper contributes to this literature with micro-evidence on the environmental repercussions of multinationals' land grabs and inquires into the relationship between this phenomenon and epidemics.

The rest of the paper is organized as follows. Section 2 presents the background and the natural experiment. Section 3 describes the data, Section 4 presents the empirical analysis and Section 5 concludes.

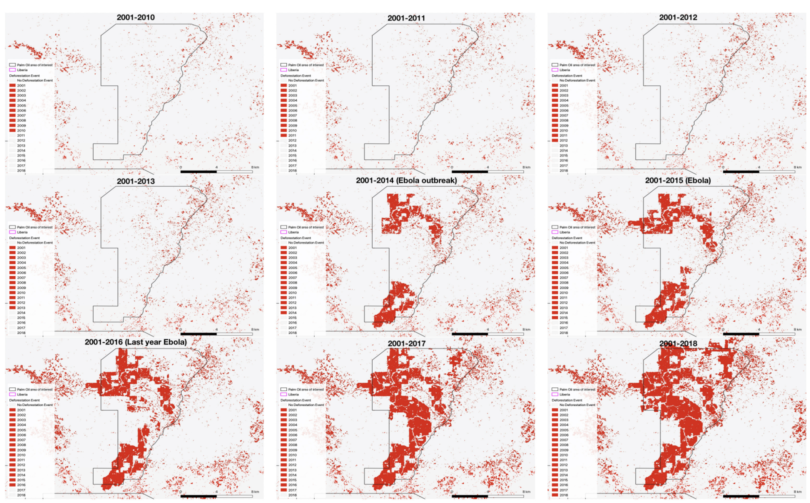
2 The natural experiment

With the end to the country's second civil war (1999-2003), Liberia turned to its natural resource endowments to galvanize the economy. Two major palm oil concessions in 2009 and 2010 granted a total of 440,000 ha to foreign MNEs. But before converting the land into plantations, the palm oil MNEs must win the consensus of the local communities.[4] From 2010 to 2014, Golden Veroleum Liberia (GVL), one of the two leading palm oil MNE, signed agreements for a

[4] Specifically, the central government allocates to a company a large piece of land, called "area of interest". The company has to sign a Memoranda of Understanding with the locals, after which the villages in the area must relocate. The area is then transformed into a concession, where the MNE can deforest and start production. This mechanism was thought to reconcile the MNEs' interests in land with the need to protect villages and their inhabitants.

total area of approximately 298 km^2. In the three months between August and October 2014, it increased the number of agreements by 45% (Global Witness, 2015). Why was this happening? As is often the case in these situations, the agreements were signed in a climate of fear. Many members of the village communities were arrested because they refused consent. There is abundant anecdotal evidence of these practices of the palm oil MNEs, and several NGOs got interested in the problem.[5] They visited the communities, monitored MNEs' operations and assisted locals in filing complaints to the authorities. However, Ebola redirected NGOs efforts towards the epidemic, leaving villages without reliable information on the MNEs' intentions or protection. Another possible mechanism by which the health crisis may have spurred agreements might simply be starvation. Ebola severely affected village families' income, making the weaker ones keener to accept the agreements, even though the benefits were quite limited. Although the anecdotal evidence suggests prevalence of the former mechanism, we cannot rule out the latter. In any case, the health crisis can be used as a natural experiment, as exogenous alteration of the grabbing capacity of palm oil multinationals.

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 first map, top-left, pixels (30×30 meters) are coloured red if a deforestation event occurred between 2001 and 2010. In the rest, one year is added for each successive map. As one can see, deforestation events were quite rare within the area of interest up to 2013, but in 2014 and 2015 there was a quantum leap.

[5] See, for example, Global Witness (2015); RSPO complain - reference PreCAP/2012/09/PR; Hollow promises - Forest Peoples Programme. Also, interviews with people living in the areas describing how the local authorities (often village chefs) took advantage of people's illiteracy to convince them to sign the Memorandum of Understanding (minute 6:52 or 7:55): interviews. In the same interviews, you can also hear all the unkept promises (e.g. building of schools, hiring locals, infrastructures) that the MNEs made.

The result can be visualized in Figure 2, which displays deforestation events for a palm oil area of interest in Liberia. In the first map, top-left, pixels (30×30 meters) are colored red if a deforestation event happened between 2001 and 2010, and one year is added to each successive map.[6] As one can see, subsequent deforestation events were quite rare within in the area of interest, up to 2013. In 2014 and 2015, there was a quantum leap in deforestation.

3 Data

In this paper, we explore the interaction between the Ebola epidemic, deforestation, and concessionary firms in Liberia. This requires geolocalized data on the percentage of trees and palm oil areas of interests, plus the additional data described below. The resulting dataset is structured as a full grid of Liberia. Each grid has an area of approximately 1 km^2, for a total of 98,123 cells observed for nine years.

Land Cover Data. The primary source of data is MODIS Vegetation Continuous Fields (Dimiceli et al., 2015) which offers a quantitative portrayal of the yearly percentage of land cover at 0.05-degree pixel resolution for the entire globe for the period 2000-2020. In particular, for each pixel, we observe the percentage covered by each class as recorded by the International Geosphere-Biosphere Programme (IGBP). This divides the types of land cover into 17, mutually exclusive, classes precisely defined, such as "Water Bodies" (permanent water bodies) or "Evergreen Needleleaf Forests" (evergreen conifer trees with canopy >2m).[7] Figure 3 shows a cross-section plot of the most wide spread class in Liberia in 2010: "Evergreen Broadleaf Forests".[8] This is our main dependent variable and, since Evergreen Broadleaf Forest is the most common type of tree cover in Liberia, we here use the term percentage of tree cover to indicate the percentage of Evergreen Broeadleaf Forest without loss of generality. The main advantage of this source of data is that we can observe the increase in deforestation, measured as decrease in the percentage of tree cover.[9] Moreover, this data allows one to measure the increase in palm oil cultivation,

[6] In order to easily visualize tree cover loss, for this picture we use data that contain areas of tree cover loss at approximately 30× 30-meter resolution. It is provided by GLAD (Global Land Analysis & Discovery) lab at the University of Maryland, Google, USGS, and NASA (Hansen et al., 2013).

[7] These data are the product of a novel production algorithm combining satellite data on surface reflectance and brightness temperature. It first uses some random sample of these satellite data as training data. Then, it creates the best predictive model for tree cover given the training sample. Finally, it applies this model to generate the data we observe.

[8] As Figure 3 shows, there is a low percentage belt in Evergreen Broadleaf Forest from Monrovia to the border with Guinea, given by the presence of "Savannas" in this area (see Figure A1 in the Appendix).

[9] MODIS offers a different type of land cover data. For example, MCD12Q1 is a more disaggregated version of our data MCD12C1, but without the land-cover differentiation. To assess the robustness of our results, we replicate

measured as the percentage cover of "Croplands".[10]

Palm Oil Areas of Interest. To define whether a cell belongs to an area of interest, we use data from Global Forest Watch, which give information about the shape, location, and ownership of palm oil areas in Liberia.[11] No information about years of concession is provided. So, we use the ownership data to retrieve this information. On the basis of several technical reports, we can conclude that all the areas of interest in our sample were granted by 2010 at the latest.[12] To avoid potential endogeneity arising from the opening of new areas, we restrict our sample to the period between 2010 and 2018.

Fire data. Granular data about fire events is obtained from USGS - MCD64A1 (Version 6). This is a monthly, global, gridded 500m product containing per-pixel burned-area. For each of these pixels, and each month, we observe whether there was a fire event or not.[13]

Other data. For population we use LandScan.[14] 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*.[15] Temperature, Water Vapor Pressure, and Precipitation data come from WorldClim climate data for 1970-2000 (Version 2.1). We use these data to construct a measure of temperature and one of humidity.[16] Rainfall data come from the Global Precipitation Climatology Project.[17] We add data on the Standardized Precipitation Evapotranspiration Index (SPEI),

the same analysis using this second more disaggregated source of data (last row of Table A5).

[10] Tan, Kanniah, and Cracknell (2014) provide a way of linking plants' age and canopy size. According to their study, palm oil trees have little canopy when they are young (<1m radius in the first 2-3 years of life), therefore, *newly* planted palm oil trees can be classified as "Croplands".

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

[12] For example, Making concessions in Liberia - Agriculture (Tamasin Ford), accessible here.

[13] Note that this database is constructed using a combination of surface reflectance imagery, active fire observations, and an algorithm to determine a dynamic threshold indicating the presence of a fire event.

[14] 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.

[15] 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.

[16] The authors collect monthly climate data for minimum, mean, and maximum temperature, precipitation, solar radiation, wind speed, water vapor pressure, and for total precipitation at the spatial resolution of our cells (Fick & Hijmans, 2017).

[17] 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.

a multiscalar drought index that combines monthly precipitation and temperature data.[18]

Descriptive statistics. Table A1 in Appendix A reports some descriptive statistics. Panel (a) shows the summary statistics for the total sample, Panel (b) focuses on areas of interest. A few elements are worth special notice. First, the mean percentage of tree cover is lower in areas of interest than in the full sample. This is as expected, as concessionaires must first deforest in order to plant palm oil trees. On the other hand, the average percentage of the cell consisting in cropland is more than twice as high in the areas of interest. This is reassuring as to data quality as well as the classification of palm oil trees. Second, there is no substantial difference in temperature pre-period, humidity pre-period, rainfall, SPEI, PM25, fire event, and temperature between cells inside and outside areas of interest. There is, however, a slight difference as regards population. In particular, the mean number of inhabitants is similar between the two categories, but the standard deviation in the cells outside the areas of interest is approximately four times as great as inside (reflecting the fact that cities are found only outside these areas). Third, though this is not relevant for this paper, temperatures have risen steadily since 1970. Fourth, as Panel (a) shows, approximately 10% of the cells are in areas of interest, and in fact Panel (b) has about 10% as many observations as Panel (a). This is an impressive figure. The total land area covered by concessions is approximately 10 thousands km^2. To put things into perspective, this figure is larger than the total surface of a small country like Cyprus.

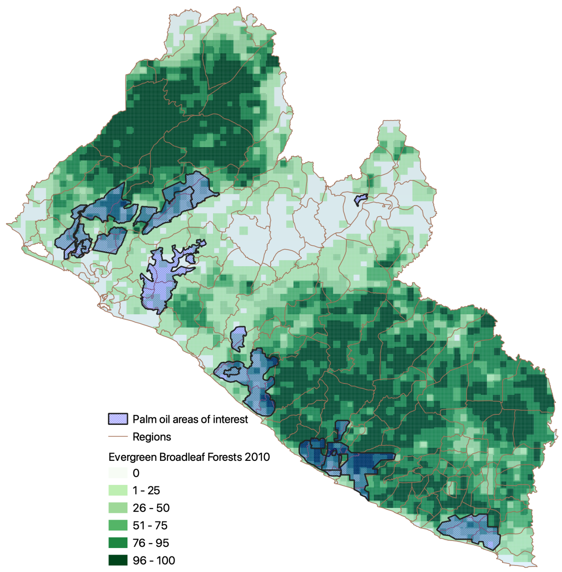
4 Empirical Analysis

In this section, we study the differential impact of Ebola on tree coverage within and outside areas of interest. Using two alternative methodologies, we show that (i) these areas undergo a sharper decline in tree coverage during the epidemic than before it, (ii) this phenomenon is amplified in areas characterized by the presence of minority ethnic groups, and (iii) fire events are more frequent during epidemic years, in particular in areas of interest with an ethnic minority. These pieces of evidence, taken together, suggest a scenario in which the palm oil companies exploit the epidemic to increase their production substantially. This is especially true in areas populated by ethnic groups not represented in the government. Interestingly, our results show that precisely the latter areas are those where we observe a significantly higher probability of fire events.[19]

[18] 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.

[19] Forest fires are often used to clear vegetation before planting of palm oil trees. Trees are cut, the wood is left to dry, and later a fire is set, so that the ash can fertilize the soil.

Figure 3: 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 blue we have the palm oil areas of interest and in gold the administrative boundaries of Liberia's regions.

4.1 Preliminary evidence

The natural experiment described in section 2 clearly suggests the difference-in-difference approach, so, we use a linear regression to estimate changes in cells' tree coverage in areas of interest during the Ebola epidemic, compared with both non-epidemic years and with non-interest areas. Denoting a generic cell k, with $k \in r$, where r is a region and t a generic year, and ignoring controls, our regression model is:

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

where T_{krt} denotes the percentage of evergreen broadleaf forest in cell k in region r in year t, E_t is a dummy equal to one in 2014 and 2015, A_{kr} is a dummy equal to one for cells in an area of interest. Table 1 summarizes results of model (1). All regressions include the Standardized Precipitation Evapotranspiration Index (SPEI) at cell level, cell (μ_k) and region×year (μ_{rt}) fixed effects. This section replicates this exact table for our two identification methods: difference in difference and difference in discontinuity. It is also replicated in a sharp geographic regression discontinuity approach (presented in Appendix C). Column 1 shows that during the Ebola epidemic, within the areas of interest the percentage of tree cover decreases (by almost 0.3% with respect to the sample mean). Column 2 augments our main specification (1) with an additional interaction, namely a dummy equal to one if in a cell there is at least one politically unrepresented ethnic group, i.e. without representation in the government. This specification confirms that during the Ebola epidemic, deforestation was more intense in areas inhabited by unrepresented ethnic groups (-3%). Columns 3 and 4 focus on the potential use of controlled fires to clear areas targeted for new productions, with serious repercussions on the environmental equilibrium as well. To do so, we replicate columns 1 and 2 replacing the dependent variable with a dummy assuming value one when in a cell there is at least one fire event during the year. During the epidemic, in the areas of interest, we observe a significantly higher likelihood of a fire event (+74%), a difference that is magnified in areas populated by ethnic minorities (+315%).

Table 1: Preliminary Evidence - Difference in Difference

	(1)	(2)	(3)	(4)
Dep. Variable	% Trees	% Trees	Fire event	Fire event
Ebola × Area of Interest	-0.116**	2.556***	0.0172***	-0.0529***
	(0.0489)	(0.0474)	(0.00206)	(0.00430)
Ebola × Ethnic Minority		0.429***		-0.0380***
		(0.0362)		(0.00257)
Ebola × Area of Interest × Ethnic Minority		-1.376***		0.0732***
		(0.0688)		(0.00465)
Obs	880,821	880,821	880,357	880,357
R2	0.979	0.966	0.228	0.228
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	48.15	48.15	0.0232	0.0232

Notes: HDFE linear regression. 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 in 2014 and 2015. *Area of Interest* is a dummy equal to one for cells in an area of interest. *Ethnic Minority* is dummy equal to one if in a cell there is at least one politically unrepresented ethnic group, i.e. without representation in the central government.

The difference-in-difference identification strategy depends on the parallel trend assumption. This requires that the same trend of no treatment before/after Ebola and within/outside areas of interest. Equivalently, in the absence of the NGO/starvation mechanism, cells within areas of interest should have had the same trend in tree cover and fire events as those outside the palm oil areas. This assumption, in this context, is particularly strong. Palm oil areas of interest have a maximum radius of 10 km, meaning that cells at the heart of them might differ from those at the boundaries. For this reason, the trends of these cells might have been different over time, even without health crisis. To address this identification issue, one should compare cells that are close to another. In other words, we need a more localized identification strategy.

4.2 Difference in Discontinuities

The difference-in-discontinuity approach compares cells just outside and just inside the palm oil areas of interest. Given their proximity, they are very likely to be similar. However, the NGO / starvation mechanism affected only cells inside the areas of interest. Thus by comparing these two groups one could retrieve the effects on our dependent variables. The most common identification method based on this reasoning is regression discontinuity, which we present in Appendix C. However, this completely neglects the time dimension, which is fundamental for the natural experiment presented in Section 2. Moreover, the non-random nature of the boundaries of the palm oil areas of interest casts doubt on the continuity of potential outcomes at the boundary, thus invalidating the sharp geographic regression discontinuity results. The solution to this identification problem comes from the combination of the two methods mentioned above (difference in difference and regression discontinuity) into a different one: difference in discontinuities. The general concept of this strategy is to perform a local difference in difference. It compares trends of cells just outside and just inside the palm oil areas of interest. This overcomes the limitation of the first method, since it is a local estimation, meaning that we consider only cells at the boundaries, and it also solves the shortcomings of the second method by comparing trends and not levels. This allows us to include cells within concessions in the control group (and thus to deal with the non-randomness of the concession boundaries) and to compare periods before and after the Ebola outbreak.

This identification strategy relies on a relaxed version of the two assumptions typical of the constituent methods, namely parallel trends and continuity. First, it requires continuity of potential outcomes to the right and to the left of the boundaries, but not necessarily *at* the boundary. In other words, it is robust to the potential discontinuity of the potential outcomes' conditional means, which would invalidate the sharp geographic regression discontinuity approach. Second, it requires a local version of the parallel trend assumption. Locally, we require the same trend of no treatment before and after Ebola, just within and just outside concessions in the absence of the health crisis. By comparing adjacent cells, this local parallel trend is more likely to be subsist than is the global one. Appendix B describes in detail the assumptions and provides an intuitive proof of identification.

Due to the local nature of the identification strategy, we restrict the sample to cells within 10 km of the boundary of the areas of interest (Figure A2 shows the geographic dimension of this restricted sample).[20] Moreover, we exclude from the sample a buffer zone of radius equal to the

[20]The distance from cells to boundaries is computed in the following way: it is the (shortest) path from centroids of each cell to areas boundaries. 10 km is the maximum distance between a cell within an area of interest and its

diagonal of a cell (1.42 km) within and outside the areas of interest for three main reasons: (i) to exclude cells with a portion, even tiny, of the complementary area (outside the area of interest for treatment and inside it for control), (ii) the possibility of non enforcement of boundaries (i.e., they are not "visible" on the ground), and (iii) even though these are "controlled" fires or deforestation actions, it is complicated to make them respect a (non visible) boundary exactly, to the meter.[21] Table A3 presents some descriptive statistics of the dependent variables in the restricted sample, as well as the difference between inside and outside the areas of interest.[22]

To estimate the local linear difference-in-discontinuities treatment effect, we combine the procedure outlined by Calonico et al. (2019) with a time dimension. In other words, we run local linear regressions of our outcome variable Y in cell k belonging to region r in year t (Y_{krt}) on a constant, a dummy indicating areas of interest A_{kr}, the distance D_k as well as their interaction, and we combine this model with the dummy variable E_t indicating Ebola years (2014 and 2015) to introduce the time dimension. As is standard, we use only units within bias-robust and optimally chosen bandwidths, and we weight observations by a kernel function according to their distance from the cutoff.[23] Hence, we estimate the following model:

$$Y_{krt} = \alpha_0 + \tau_0 A_{kr} + \beta_0 D_k + \gamma_0 A_{kr} \times D_k + E_t(\alpha_1 + \tau_1 A_{kr} + \beta_1 D_k + \gamma_1 A_{kr} \times D_k) + u_{krt}. \quad (2)$$

The coefficient of interest of the difference in discontinuity is τ_1. The results are summarized in Table 2, robustness tests reported in tables A4 and A5. As one can see, the table replicates the structure of Table 1. Column 1 shows that, near the boundaries, within areas of interest, during Ebola, there was a decrease in tree cover. This decrease is considerable in magnitude, approximately 3% of the sample mean. In areas populated by ethnic minorities (column 2), the decrease is more than doubled to approximately 6.5%. Columns 3 and 4 explore the other mechanism in play: controlled fires. During Ebola, within areas of interest, with respect to cells just outside,

boundary. Hence, by restricting the sample to cells within 10 km of the borders we are sure to include in the sample all cells within the "treatment" group.

[21] In setting the dimension of the buffer, we face a classical bias-noise trade-off. If one increase the size of the buffer, there will be less noise but less similar cells, hence a greater bias. On the other hand, if one decreases it, there will be more noise, for the reasons above, but less bias in the estimates. In the main specification we favor the bias dimension, showing results with the minimum buffer to satisfy reason (i). A sensitivity analysis is presented in Appendix D, Table A4.

[22] Within areas of interest there is significantly less evergreen broadleaf forest cover and, instead, a higher percentage of crop cover. This is consistent with palm oil trees being cultivated within these areas.

[23] Specifically, the optimally chosen bandwidths h are such that $D_k \in [-h, h']$. Moreover, the exponential kernel function is of the form: $K(D/h) = \frac{e^{h-|D|}}{e}$. Sensitivity to other kernel functions, as well as other buffer radii are presented in tables A5 and A4 respectively. Since the bandwidth is chosen optimally for the two dependent variables (% Trees and Fire event), the number of observations in Table 2 differs between columns 1-2 and 3-4.

there is an increase in the probability of a fire event of more than 125% (column 3). And in ethnic minority areas it more than triples, to 420% of the sample mean.

Table 2: Difference in Discontinuities

	(1)	(2)	(3)	(4)
Dep. Variable	% Trees	% Trees	Fire event	Fire event
Ebola × Area of Interest	-0.909**	1.383	0.0277**	-0.0614*
	(0.424)	(0.999)	(0.0134)	(0.0336)
Ethnic Minority × Ebola × Area of Interest		-2.361**		0.0935**
		(1.092)		(0.0364)
Observations	60,471	60,471	155,124	155,124
R-squared	0.979	0.979	0.209	0.209
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	37.80	37.80	0.0223	0.0223

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within the optimal bandwidth computed following the procedure outlined by Calonico et al., 2019. Observations weighted by an exponential kernel function of distance and 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 in 2014 and 2015. *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.

Table A4 replicates the difference-in-discontinuity analysis for different choices of internal buffer. The main results consisting in deforestation within areas of interest during Ebola and its interaction with the ethnic dimension are robust to almost all the various radii for this buffer. Models with fire as dependent variable, instead, are more sensible to model specification. This is in line with this variable being harder to be perfectly "controlled". However, overall, the results with this dependent variable are quantitatively and qualitatively similar across different radii. Table A5 presents the sensitivity of the results to the inclusion of controls and other fixed effects, to change in the kernel weighting function, and to computation of the standard errors. The results are robust to the inclusion of different weather controls (rainfall, temperature, humidity, vapor pressure, PM25), cell characteristics (nightlight and population) and other fixed effects (no cell, no region × year, province). Different choices for the kernel function (no weighting, triangular, uniform and epanechnikov) produced similar results. The results are also unchanged when standard errors are clustered at the province level, when robust standard errors are used, and when their spatial and time correlation is considered as in Colella et al. (2019), who elaborated on Conley (1999). Finally, the results are also robust to the use of a different, more disaggregated, source of data for the percentage of tree cover.[24]

To assess the weaker parallel trend assumption described in the identification Section B, we use a staggered difference-in-discontinuity approach, with 2013 as reference year. In particular, we modify model 2 as follows:

$$Y_{krt} = \alpha_0 + \tau_0 A_{kr} + \beta_0 D_k + \gamma_0 A_{kr} \times D_k + \sum_{t=2010}^{2018} T_t(\alpha_1 + \tau_1 A_{kr} + \beta_1 D_k + \gamma_1 A_{kr} \times D_k) + u_{krt}. \quad (3)$$

The results are summarized in Figure 4, which presents $\tau_{1,t}\ \forall t = 2011, 2016$.[25] Clearly, there is no pre-trend in deforestation within the areas of interest. In other words, close to the boundaries, there is no significant difference in tree cover for the years before the Ebola outbreak. But, starting in 2014, there in considerably less tree cover in cells inside the areas of interest than outside. In Figure A4 (Appendix E) we replicate the same assessment for the ethnic minority interaction coefficients, and again the results are in line with the foregoing. One the one hand, the magnitude of the deforestation is much greater in these areas, and the interaction coefficients does not become statistically different from 0 until the Ebola outbreak. In other words, here too there is no significant difference in tree cover, even in ethnic minority areas, until 2014.

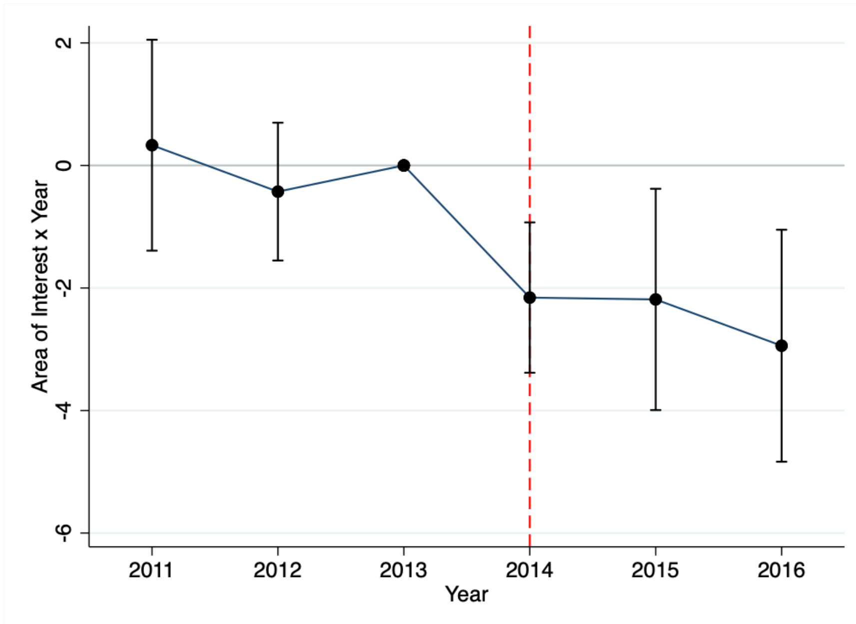
4.3 Discussion

One remaining open point from the previous section is whether this deforestation translated to increased production by multinationals. To enquire into this, we use a particular feature of our dependent variable. Out data give, for each pixel, the cover percentage of 17 typologies of land-cover classes (see Section 3). Hence, we can monitor whether - together with a decrease in evergreen broadleaf gorests - we also find an increase in the type of cultivation associated mostly with *newly planted* palm oil trees, namely, "cropland". We replicate the analysis taking as dependent variable the percentage of "cropland" cover in each cell. First, this permits us to investigate whether palm oil multinationals translate deforestation into production. At the same time, makes us more confident about the role of the multinationals in deforestation. Indeed, if deforestation were caused by other factors, they would be likely to affect cultivation in the same direction. If instead we observe an increase in the percentage of cultivated pixel, this is evidence

[24] In this robustness we test another MODIS' product: MCD12Q1. Differently from MCD12C1, which we use troughout the paper, MCD12Q1 displays only the percentage of tree cover for each pixel over time. Hence, we do not observe the percentage cover of the 17 IGBP categories as in MCD12C1. However, the data here is more disaggregated. Indeed, we observe the percentage of tree cover for each 30m $\times$ 30m pixel. Therefore, we aggregated this data at the 1km^2 cells used as units in the analysis. A cross-section plot of this more granular dependent variable is depicted in Figure A3 in appendix E.

[25] The regression includes all years, but for graphical purposes here we present the coefficients only for 2011-2016.

Figure 4: Staggered coefficients



in support of the multinational mechanism. The results, summarized in Table A6 of Appendix D, confirm that the extensively documented *decrease* in tree cover is paired with a 150% *increase* in newly planted palm oil trees (i.e. Cropland), which is in line with the impressive +1428% jump in Liberian palm oil exports in the next 2-3 years.

As noted in Section 2, substantial evidence suggests that these results may be due to a diversion of attention of local and international NGOs (Global Witness, 2015; RSPO complain; Forest Peoples Programme, 2015). Before the Ebola outbreak, these groups were protecting villages in the palm oil areas of interest by monitoring MNEs' operations, assisting villagers in filing complaints to the relevant authorities, and providing information about MNEs' intentions. But, Ebola redirected NGOs efforts towards the disease, leaving villages without their protection. This mechanism can be formalised in a setting of limited attention (see among others Gabaix & Laibson, 2006; Chetty, Looney, & Kroft, 2009; DellaVigna, 2009; Gabaix, 2014). These organizations have a limited span of attention to allocate among various issues. Before the health crisis, they had the MNE situation under control. However, with the Ebola epidemic, they had to allocate their attention towards the health crisis, reducing the attention paid to fighting the consequences of the palm oil incentives. This theoretical framework sheds light on how effective correct information is in preventing MNEs' rent-seeking in fragile countries. Most fragile countries have regulations limiting MNEs' activities, but asymmetric information results in weak enforcement. Providing correct information about the consequences of agreements with these companies may strengthen enforcement, moderating the adverse impact of MNEs' presence while retaining the potential benefits for economic development. Providing sound information, in other words, could be an extraordinarily cost-effective solution.[26]

5 Conclusions

This paper provides novel granular evidence on the interaction between the Ebola epidemic, deforestation, and palm oil plantations in Liberia. The palm oil multinationals, exploiting the health crisis, stepped up deforestation to increase output. The effect on deforestation is more severe in areas inhabited by politically unrepresented ethnic groups, characterized by a reduction in tree coverage by 6.5%. We also document an increase of more than 125% in the likelihood of fire events within concessions during the epidemic. This suggests that not only did the palm oil companies foster deforestation, but further that they used forest fires to do so. This is particularly harmful to the environment, and the smoke and the haze may have severe health consequences, apart from being a source of carbon dioxide. This deforestation was accompanied by a 150% increase in the amount of land dedicated to cultivation. This exploitative behaviour was highly profitable for palm oil companies, with a 1428% increase in the value of Liberian palm oil's exports compared with the pre-Ebola period. Unfortunately, we cannot say the same for local people or the local environment.

[26]As noted earlier, another possible mechanism through which the health crisis may have spurred agreements with local communities might be starvation. Ebola severely reduced the income of village families. As a result, they were more likely to sign agreements despite the few benefits accruing to them. Although anecdotal evidence suggests the prevalence of the former mechanism, we cannot rule out the latter.

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Appendix

A Descriptive Statistics

Table A1: Descriptive Statistics

	Obs.	Mean	S.D.	Min	Max
Panel (a): All Sample					
% Trees	881,883	48.12451	37.97548	0	100
% Crop	881,883	.1537871	1.039155	0	25
Area of Interest	883,107	0.0997	0.300	0	1
Fire event	881,365	0.0232	0.150	0	1
SPEI	882,045	-0.0972	0.880	-2.421	1.832
Population	882,685	38.40	441.0	0	51,859
Humidity pre-period	880,497	0.0542	0.00304	0.0495	0.0637
Rain	883,107	210.1	46.72	-4,297	461.8
Pm 25	882,702	33.21	4.488	22.30	45.60
Nightlights	883,107	0.294	1.551	0	45.12
Temperature	883,035	27.75	0.580	23.86	29.90
Panel (b): Areas of Interest					
% Trees	88,056	37.38392	31.74739	0	100
% Crop	88,056	.436153	1.67144	0	17
Fire event	87,988	0.0222	0.147	0	1
Population	88,043	37.57	141.5	0	5,675
Humidity pre-period	88,029	0.0569	0.00272	0.0505	0.0635
Rain	88,056	235.4	40.91	142.0	407.8
SPEI	87,975	-0.0739	0.802	-2.421	1.832
Pm 25	88,056	32.44	4.452	22.70	43.60
Nightlights	88,056	0.417	1.676	0	25.81
Temperature	88,056	27.76	0.646	26.34	29.72

B Identification

In this section we will look in detail at the identification procedure of the difference in discontinuities (Calonico et al., 2014, Ludwig & Miller, 2007, Grembi et al., 2016). Let t=0,1 be the time, t=0 no-Ebola and t=1 Ebola. Let $Y_t(p)$ be the potential outcome p=0,1 of the percentage of three cover of a generic cell at time t=0,1. Our goal is to identify the following:

$$\mathbb{E}\{Y_1(1) - Y_1(0)|X = 0\} \tag{4}$$

where X is the distance from the concession boundaries (negative values of X indicate that the cell is *outside* the area of interest). This is the average treatment effects at the area's boundaries during Ebola. A simple sharp regression discontinuity approach would have assumed continuity of potential outcomes:

$$\mathbb{E}\{Y_1(1)|X\}, \mathbb{E}\{Y_1(0)|X\} \text{ both continuous at } X = 0$$

and identified 4 by taking

$$\text{ATEc} = \lim_{x \to 0^-} \mathbb{E}\{Y_1|X = x\} - \lim_{x \to 0^+} \mathbb{E}\{Y_1|X = x\}$$

Here we make two different assumptions that take advantage of the time dimension.

Assumption 1. $\mathbb{E}\{Y_t(p)|X\}$ *is right continuous* $\forall t, p$ *for* $X > 0$ *and left continuous* $\forall t, p$ *for* $X < 0$

Assumption 2. $\lim_{x \to 0^-} \mathbb{E}\{Y_1(0)|X = x\} - \lim_{x \to 0^-} \mathbb{E}\{Y_0(0)|X = x\} = \lim_{x \to 0^+} \mathbb{E}\{Y_1(0)|X = x\} - \lim_{x \to 0^+} \mathbb{E}\{Y_0(0)|X = x\}$ *that is our new parallel trend assumption at the threshold.*

Assumption 1 is weaker than continuity because it does not require potential outcomes to be continuous across the threshold but only right and left continuous respectively at the right and at the left of the threshold. In other words, potential outcomes could be highly discontinuous at the threshold, a condition that would violate the internal validity of the regression discontinuity approach. Though we need this weaker version of continuity because we need to take the limits of these expectations as the running variable approaches to the threshold and, hence, we need to be sure that such limits exists. Assumption 2 resemble the parallel trend assumption seen in the difference in difference approach. However, it is much weaker. Indeed, we do not assume that, on average, trends of *all* the treatment and control group would have been the same in absence of treatment. We only assume that this is the case for cells very close to each other, because both are very close to the threshold. Hence, assumption 2 is more likely to be satisfied than the classic parallel trend assumption. The identification theorem follows.

Theorem B.1. *In difference-in-discontinuities, under assumptions 1 and 2, ATE at the threshold* $\mathbb{E}\{Y_1(1) - Y_1(0)|X = 0\}$ *is identified by*

$$\beta = \lim_{x \to 0^-} \{\mathbb{E}\{Y_1|X = x\} - \mathbb{E}\{Y_0|X = x\}\} - \lim_{x \to 0^+} \{\mathbb{E}\{Y_1|X = x\} - \mathbb{E}\{Y_0|X = x\}\}$$

Proof. To prove theorem B.1 notice that observed potential outcomes are:

$$\begin{aligned} &Y_0(0) \quad \forall x \in \chi \\ &Y_1(1) \quad \forall x \geq 0 \\ &Y_1(0) \quad \forall x < 0 \end{aligned}$$

Substituting them in our expression we get:

$$\beta = \lim_{x \to 0^-} \{\mathbb{E}\{Y_1(1)|X = x\} - \mathbb{E}\{Y_0(0)|X = x\}\} - \lim_{x \to 0^+} \{\mathbb{E}\{Y_1(0)|X = x\} - \mathbb{E}\{Y_0(0)|X = x\}\}$$

where we can take limits thanks to assumption 1. Substituting assumption 2 we get the following:

$$\beta = \lim_{x \to 0^-} \{\mathbb{E}\{Y_1(1) - Y_1(0)|X = x\}\} = \mathbb{E}\{Y_1(1) - Y_1(0)|X = 0\} = \text{ATEc}$$

$\square$

C Sharp Geographic Regression Discontinuity

An alternative to the difference in discontinuities approach, more common although not perfect for this context, is a simple sharp geographic regression discontinuity identification strategy. In this case we simply compare cells at the areas of interests' boundaries. The basic idea behind this method is to compare cells just outside and inside palm oil areas of interest. Indeed, given their proximity, they are very likely to be similar. However, the NGOs/starvation mechanism affected only those cells which were inside palm oil areas of interest. Hence, comparing these two groups, one could recover the effects on our dependent variables. An immediate, and resolutive, limitation of this approach is that it ignores totally the time dimension, which instead is crucial in the natural experiment presented in Section 2. In the following section, we present results using this approach.

As in the difference in discontinuities analysis presented in Section 4, we first restrict our sample to those cells within the 10 km radius around areas of interests boundaries. Then, we apply an internal buffer of 1.42 km to both sides of the areas to deal with noisiness produced by geographic measures.

To estimate the local linear regression discontinuity treatment effect we follow the procedure outlined by Calonico et al. (2019). We run local linear regressions of Y_{krt} on a constant, a dummy indicating areas of interest A_{kr}, the distance D_k and their interaction, using only units within bias robust and optimally chosen bandwidths ($D_k \in [-h, h']$), and weighting observations through a kernel function according to their distance from the cutoff.[27]

$$Y_{krt} = \alpha + \tau A_{kr} + \beta D_k + \gamma A_{kr} \times D_k + u_{krt} \tag{5}$$

Table A2 presents results differentiating between Ebola periods and non Ebola ones. Results are consistent with the ones outlined before: during the health crisis, there is a lower percentage of trees within areas of interest, an higher probability of experiencing a fire event, and these effects are larger when considering areas populated by ethnic minorities. Interestingly, both coefficients of interest τ and its interaction with the ethnic dimension are statistically different from 0 only during Ebola periods. This is also true when analysing the probability of observing a fire event in columns 5 and 6 of the table. These results suggest that being within an area of interest, although usually associated with a lower percentage of tree coverage, makes truly a difference at the border only during the Ebola period.

The identification assumption in this case is the continuity of potential outcomes' conditional means at the boundaries: in the absence of treatment, the average three coverage of cells just outside and inside palm oil areas of interest should have been the same. In other words, cells should be almost randomly allocated at the boundaries. However, this is not the case. Areas of interest boundaries are not random; they have been decided in the past based on some unobserved characteristics. This could lead to a possible

[27] Specifically, the exponential kernel function is of the form: $K(D/h) = \frac{e^{h-|D|}}{e}$.

Table A2: Sharp geographic regression discontinuity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	% Trees	% Trees	% Trees	% Trees	Fire event	Fire event	Fire event	Fire event
Area of Interest	-4.094***	-2.978	0.166	-3.403	0.0249*	-0.00173	-0.0859**	-0.0199**
	(1.579)	(2.055)	(1.488)	(2.783)	(0.0132)	(0.00209)	(0.0379)	(0.00911)
Distance	-1.663***	-1.858***	-0.677**	-1.205	0.000923	0.000137	0.0118	-0.000581
	(0.304)	(0.533)	(0.299)	(1.155)	(0.00235)	(0.000374)	(0.0114)	(0.00146)
Ethnic Minority			-0.534	-3.116			-0.0245	-0.0108
			(1.559)	(2.929)			(0.0386)	(0.00953)
Distance × Area of Interest	1.916***	2.308***	0.728**	1.764	-0.0119***	0.000688	-0.00999	0.00217
	(0.523)	(0.802)	(0.313)	(1.154)	(0.00422)	(0.000677)	(0.0111)	(0.00170)
Ethnic Minority × Area of Interest			-6.311***	0.487			0.115***	0.0187**
			(1.806)	(3.514)			(0.0403)	(0.00938)
Ethnic Minority × Distance			-0.679**	-0.684			-0.0115	0.000738
			(0.321)	(1.282)			(0.0117)	(0.00151)
Ethnic Minority × Distance × Area of Interest			0.722*	0.511			-0.00113	-0.00149
			(0.400)	(1.432)			(0.0120)	(0.00183)
Observations	30,510	54,341	30,510	54,341	34,474	120,650	34,474	120,650
R-squared	0.523	0.533	0.548	0.533	0.0858	0.0127	0.0869	0.0131
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Ebola	No Ebola	Ebola	No Ebola	Ebola	No Ebola	Ebola	No Ebola
Mean Y	37.54	37.98	37.54	37.98	0.0781	0.00634	0.0781	0.00634

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within the optimal bandwidth computed following the procedure outlined by Calonico et al., 2019. Observations weighted through an exponential kernel function of distance and 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. Ethnic Minority is dummy equal one if a cell there is at least one politically unrepresented ethnic group, i.e. without representation in the government.

violation of the continuity assumption. Moreover, the NGOs/starvation mechanism requires comparing periods during the health crises with those before the Ebola outbreak. This means that we need to compare trends and not levels. In addition to that, comparing trends also offsets the first limitation outlined before since one takes out all unobserved characteristics that are unchanged over time of each cell. These are exactly those characteristics that, likely, have driven to the areas of interests' drawing decisions, such as the suitability of soil. For these reasons the difference in discontinuities approach is much more robust in this analysis than the one presented in this section.

D Extra-Tables

Table A3: Balances for different thresholds

Buffer, Bandwidth	*B = 1.42 km, h = 3 km*		
	Outside Area of Interest	Within Area of Interest	Difference
% Trees	41.232	38.959	-2.273***
	(37.114)	(31.211)	(0.193)
SPEI	-0.087	-0.068	0.019***
	(0.799)	(0.823)	(0.004)
Fire event	0.020	0.021	0.001
	(0.139)	(0.143)	(0.001)
% Crop	0.197	0.355	0.157***
	(1.073)	(1.391)	(0.006)
Observations	107,766	48,771	156,537

Notes: Standard deviations in columns 1-2 and p-values in column 3. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A4: Difference in discontinuities - sensitivity buffer

Dep. Variable	(1) % Trees	(2) % Trees	(3) Fire event	(4) Fire event
Panel A: Buffer radius = 1.42km				
Ebola × Area of Interest	-0.909**	1.383	0.0277**	-0.0614*
	(0.424)	(0.999)	(0.0134)	(0.0336)
Ethnic Minority × Ebola × Area of Interest		-2.361**		0.0935**
		(1.092)		(0.0364)
Observations	60,471	60,471	155,124	155,124
R-squared	0.979	0.979	0.209	0.209
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	37.80	37.80	0.0223	0.0223
Panel B: Buffer radius = 0km				
Ebola × Area of Interest	-2.098***	0.812	0.00433	-0.0247
	(0.796)	(0.957)	(0.00605)	(0.0214)
Ethnic Minority × Ebola × Area of Interest		-3.101**		0.0301
		(1.269)		(0.0223)
Observations	44,577	44,577	154,907	154,907
R-squared	0.980	0.980	0.202	0.203
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	35.10	35.10	0.0226	0.0226
Panel C: Buffer radius = 1km				
Ebola × Area of Interest	-0.500**	0.280	0.0199**	-0.0557***
	(0.232)	(0.519)	(0.00778)	(0.0197)
Ethnic Minority × Ebola × Area of Interest		-0.449		0.0785***
		(0.589)		(0.0213)
Observations	83,916	83,916	138,093	138,093
R-squared	0.979	0.978	0.206	0.206
Cell FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	38.15	37.46	0.0220	0.0220
Panel D: Buffer radius = 2km				
Ebola × Area of Interest	-0.628***	2.099***	-0.00413	-0.0835***
	(0.223)	(0.349)	(0.00944)	(0.0244)
Ethnic Minority × Ebola × Area of Interest		-2.733***		0.0820***
		(0.425)		(0.0264)
Observations	137,097	137,097	136,559	136,559
R-squared	0.981	0.981	0.206	0.206
Cell FE	Yes	Yes	Yes	Yes
Region × Year	Yes	Yes	Yes	Yes
SPEI	Yes	Yes	Yes	Yes
Mean dependent	40.05	40.05	0.0208	0.0208

Notes: MWFE estimator. HDFE local linear regression. Sample restricted to be within the optimal bandwidth computed following the procedure outlined by Calonico et al., 2019. Observations weighted through an exponential kernel function of distance and 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. Ethnic Minority is dummy equal one if a cell there is at least one politically unrepresented ethnic group, i.e. without representation in the government. Panels differ in the length of the buffer's radius. Only coefficients of interest shown in the table.

Table A5: Sensitivity

	(1)	(2)	(3)	(4)
Dep. Variable	% Trees - Base	% Trees - Minorities	Fire event - Base	Fire event - Minorities
Baseline	-0.909	-2.361	0.027	0.094
Std. clustered at cell level	(0.424)**	(1.092)**	(0.013)**	(0.036)**
Std. clustered at province level	(0.436)**	(1.180)**	(0.020)	(0.047)**
Conley std.	(0.502)*	(1.147)**	(0.013)**	(0.036)**
Robust std.	(0.367)**	(0.835)***	(0.019)	(0.069)**
Nightlights	-0.899**	-2.374**	0.027**	0.93**
	(0.424)	(1.095)	(0.013)	(0.037)
Population	-0.908***	-2.368**	0.028**	0.094**
	(0.424)	(1.091)	(0.013)	(0.036)
Excluding SPEI	-0.907**	-2.357***	0.028**	0.094***
	(0.423)	(1.092)	(0.013)	(0.036)
Rainfall	-0.958**	-2.499**	0.028**	0.093**
	(0.424)	(1.083)	(0.013)	(0.036)
Rainfall (lag)	-0.940**	-2.417**	0.028**	0.094**
	(0.424)	(1.092)	(0.020)	(0.036)
Temperature	-0.893**	-2.351**	0.028**	0.094**
	(0.423)	(1.061)	(0.013)	(0.037)
Excluding Cell FE	-0.957**	-2.418**	0.028**	0.093**
	(0.426)	(1.093)	(0.013)	(0.036)
Excluding Region × Year FE	-0.866**	-0.977*	0.107***	0.042***
	(0.354)	(0.506)	(0.011)	(0.015)
Province FE	-0.808**	-1.461**	0.027**	0.093***
	(0.397)	(0.692)	(0.013)	(0.031)
Cell & Year FE	-1.142***	-3.248***	0.039***	0.133***
	(0.440)	(1.222)	(0.014)	(0.041)
No weights	-0.671*	-2.660***	0.004	0.088***
	(0.381)	(0.314)	(0.007)	(0.021)
Triangular kernel	-0.976**	-2.400***	0.012	0.091***
	(0.441)	(1.129)	(0.008)	(0.021)
Uniform kernel	-0.671*	-2.475**	0.004	0.088***
	(0.381)	(1.021)	(0.007)	(0.021)
Epanechnikov kernel	-0.952**	-2.249**	0.010	0.094***
	(0.429)	(1.087)	(0.007)	(0.021)
MCD12Q1	-2.421***	-4.009**		
	(0.340)	(1.458)		

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 2, column (1), under different specifications. Column (3) shows the same coefficient but for model (3) of the same table.. Column (2) shows coefficient Ebola × Area of Interest × Ethnic Minority of table 2, column (2), under different specifications. Column (4) shows the same coefficient but for model (4) of the same table. Conley std. with 250km of possible spatial correlation and 100 years of time correlation.

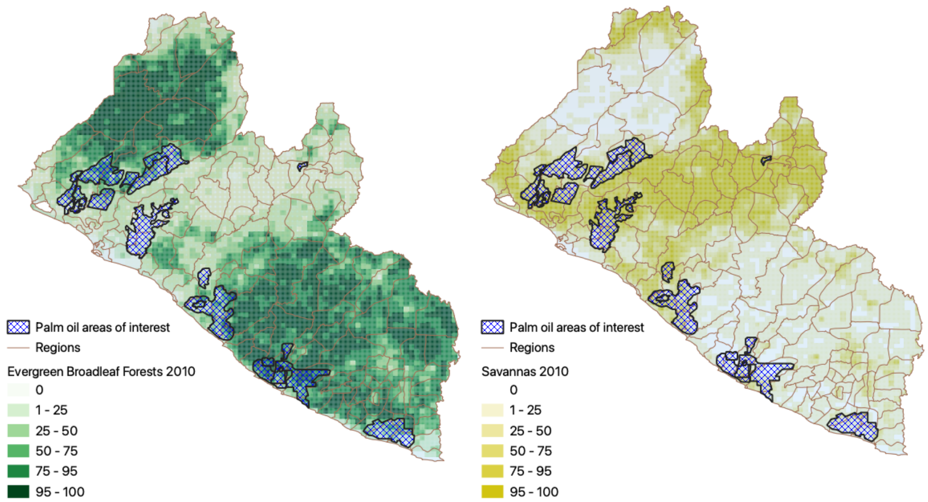
Table A6: Cropland

	(1)	(2)
Dep. Variable: % Cropland	Difference in Difference	Difference in Discontinuities
Ebola $\times$ Area of Interest	0.271***	0.483***
	(0.0133)	(0.087)
Observations	880,821	137,961
R-squared	0.807	0.6583
Cell FE	Yes	Yes
Region $\times$ Year FE	Yes	Yes
SPEI	Yes	Yes
Mean dependent	0.154	0.321

Notes: MWFE estimator. HDFE local linear regression. Difference in Difference analysis in column (1); difference in discontinuities in column (2). Sample restricted to be within the optimal bandwidth computed following the procedure outlined by Calonico et al., 2019 in columns (2). Observations weighted through an exponential kernel function of distance and bandwidth in column (2). 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 in 2014 and 2015. *Area of Interest* is a dummy equal to one for cells in an area of interest.

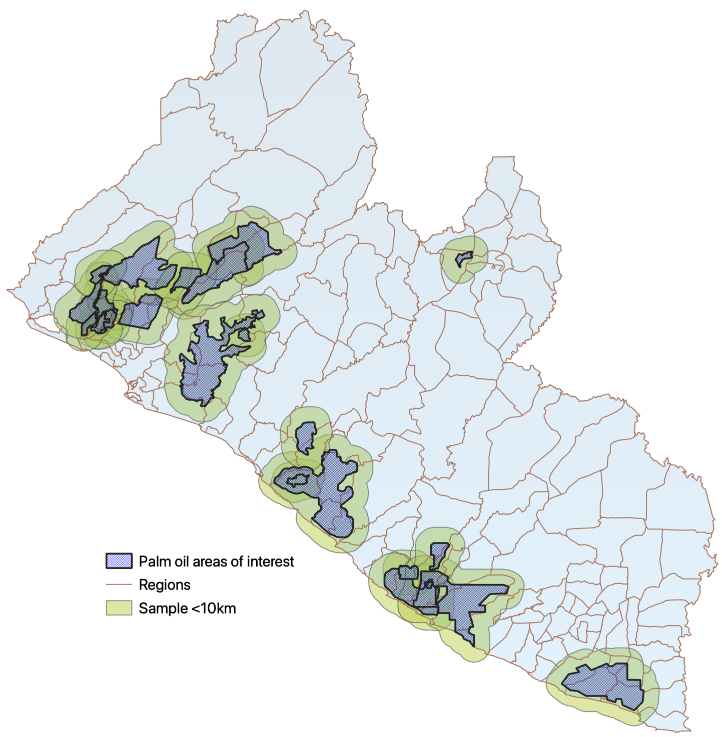
E Extra-Figures

Figure A1: Percentage tree cover Liberia 2010



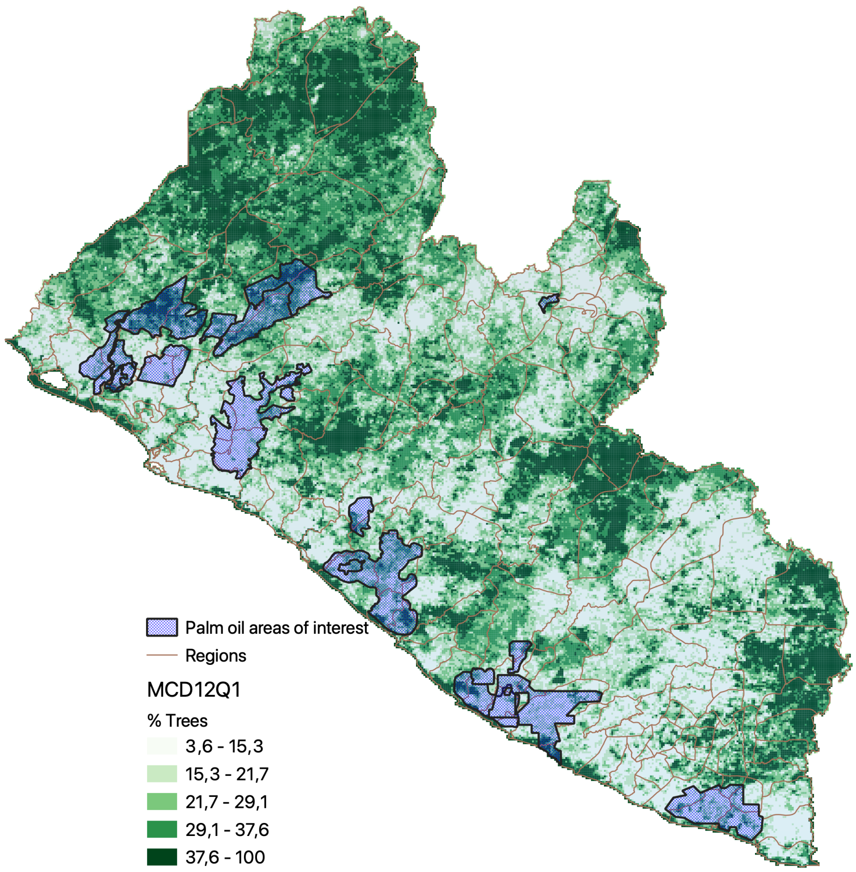
Notes: The figure presents the percentage of cell covered by "Evergreen Broadleaf Forests" on the right, and "Savannas" on the left in 2010 in Liberia. The darker is the cell, the higher the percentage of land cover by the IGBP class considered. In blue we have the Palm Oil Concessions and in gold the administrative boundaries of Liberia's regions.

Figure A2: 10km Sample



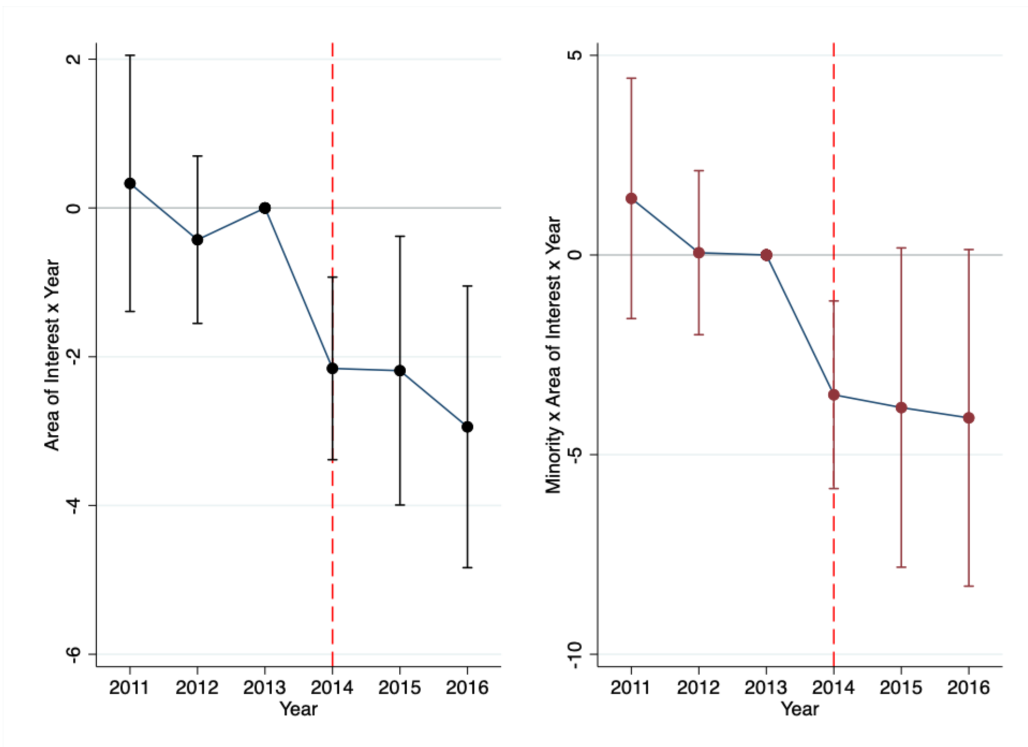
Notes: The figure presents sample used in the difference in discontinuities analysis.

Figure A3: Percentage tree cover Liberia 2010 MCD12Q1



Notes: The figure presents the percentage of trees per each pixel in the MCD12Q1 data in 2010 in Liberia. The darker is the cell, the higher the percentage of tree cover. In blue we have the Palm Oil Concessions and in gold the administrative boundaries of Liberia's regions.

Figure A4: Staggered coefficients with minorities



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