The Environmental Impact of Multinational Firms

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Abstract: Air pollution, deforestation, biodiversity loss, and climate change are among the most pressing global problems, but while environmental conditions are improving in many developed countries, environmental degradation is still widespread across the developing world. Multinational enterprises could play a central role in solving or fuelling these global environmental problems. On the one hand, they could help to transfer clean technologies and sustainable management practices to less developed regions, but on the other hand, they may contribute to the problem by shifting polluting production to developing countries or by lowering local environmental standards. Here, we use a unique geospatial panel of millions of multinational and domestic companies to quantify their impact on the environment in Africa. Our results show that an expansion of multinational activity causes severe loss of forest cover, erodes local crop diversity, and, to some extent, increases greenhouse gas emissions. They show further that the adverse environmental impact of multinationals is significantly larger than the impact of domestic firms, even after controlling for firm characteristics. Our results highlight the tradeoffs that many developing countries face. While multinationals contribute more to local economic activity than domestic firms, they also cause more environmental damage than their domestic counterparts. Our findings also suggest a solution to this dilemma. They show that governance in the parent corporation and the multinational affiliate's country plays an important role in reducing environmental damage.

Introduction

Views on the contribution of multinational enterprises (MNEs) to environmental degradation in developing countries could not diverge more. While for many politicians, journalists, and activists, MNEs are a major source of environmental problems,[1] for others the same international firms are a key part of the solution.[2]

Unfortunately, the debate on the role of MNEs in environmental degradation are often based on data-free ideology or an "accounting" approach, which focuses on the carbon footprint of international firms without considering a counterfactual comparison point where these firms are absent. Studies that address the question of the causal impact of multinational firms on the environment are rare. Only a few studies quantify the environmental impact of multinationals and mostly for specific environmental outcomes and restricted locations, often with different results (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12). For example, three insightful recent studies on the impact of MNEs in the primary sector (agriculture and resources) on deforestation reach contradictory conclusions. While Goldblatt et al. (11) find that MNEs have less effect on forest cover than domestic firms, Cust et al. (12) find no difference between MNEs and domestic firms in their impact on forest loss. In contrast, Davis et al. (8) show that MNEs substantially contribute to tropical deforestation. These different conclusions are possibly due to different approaches and their focus on different economic activities, environmental outcomes or regions.

Here, we address this critical gap in the literature and provide novel estimates of the causal and spatially explicit impact of MNEs' presence on forest cover, crop diversity, air pollution, and greenhouse gas emissions for a whole continent (Africa) in high spatial resolution and using a consistent approach across firms in different sectors and environmental outcomes. To the best of our knowledge, this is the first paper that studies the causal impact of MNEs on the environment using exogenous variation in the MNEs' presence on a large range of environmental indicators.

Deforestation, air pollution, and climate change are among the leading global environmental threats, and tackling them is among the key United Nations Sustainable Development Goals. Deforestation is a major environmental concern, threatening not only traditional lifestyles and biodiversity but also fuelling global warming (13). Hence, our first two dependent variables are related to deforestation. Here, we use two measures of forest cover change based on satellite im-

[1] See e.g. The Guardian 2010, https://www.theguardian.com/environment/2010/feb/18/worlds-top-firms-environmental-damage; Business Today, 2019, https://journal.businesstoday.org/bt-online/2019/the-profitability-of-destroying-our-planet.

[2] CBS, 2014, https://www.cbsnews.com/media/10-companies-working-to-save-the-planet/; Los Angeles Times, https://www.latimes.com/business/story/2019-09-20/how-businesses-profit-from-environmentalism.

agery (14, 15). While the first dataset only captures forest losses, the second dataset, although with coarser spatial resolution, also captures increases in forest cover. Air pollution is considered one of the major global health burdens (16), and particularly important for Africa (17). Particulate matter is one of the most severe air pollutants associated with more than four million deaths annually (16). Measuring air pollution has improved tremendously over the last decades. New methods combine satellite images of optical depth with ground measurement stations of air pollution to create a comprehensive data set of air pollution from particulate matter (18), which we use in our study. We complement these environmental indicators with measures of greenhouse gas emissions as drivers of climate change. Climate change also has significant health, economic, and environmental consequences (19, 20), and is, to a sizeable extent, caused by greenhouse gas emissions from economic activity. Although climate change is a major environmental threat, measuring the emissions of greenhouse gases in high spatial resolution is still in its infancy. We, therefore, regard our analysis of greenhouse gas emissions as complementary to our other key results. Loss of crop diversity has major consequences for food security, ecosystem service provision, and biodiversity conservation (21, 22, 23, 24, 25). Yet, it is notoriously difficult to measure on a large geographic scale and over long time periods. Here, we build a new dataset on crop diversity using predicted crop cover data based on production statistics, agricultural suitability, and satellite data on 10×10 km resolution (26). Data on these environmental outcomes allow us to track some of the most severe environmental threats.

MNEs may play a disproportionately large role in environmental degradation for several reasons. A key to understanding their environmental impact lies in their structure, consisting of a parent corporation, mostly in developed countries, and several subsidiaries, often in developing countries. This structure allows MNEs to shift economic activity between different locations (e.g. (27)), with several environmental implications. First, local environmental outcomes may not affect MNEs' operations in the long term because they can reallocate economic activity to other locations when local conditions deteriorate. Second, MNEs may threaten host governments to "vote with their feet" and dislocate to more accommodating countries if environmental regulations are not reduced (28). They could further use their financial market power and their home country's political and informational clout to negotiate regulatory exceptions that make the environmental regulations less binding for them than for other firms. Third, MNEs may avoid regulation by shifting "dirty" production to less regulated countries that then become "pollution havens" (29). While in low stringency environments, domestic and multinational polluters thrive alike, the domestic firms may engage in a whole range of activities, whereas lenient regulation may disproportionately attract MNE affiliates specializing in polluting activities.

In contrast to those negative views on MNEs, MNEs can also contribute to solving environmental problems and contribute to economic development in general by transferring modern and clean technologies to developing countries (4, 30). In addition to their contribution to environmental solutions, they can also contribute to economic development in general (31, 32, 33). While this positive effect on local economies may increase overall pollution and deforestation levels, these negative effects may be outweighed by the positive impact on human welfare through economic development.

Using additional data on regulation in the parent corporations and affiliates' countries combined with economic outcomes, we show evidence for the presence of both mechanisms. While MNEs cause more environmental damage per unit of production and activity, measured in sales and capital, they also contribute more to economic activity in general compared to domestic firms, suggesting positive economic spillovers. We provide further evidence that their negative environmental impact declines with the regulation of the affiliate's country and increases with the regulation of the parent corporation's country.

Quantifying the environmental impact of multinationals: Our main approach to quantifying the impact of MNEs on the environment is to compare changes in environmental outcomes in grid cells with changes in MNE activity to grid cells without changes in multinational activity. To do so, we combine data on the activity, structure, and location of millions of MNEs and domestic firms with spatial data on environmental outcomes, as described in the online Supplementary Information (SI). Specifically, we measure their impact on tree cover (*Forest Cover*) using NASA's Vegetation Continuous Fields (VCF) data, forest cover loss (*Deforestation*) from Hansen et al. (15), crop diversity (*Crop Diversity*) measured as effective species numbers (Inverse Simpson index - SDI) based on crop cover data from the Spatial Production Allocation Model (34), air pollution (*PM2.5*) measured as fine particulate matter (18), and greenhouse gas emissions (*CO2, N2O, CH4*) based on the Emissions Database for Global Atmospheric Research (35). We then match these environmental outcomes with detailed data on millions of multinational and domestic firms from the Orbis database (Bureau van Dijk). The data provide detailed information on ownership structure, firm size, activity, and credit dependency. These data allow us to further express the activity of MNEs and domestic firms as the number of firms as well as their aggregate capital and sales to take differences in firm sizes into account. We then aggregate the combined data to 0.5° grid cells, which is the main unit of our analysis. The advantage of this relatively coarse scale is that it may capture the local economic and environmental spillovers, i.e., the impact of an agricultural firm on the forests in proximity to its headquarters or the impact of a manufacturing

plant on air pollution in a larger radius. The resulting dataset allows us to observe the relationship between MNEs' activity and environmental outcomes in each African grid cell annually between 2007 and 2018.[3]

Environmental quality and degradation are not homogenous in Africa (Figure 1). Similarly, MNEs and domestic firms are not equally distributed, but are concentrated in some areas. However, not all environmental outcomes are driven by multinationals or domestic firms. Large variations in environmental outcomes across space and over time are potentially independent of MNEs or could be determined by a common driver such as economic growth, conflict, or climate. Therefore, our baseline estimation strategy is based on the association of the spatially heterogeneous dynamics of multinational expansion and environmental change while simultaneously controlling for time-constant spatial heterogeneity and regional fluctuations of our outcomes over time. Specifically, we use a two-way fixed effects approach with pixel and year-by-sub-national region[4] fixed effects (dummies) while additionally controlling for weather. This approach isolates the impact of MNEs on the environment from cell-specific but time-constant differences in environmental outcomes due to e.g. climate zone or distance to population centers, as well as from region-specific temporal fluctuations of environmental outcomes due to e.g. political unrest, local economic growth, or weather fluctuations. However, MNEs are not randomly distributed (Figure 1). This raises concerns that MNEs localize specifically in areas with high economic growth or high resource density. Put differently, there may be spurious correlations between MNE expansion and local trends in environmental outcomes. We overcome this challenge by predicting the expansion or contraction of MNEs in Africa using financial shocks to their parent corporation, mostly in developed countries, following the approach by Sonno (36), who studies the impact of MNEs on conflict. We use this instrumental variable (IV) approach to predict the expansion of MNE activity in Africa, independently of the local economic and environmental conditions and trends, using financial shocks to their headquarters. A key assumption of our approach is that outcomes would have developed similarly in MNE and non-MNE areas in the absence of MNE expansion. While it is difficult to test this assumption directly, we use an event study approach to compare the outcome dynamics of treated and non-treated units before the treatment date. It further allows us to address potential concerns that heterogeneous treatment effects and the staggered expansion of multinationals may bias our estimates (37).

[3] An exception is the data on crop diversity, which we only observe in 2010 and 2017 and only for Sub-Saharan Africa.

[4] Our 755 regions are political units at the sub-national level.

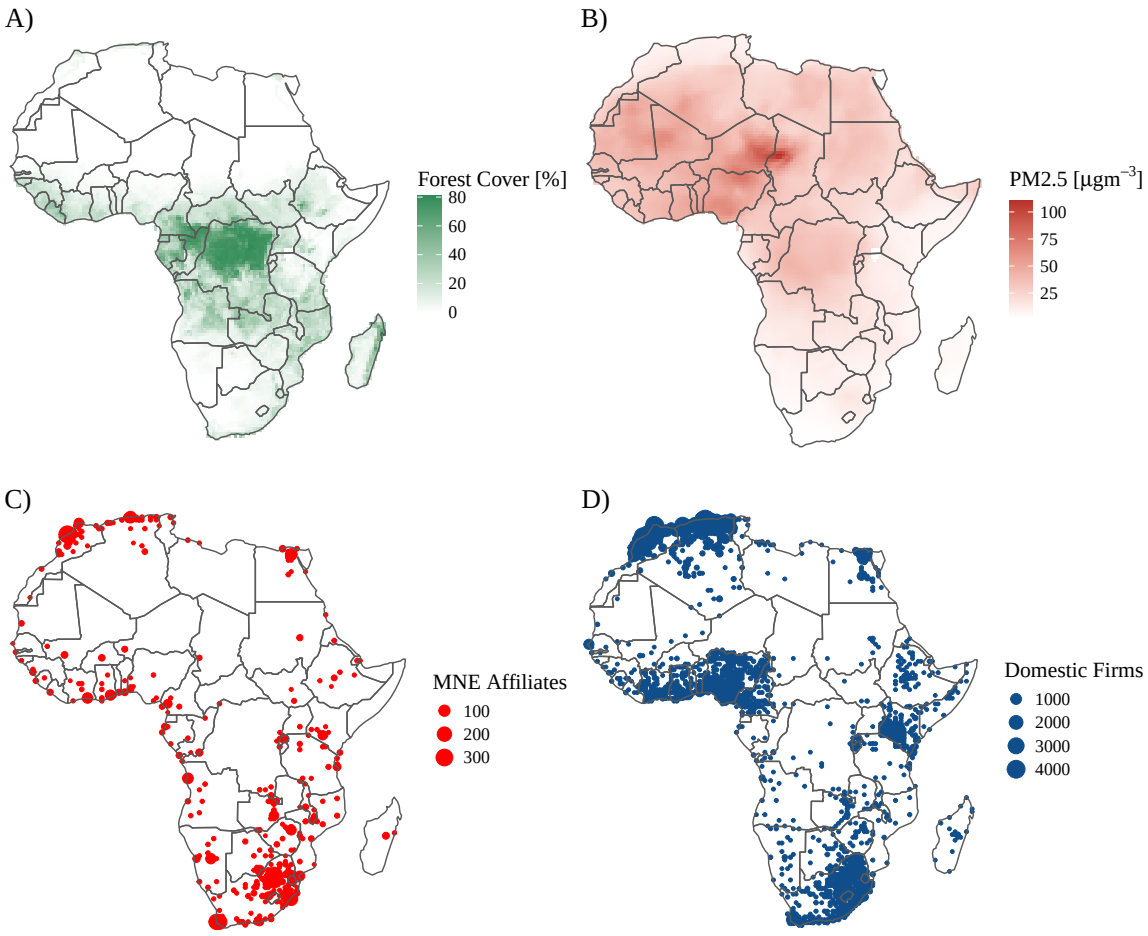


Figure 1: Economic Activity and Environmental Outcomes in Africa: The maps show mean levels of A) tree cover, B) air pollution measured in PM2.5, C) number of MNE affiliates, and D) number of domestic firms across the study period (2007 to 2018).

Results

The expansion of MNEs in Africa causes an increase in deforestation, a loss of forest cover taking reforestation into account, and a loss of crop diversity. It also increases greenhouse gas emissions and air pollution. We do not focus on the latter results because of data quality concerns (greenhouse gas emissions) and imprecise estimates (PM2.5).

The detrimental environmental impacts do not depreciate quickly over time, and current (*Current*) as well as lagged (*Lag*) effects of MNEs have similar magnitudes (Figure 2, panel A). Multinationals may be explicitly located in areas with high economic activities. If MNEs and economic activity are highly correlated, our estimates would also capture the effect of general economic activity on the environment, and our effects would be overestimated. However, controlling for lagged night lights and lagged night lights squared (*Night lights*) as proxies for general economic activity does not reduce the effect of MNEs on the environment. Here, we use lagged night lights because night lights could also respond to economic activity and, therefore, are 'bad controls' as suggested by our results below. In an additional specification, we include the lagged number of domestic firms per grid cell (*Domestic firms*) to test the robustness of this statement further. Adding the lagged number of domestic firms as control has no major impact on the estimates for the environmental impact of MNEs. These results suggest that the negative effect on environmental outcomes is not explained through general economic activity but is indeed specific to MNEs. We explore the differences between the environmental impacts of MNEs and domestic firms further in the next subsection. Despite the robustness of our results with respect to controlling for lagged general economic activity and the lagged activity of domestic firms, we are concerned that the non-random location choices of MNEs may bias our ordinary least squares (OLS) estimates. Hence, next, we present the IV results (Figure 2, panel B). Correcting for these biases with our IV specification increases the magnitude of the estimates but leaves the results otherwise qualitatively unchanged.[5] The increased magnitude of the IV estimates compared to the OLS estimates could suggest a location bias, i.e., that MNEs are located especially in areas with positive environmental trends. Although the selection of MNEs into areas with environmental improvements seems likely,[6] there are also additional explanations. In particular, if there is measurement error in the presence of MNEs, this would be tackled by IV estimates, contrary to OLS estimations.[7] The OLS estimates are, therefore, likely biased towards zero. The IV estimates

[5] Our instrument is strong, with a Kleibergen-Paap F statistic between 20 and 30, depending on the specification. We further show tests that support the validity of the instrument in the SI.

[6] Note that most of the MNEs are not in the most polluting sectors, as discussed later.

[7] Further explanations for the differences in the magnitudes of OLS versus IV coefficients include the fact that

correct for this bias, resulting in increased estimates.

Quantitatively, the impact of MNEs is important. An additional MNE affiliate increases deforestation by 24 % compared to the baseline forest loss (annual forest loss in cells with forest loss), reduces forest cover by 0.23 % in cells with forest cover, and reduces crop diversity by 0.6 % in cells with crop production, based on our IV estimates. We report the results and standard errors in table form in the SI.

A main concern of our analysis is that cells with multinationals are different from cells without multinationals, even in the absence of multinationals. In other words, we may be comparing Nairobi with the Sahara desert. This could bias the results if outcomes of the control group, i.e., cells without multinationals (e.g. in the Sahara), follow different outcome dynamics than cells with multinationals. To address this concern, panels C) and D) of Figure 2 show results for a balanced panel of cells with a) forest cover, b) night lights, and c) subnational regions with multinationals in at least one year of the study period. We show maps with the spatial extent of these sub-samples in the SI. All regression specifications are otherwise similar to the 'Current' specification in our main results. However, the results based on the restricted sample are almost identical to those based on the whole sample. The only difference is that the PM2.5 estimates are statistically significant in the MNE Region specification, possibly by excluding areas with high natural PM2.5 levels and variations, such as the Sahara desert (Figure 1).

A second concern is that MNEs are spatially clustered and that MNEs in neighboring grid cells may lead to an overestimation of the effect. Adding the number of MNE affiliates in the neighboring grid cells as a control slightly reduces the estimates but does not change our results qualitatively. We report the results in the SI. The results also show that there are spillovers. Multinationals in neighboring grid cells also affect the outcomes in the focal grid cells, although their impact generally diminishes with distance.

Heterogeneity of the results across sectors: The impact of multinationals may differ substantially by sector. While we expect a large impact of affiliates in the primary (agriculture, fishing, forestry, mining) and secondary sectors (processing, manufacturing, construction) on land use, air pollution, and emissions, the tertiary or service sector (including trade) may have smaller and mostly indirect impacts (e.g., through increased local consumption or shift of production to export-oriented goods) on the environment. To compare the impact across industries, we es-

IV estimates take better into account firm sizes and that the estimation samples differ – as the IV uses only the MNEs that were already present in the first period, as mechanically implied by the way the IV is constructed. Still when investigating these potential explanations empirically, we do not find that they are major drivers of the wedge between IV and OLS estimates (results available upon request).

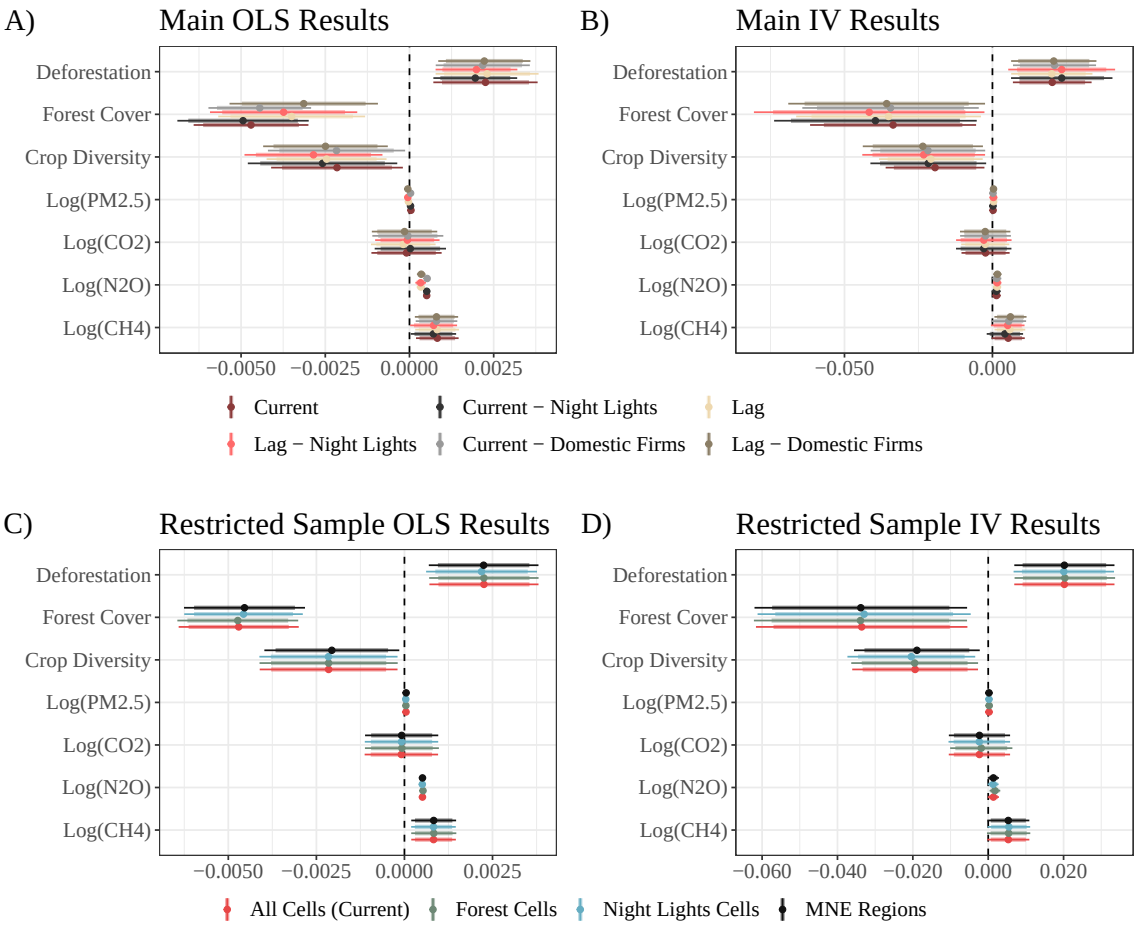


Figure 2: Main results: A) OLS and **B)** IV baseline results. The independent variable is the current (*Current*) and the lagged (*Lag*) number of affiliates. Additional specifications include the lagged number of domestic firms (*Domestic firms*) as well as lagged night lights and lagged night lights squared (*Night lights*) as controls. **C)** OLS and **D)** IV results for subsamples of data. The first specification is based on the complete sample and identical to the 'Current' specification of panels A) and B), respectively. The specifications *Forest Cells*, *Night Lights Cells*, and *MNE Regions* restrict the sample to cells with forest cover, cells with night lights, and sub-national regions with MNEs in at least one year of our sample period. The independent variable is the current number of MNE affiliates for all specifications in C) and D). The environmental outcomes are cumulative tree cover loss in 100 km^2 (Deforestation), tree cover in percent (Forest Cover), crop diversity in effective species numbers (Crop Diversity), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region fixed effects, cell fixed effects, mean precipitation, and temperature levels as controls. Standard errors are clustered at the country level. All panels show the point estimates as well as the 90 % confidence intervals (thick lines) and 95 % confidence intervals (thin lines).

timate the effects of MNE affiliates separately by sector. Although we use sector-specific instruments, we cannot estimate the coefficients jointly because the instruments are colinear. However, we report sector-specific OLS results for a joint estimation in the online SI and the results of Figure 3 in table form.

The results of our main specifications are reported in Figure 3. They generally confirm our predictions. In the OLS estimation, the environmental impact of the primary and secondary sectors is larger than that of the tertiary sector.[8] However, the differences in the estimates are mostly statistically insignificant due to the increased confidence intervals. The reduced precision of the estimates is largely a result of the reduced number of affiliates in each sector, especially the primary sector, compared to our main results. The difference between the sector-specific estimates increases even further when we use sector-specific instruments in the IV approach. The joint estimation results reported in the SI generally confirm this result.

Dynamic effects of multinationals

A major concern for our analysis is that environmental outcomes in cells with and without MNEs may have followed different trends, even in the absence of MNEs. While our IV approach already addresses this concern, we provide additional evidence in Figure 4, by depicting the trend of environmental outcomes in treated and non-treated cells before and after their treatment. For this approach, we convert our continuous and potentially non-absorbing treatment of MNE expansion and contraction into a binary and absorbing treatment. In this specification, we consider a cell as treated if the number of MNE affiliates increases for the first time. Here, we focus on deforestation rates because 1) they represent the instantaneous impact compared to aggregated outcomes such as forest cover, and 2) we observe them continuously in contrast to crop diversity. Our results show that deforestation followed similar trends in areas with and without MNE affiliates before MNE activity started in a grid cell. They also show that deforestation increased after MNE activity started in a grid cell, supporting our previous results. The impact increases over time, possibly due to an increased impact of MNEs but also possibly due to additional MNEs entering the same location.

In a related specification (also displayed in Figure 4), we restrict the treatment to the first MNE affiliate and remove all cells with MNE activity throughout the whole time period from the sample (the always treated).

[8]Especially the finding of a substantial effect for the primary sector is remarkable, as policy discussions quite often focus on industrial production (see e.g. https://unctad.org/news/blog-how-tackle-pollution-fuelled-manufacturing-developing-countries).

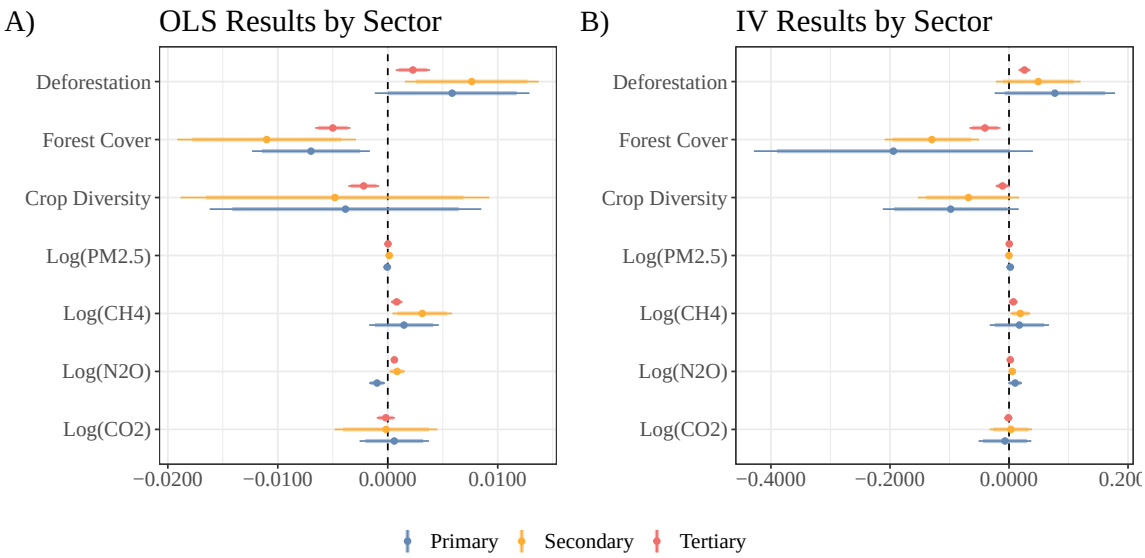


Figure 3: Sector-specific environmental effect of multinationals: The figure shows the point estimates as well as the 90 % confidence intervals (thick lines) and 95 % confidence intervals (thin lines) of the OLS approach in Panel A) and the IV approach in panel B). The instrument is sector-specific. The independent variable is the current number of affiliates per cell. All specifications include year-region and cell fixed effects (dummies) as well as mean precipitation and temperature levels as controls. The environmental outcomes are cummulative tree cover loss in 100 km^2 (Deforestation), tree cover in percent (Forest Cover), crop diversity measured as effective species numbers (Crop Diversity), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). Standard errors are clustered at the country level.

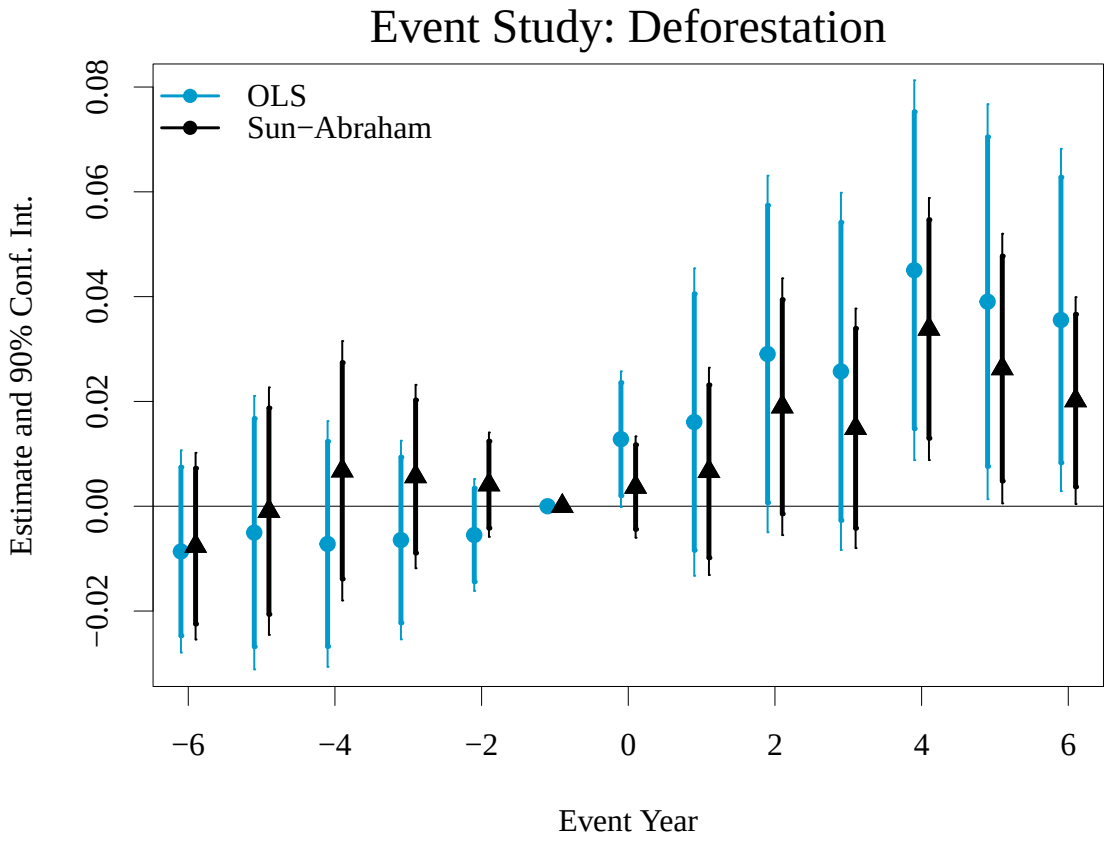


Figure 4: Event Study of Deforestation Rates: The figure shows the point estimates as well as the 90 % confidence intervals (thick lines) and 95 % confidence intervals (thin lines) of deforestation rates in areas with MNE activity introduction compared to control areas over time. Time is expressed in event years i.e. time relative to the first MNE affiliated occurence in this cell. We removed the always treated cells (37) and control for the staggered timing of MNE introduction using the approach by Sun and Abraham (38). The outcome is tree cover loss in 100 km^2 (Deforestation). Both specifications include lagged night lights, lagged night lights squared, temperature, and precipitation as controls, as well as cell and region-by-year fixed effects. Standard errors are clustered at the country level.

Comparing multinational and domestic firms: While the above quantification is very valuable, it is equally important to "benchmark" the environmental effects of MNEs vis-à-vis the ecological footprint of domestic firms. Conceptually, as discussed above, there are several arguments for why the pollution caused by MNEs could potentially be larger than for domestic firms.

To compare the environmental impact of MNEs to the impact of domestic firms, we estimate their impact simultaneously using otherwise the same empirical OLS approach as before. Our previous results suggest that the environmental impact may differ by sector. We, therefore, include the share of firms in each sector for multinationals and domestic firms separately as controls in each specification. Estimating the impact of MNEs and domestic firms simultaneously restricts the approach to OLS because the IV approach is based on the (global) ownership structure of MNEs and is not transferable to domestic firms. Therefore, we focus on the estimates' relative size and abstain from interpreting the absolute levels. In Panel A) of Figure 5, we compare the impact of an additional multinational affiliate and domestic firm on the environmental outcome. The estimates for multinational affiliates repeat the abovementioned main results of the 'Current' specification.[9] The results show that the estimates for domestic firms are much smaller than those for MNE affiliates, mostly indistinguishable from zero. All coefficients except crop diversity and CO_2 emissions are statistically different between multinational affiliates and domestic firms based on a Wald test. Firm size could differ systematically between MNEs and domestic firms. If, for example, MNEs are systematically larger than domestic firms, the larger environmental impact of MNEs could result simply from their larger size. To take size differences into account, we, therefore, measure domestic and multinational activity in capital and sales in two additional specifications, following the literature on firm size measurement (39). The estimates can be interpreted as the impact of one additional million USD in multinational or domestic firm capital or sales on the environment. While this comparison addresses the main concern, it suffers from incomplete capital and sales data. We, therefore, report results using 1) the grid cell-ownership (MNE or Domestic)-specific mean firm size (Cell specification) and 2) the onwership-sector-country-specific mean firm size (Country-Sector specification). In these specifications, the economic activity of MNEs and domestic firms is measured as the number of firms multiplied by their size while simultaneously controlling for MNE and domestic firm sector shares. The results of these specifications are reported in Panels B) and C) of Figure 5. They show that measuring economic activity by size reduces the gap between the environmental impact of MNEs and domestic firms slightly, especially when using sales to measure size, but does not fully

[9]Note that the estimates have changed slightly in response to including the current number of domestic firms instead of the lagged number as in the main specification above.

explain the differences in their environmental impact.

Economic activity and regulation as a mechanisms: Multinationals could have a worse environmental impact than domestic firms either because their economic activity is more harmful to the environment than the activity of domestic firms or because they generate more economic activity but with the same environmental impacts per unit of activity. Above, we have argued that the production of multinational's affiliates may be particularly 'dirty' if multinationals can influence the regulator of the affiliate's country to lower environmental standards or if multinationals reallocate 'dirty' production to the affiliate in response to stringent environmental regulation in the location of the parent corporation. Below, we test these hypotheses using the mean World Bank Rule of Law (ROL) index in the parent corporation and the affiliate country.[10] We take the mean ROL index over the whole time period to avoid reverse causality, i.e., the possibility that MNEs affect the affiliate country's ROL. Further, we normalize the index so that zero represents complete lawlessness and one perfect ROL. Governance and the regulatory environment are difficult to measure. Classical or differential measurement errors could lead to overestimating or underestimating the effects. Additionally, we are restricted to our OLS approach since our instrument does not predict the activity of domestic firms, as explained above.

The direct effect of affiliates in this specification is difficult to interpret because it reflects the impact of additional affiliates in a hypothetical world with absolute lawlessness in both countries of the parent corporation and the affiliate. Therefore, we focus on the interaction terms. Our results (Table 1) generally suggest that a higher ROL in the parent corporation's country increases the environmental impact of the affiliate. In comparison, a higher ROL in the affiliate's country reduces its environmental impact. These results are most pronounced for forest cover. To illustrate the effect of governance, consider a scenario with an intermediate ROL in both countries (ROL =0.5). In this scenario, an additional affiliate has little impact on forest cover (i.e., forest cover changes by 0.011 - 0.5×0.062 + 0.5×0.042 = 0.0006). However, increasing the regulation of the parent corporation countries' to unity exacerbates the forest loss caused by an additional affiliate to 0.03 % (i.e., forest cover changes by 0.011 - 1×0.062 + 0.5×0.042 = -0.03). Similarly, reducing the ROL in the affiliate country to lawlessness while keeping intermediate levels in the parent corporation country aggravates the forest cover loss to 0.02 % (i.e., forest cover changes by 0.011 - 0.5×0.062 + 0×0.042 = -0.02). We provide results using Transparency International's Corruption Perceptions Index in the affiliate's country and the parent corporations' exposure to environmental regulation using the World Economic Forum's Stringency of Environmental

[10] For a similar approach, see Goldblatt et al. (11).

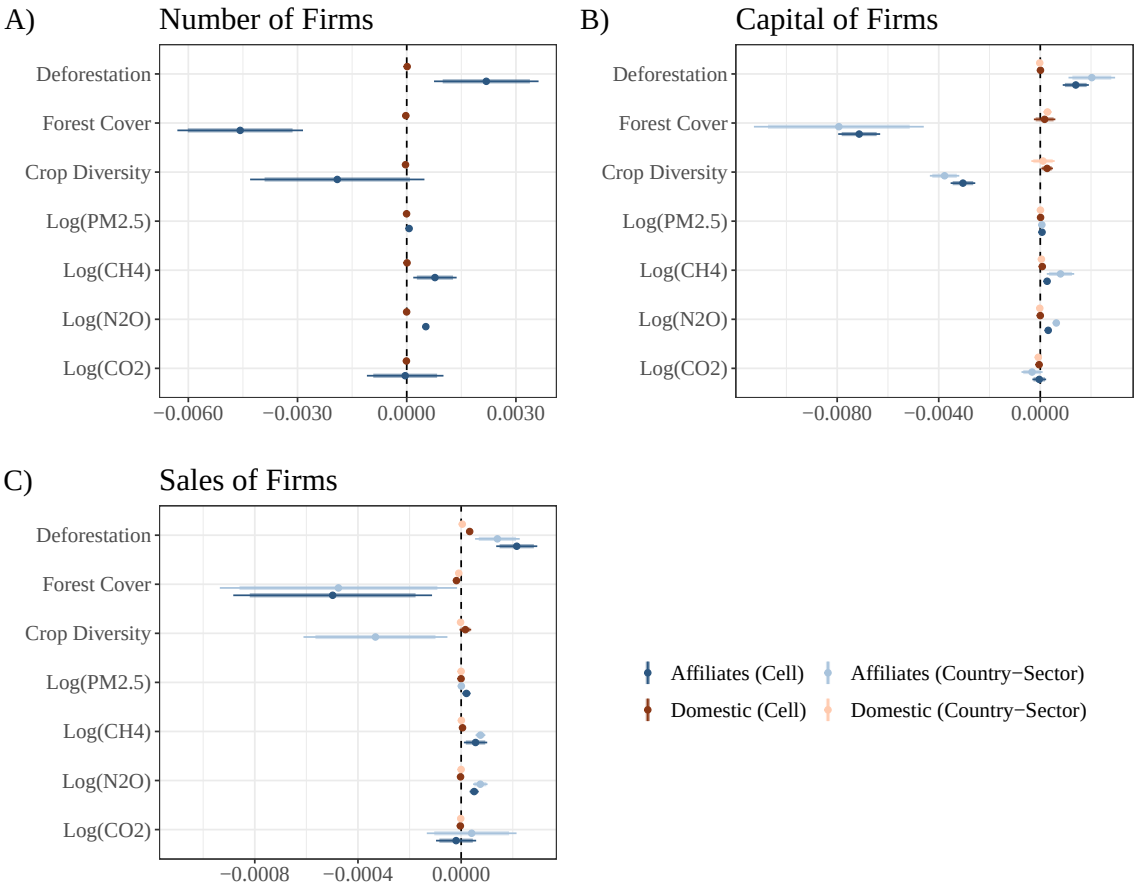


Figure 5: Environmental Impact of Domestic and Multinational Firms: The figure shows the point estimates as well as the 90 % confidence intervals (thick lines) and 95 % confidence intervals (thin lines) for OLS regression results on the impact of MNE affiliates (Affiliates) and domestic firms (Domestic) on all environmental outcomes. Panel A) measures affiliates and domestic firms as the number of firms, panel B) uses total capital (mean capital $\times$ number), and Panel C) uses total sales (mean sales $\times$ number). In panels B) and C), the first specification (Cell) uses mean grid cell-ownership-specific means. It omits cells with missing capital and sales data. The second specification (Country-Sector) uses ownership-sector-country-specific means. All specifications include year-region and cell fixed effects (dummies), mean precipitation, and temperature levels, as well as the share of affiliates and domestic firms in the primary sector and the secondary sector as controls. The environmental outcomes are cumulative tree cover loss in 100 km^2 (Deforestation), tree cover in percent (Forest Cover), crop diversity measured as effective species numbers (Crop Diversity), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). Standard errors are clustered at the country level. We omitted the crop diversity results for the Affiliates (Country-Sector) specification in panel C) because the confidence intervals exceeded the figure margins on both sides, making the figure difficult to interpret. We report the complete result tables in the SI.

Regulations index of the parent corporations' country in the SI. The results remain qualitatively unchanged.

Table 1: Regulation in the Parent Corporations' and Affiliates' Countries

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.005	0.010***	0.006	-0.0004***	0.001	0.0009***	0.007***
	(0.003)	(0.003)	(0.005)	(0.0001)	(0.001)	(0.0003)	(0.001)
Affiliates × ROL Parent	0.002	-0.062***	-0.032	0.0005	0.014**	0.003*	-0.006
	(0.012)	(0.017)	(0.021)	(0.0004)	(0.006)	(0.002)	(0.006)
Affiliates × ROL Affiliate	-0.006	0.043**	0.022	0.0001	-0.015**	-0.004*	-0.005
	(0.014)	(0.017)	(0.022)	(0.0004)	(0.007)	(0.002)	(0.007)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: OLS results for the effect of regulation in the parent corporations' and affiliates' countries on the environmental impact of MNEs. The independent variables are the number of affiliates non-interacted and interacted with the Rule of Law (ROL) index in the parent corporation's and the affiliate's country. The index is normalized between 0 and 1, with higher values indicating better governance. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects, as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

In addition to regulatory capture and pollution havens, multinational corporations may generate more economic activity, which could (partly) explain the larger impact on the environment. We quantified the environmental impact per dollar of capital or sales above and thus compared the differential effects between MNEs and domestic firms while controlling for size. However, it is still possible that multinationals create economic spillovers that lead to economic growth in the entire region, including positive growth effects on domestic firms. To quantify these effects, we repeat our ownership-specific analysis from Figure 5 but using night lights in the *current* period as a proxy for economic activity as an outcome. The results (Table 2) suggest that both domestic and multinational firms increase economic activity. However, the impact of multinational firms on night lights is much larger than the impact of domestic firms on the same outcomes, mirroring

the previous findings on the positive effects of multinationals on economic activity (31, 32, 33).

Table 2: The Impact of Multinational and Domestic Firms on Night Lights

	Night Lights				
	(1)	(2)	(3)	(4)	(5)
Affiliates	0.01371**	0.00579***	0.01241***	0.00174***	0.00136***
	(0.00559)	(0.00161)	(0.00388)	(0.00056)	(0.00028)
Domestic Firms	0.00033***	0.00172**	0.00195**	0.00005	0.00003***
	(0.00010)	(0.00065)	(0.00083)	(0.00005)	(0.00001)
Cell FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Firm Size	Number	Capital (Cell)	Capital (Country-Sector)	Sales (Cell)	Sales (Country-Sector)
Observations	125,076	121,363	124,039	120,110	119,479

Notes: OLS results for the impact of MNE affiliates and domestic firms on economic activity. The independent variables are the number (Column 1) and the aggregate size of affiliates and domestic firms (Columns 2 to 5). We measure firm size with the cell-ownership-specific mean capital (Column 2) and sales (Column 4), as well as the onwership-sector-country-specific mean capital (Column 3) and sales (Column 5). We drop cells with missing size information. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects, as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

The results suggest that the impact of affiliates on night lights is 42 times larger than that of domestic firms. This difference reduces to 3 to 6 times when measuring activity in total capital instead of the number of firms, but it remains constant when measuring firm size with sales.

Although these differences are large, they are dwarfed by the differences in impact between multinationals and domestic firms on environmental outcomes reported in Figure 5. For example, the impact of multinationals on forest cover is 164 times larger than that of domestic firms, and this difference is only reduced to 60 times when measuring firm size with sales. Although these numbers are potentially biased from the OLS approach and should be interpreted cautiously, they suggest that while multinationals have positive economic spillovers, these spillovers only explain a fraction of the differential impact on the environment. This is confirmed by a specification in which we estimate the effect of multinationals on the environment while controlling for *current* night lights. While current night lights are a "bad control" since they could absorb the indirect effect of multinationals, the direct effect after controlling for current night lights remains largely unchanged. The residual effect can, therefore, be interpreted as the direct effect of multinationals net of the effect through general economic activity. In addition to a strong direct effect through particularly environmentally damaging activity, another reason for the minor impact of

controlling for night lights on the result could be measurement error since night lights are only an imperfect measure of economic activity.

Discussion

To conclude, investigating the impact of MNEs on environmental outcomes is heatedly debated, yet a hard problem to study, given the non-random (i.e. endogenous) location decisions of international firms. Simply correlating firm presence and outcomes could result in seriously flawed spurious correlations that are driven by confounding factors such as fertile soils, mineral deposits, or fossil fuel reservoirs. Drawing on an instrumental variable strategy to attenuate these methodological pitfalls, we are able to present novel evidence on the environmental footprint of MNEs. In a nutshell, the news is not good: Crop diversity, forest coverage, and (to some extent) air quality and the combat against greenhouse gas emissions suffer substantially from MNE presence, both in absolute terms and when keeping economic production constant. This negative impact of multinationals is also substantially larger than the impact of domestic companies, holding their size and sector composition constant. The culprits are essentially firms operating in the primary and secondary sectors, with the tertiary service industry having a much less detrimental effect. We also find evidence of a pattern that is consistent with a pollution haven configuration.[11]

The conclusion that MNEs are necessarily bad for developing countries is false, however. Recent evidence suggests that MNEs contribute to local economic development with benefits for economic growth, education, and poverty reduction (32, 33). Our results also show that their impact on economic activity, measured with night lights, is much larger than the impact of domestic firms, underlining their importance for economic development.

In contrast to the bad news on MNEs and the environment, a series of policies appear promising. First of all, binding international standards are paramount. If some key rules apply everywhere, there is less scope for strategically moving to pollution havens. Thankfully, satellites allow the monitoring of pollution, deforestation, and potential environmental damage remotely. Hence, stringent international rules monitored by an international organization could be technically feasible. In order to get all countries on board, richer nations could financially compensate

[11] In particular, firms that are in a pollution haven configuration (with headquarters in places with stringent environmental rules and local operations in areas with laxer regulation) seem to produce more environmental damage. Yet, this does not mean that these firms are there *because* of a pollution haven effect, and (ii) a pollution haven interpretation would not explain why these firms are *more* damaging than other firms operating in the same regulatory environment (in the presence of pollution havens, firms would relocate activities to less regulated contexts, but there's no specific reason to believe that they would behave *worse* than other firms that were already there.

poorer ones for (short-term) economic losses due to stricter ecological rules.

Second, legislation at home should cover activities by MNEs operating abroad (e.g., French MNEs should follow French environmental laws even for activities abroad unless the foreign rules are more stringent).

Third, border taxes accounting for differences in environmental standards may play a critical role (for the European Union, for example, the so-called "Carbon Border Adjustment Mechanism" was adopted in 2023). For instance, as far as CO2 emissions are concerned, a carbon border tax can warrant a level playing field if some companies benefit from a competitive edge by dodging emission taxes (40).[12] Importantly, the logic could be extended beyond carbon taxation, and target other dimensions of illicit competition arising from environmental misconduct. There are a whole series of further legislative advances, e.g., for the European Union alone, the incoming Due Diligence law or the Deforestation law (for recent articles discussing international environmental policy coordination, see (41, 42, 43, 44, 10)).

[12] See https://theconversation.com/what-if-carbon-border-taxes-applied-to-all-carbon-fossil-fuels-too-189759.

Matrials and Methods

Data

Here, we describe the data on the MNEs' activity, the environmental outcomes (pollution, crop diversity, forest cover, deforestation, greenhouse gas emissions), our control variables (weather and economic activity), and the governance indicators. For the statistical analysis, we aggregate all variables to 0.5° × 0.5° spatial (approx. 55km × 55km at the equator) and annual temporal resolution. The spatial resolution is coarse enough to capture the spatial extent of the MNEs' economic activity. The combined dataset spans the period from 2007 to 2018 and the whole African continent. The unit of analysis is the grid cell in a given year. We provide summary statistics in the SI.

Multinationals: To measure MNEs' activity, we combine information on the ownership of all firms connected through an ownership link from the *Historical Ownership Database* of Bureau Van Djik (see Sonno (36)). Each business group's ownership network relies on the definition of direct or indirect majority ($\geqslant 50.01\%$) of the voting rights.[13] The final dataset maps the hierarchical structure of business groups by ascending the ownership structure, constructing the network of business groups for more than 200 countries, from 2007 to 2018, and then geolocates them using zipcodes. This dataset includes more than 6.3 million business groups, with 12.8 million affiliates from 2007-2018. For the scope of this paper, we focus on African affiliates of MNEs (i.e. business groups with at least one affiliate located in a country different from the one of the headquarters). The final sample covers the full continent and the MNE affiliates operating within it, with precise information on location, sector of activity, sales, capital, and parent company financial data.[14] We then aggregate the data to the total number of affiliates per grid cell and year.

Domestic Firms: We identify all firms located in African countries within the Orbis database

[13] This definition of control follows the international standards for MNEs e.g. OECD (45). Bureau Van Dijk's dataset provides, for each company, information on all its shareholders, corporate or non-corporate (e.g., individuals or partnerships), and identifies direct and indirect voting rights. Corporate control can be derived by a direct, indirect, or consolidated concentration of voting rights. For example, a parent company P owns 90% of the voting rights in company C1 and 100% in company C2. Company C1 also owns 35% of voting rights in C3. Company C2, instead, owns 60% of C4 and another 25% of C3. In this example, P controls more than 50% of the voting rights in all the other companies, directly or indirectly. Indeed, P controls directly C1 and C2, indirectly C4, and enjoys consolidated control of C3 through C1 and C2. The literature identifies this as the principle of the Ultimate Controlling Institution in the OECD FATS Statistics.

[14] See the Appendix of Sonno (36) for an extensive description of the data and its validation with the available country-year-specific census data, among which the OECD FATS Statistics. Moreover, the affiliates' locations obtained from the Bureau van Dijk database are compared with locations directly scraped from Google Maps for each MNE affiliate (with a correlation of latitude and longitude higher than 99%).

(Bureau van Dijk) that are (i) not part of an MNE, (ii) which we can geolocalise, i.e. with information on their zip code or, when missing, their city, and (iii) for which we have information about their activity. We are able to geolocate approximately 2.2 million firm-year observations for around 1.1 million distinct domestic firms within our time period. After obtaining the latitude and longitude of these firms, we aggregate the data to the number of domestic firms at the year-cell level ($0.5° \times 0.5°$).

Firm Size: In two additional empirical specifications, we measure domestic and MNE firm activity by their aggregate capital and sales instead of firm numbers. While this variable is less precisely measured, it also captures the intensive margins of MNE and domestic firm expansion, i.e., the growing or shrinking of firms. Following the literature on firm size (39), we measure firm size of MNEs and domestic firms using sales and, in an alternative specification, firm capital. 14 % of all firms have missing capital data, while 39 % of all firms have missing sales data. We, therefore, use year, cell, and ownership-specific (domestic, MNE) capital and sales means in one specification and year, sector, country, and ownership-specific means in another specification to measure firm size.

Sector: To classify the economic activity of firms, we follow the classic three-sector model widely used in development economics. Primary sector industries include agriculture, forestry, fishing, mining, and quarrying. Secondary sector industries include industry, manufacturing, and construction. Tertiary industries include the service sector.[15]

Deforestation: Our measure of deforestation is derived from the Global Forest Change data (15), which measures forest cover loss in 30 m resolution. We use the number of pixels with forest loss within our 0.5° grid cells to measure contemporaneous forest loss. We then convert the forest loss into approximately km^2 by dividing the number of pixels by 1111.[16] Since deforestation may respond with some time lag or may increase over time in response to economic activity, we use cumulated forest loss. This conversion makes it also directly comparable to our second forest outcome, forest cover, since in the absence of forest gain $Forest\,Cover_t = Forest\,Cover_{t=0} - Cumulative\,Forest\,Loss_t$ while our unit fixed effects absorb the baseline forest cover (*Forest Cover*$_{t=0}$). Throughout the paper, we call cumulative forest loss 'deforestation.' A main difference between deforestation and forest cover in our analysis is that the forest cover also includes reforestation. Deforestation calculated from satellite images may have classical

[15] The industry aggregation proposed is mainly based on the High-level ISIC/NACE sector aggregation, which is the most aggregated classification identified by national accountants to be used for reporting Systems of National Accounts data from a wide range of countries (46).

[16] This approximate conversion is only for the interpretation of the results. It is based on the approximate pixel size of 30m i.e. $1000^2 \times 30^{-2}$.

or non-classical measurement error (47, 48). We are not concerned about classical measurement errors because they do not bias the result if they occur in the outcome or dependent variable. In the SI, we provide several tests based on Proctor et al. (48) and Garcia and Heilmayr (49) to show that non-classical measurement error does not affect our results either.

Forest Cover: Similar to e.g. Asher et al. (50), we measure forest cover using NASA's Vegetation Continuous Fields (VCF) data in an alternative specification. Like deforestation data, the VCF data draws on satellite imagery and applies machine learning algorithms to distinguish tree coverage from other land use, including agricultural use. We measure forest cover in percent in 250×250 m pixels and aggregate forest cover by taking the mean across all pixels within each of our $0.5° \times 0.5°$ grid cells.

Crop Diversity: We calculate local crop diversity using the crop cover data from the Spatial Production Allocation Model (SPAM) from HarvestChoice (34). The SPAM data uses agricultural statistics at the sub-national level and then allocates the production data in space using satellite images and crop suitability maps.[17] The SPAM maps contain information about the distribution of 42 crops in 10×10 km grid cells for the years 2000, 2005, 2010, and 2017. We calculate crop diversity using the inverse Simpson Diversity Index (SDI). We use the SDI (also known as effective species numbers) because of its simple interpretation and its wide application across disciplines, including ecology, economics (Herfindahl-Hirschman Index), and political science (effective number of parties). The index equals the number of species or crop types if the land is allocated equally among those species. It declines with increasing inequality of the land allocation among a given number of species or crops as well as with a declining number of species or crops. We first calculate diversity in the 10×10 km SPAM grid cells and then aggregate the diversity data to our $0.5° \times 0.5°$ grid cells using the mean. The benefit of calculating crop diversity in smaller spatial units instead of calculating the overall diversity in our larger grid cells is that it is more sensitive to the expansion of large-scale plantations, which may reduce crop diversity at the local scale but contribute to diversity at a larger geographic scale. Only the SPAM maps for 2010 and 2017 fall in our study period. Further, only cells south of the Sahara were included in the SPAM data for 2017. Our crop diversity sample, therefore, only comprises observations south of the Sahara for 2010 and 2017.[18]

[17] See `https://www.mapspam.info/methodology/` for a detailed discussion of the methodology.

[18] Given that crop diversity is measured in levels, the lower frequency of observations does not mechanically lead to an altered coefficient magnitude than for annual data. However, there could, of course, still arise certain frequency-dependent differences, in particular in the presence of lagged effects or impacts that grow or decrease over time. Put differently, with a lower time-frequency, we may capture a larger fraction of potential lagged effects, which are only partially captured in the TWFE with annual data.

Air Pollution: Air pollution with fine particles below a diameter of 2.5 μm (PM2.5) is especially harmful and well-studied (16). We therefore focus on PM2.5 in this study using the estimates from van Donkelaar et al. (18). van Donkelaar et al. (18) applies satellite retrievals of aerosol optical depth, chemical transport modeling, and ground-based measurements to create a gridded data set of PM2.5 air pollution at 0.1° × 0.1° and monthly resolution. We aggregate the data to mean annual pollution levels in our 0.5° × 0.5° grid cells.

Greenhouse Gas Emissions: Greenhouse gas emissions are the main driver of climate change. They are composed of different gases, mainly Carbon dioxide (CO2), Methane (CH4), and Nitrous oxide (N2O), and originate from different sources such as burning fossil fuels, chemical processes, agriculture, and deforestation. Greenhouse gases are difficult to measure, and satellite measures are not available over larger geographic areas and longer time periods (51). Here, we rely on the Emissions Database for Global Atmospheric Research (EDGAR), a joint project of the European Commission Joint Research Centre and the Netherlands Environmental Assessment Agency. The data are based on sector-specific national emissions data that are then allocated across space using the time-varying spatial distribution of emission sources, including manufacturing facilities, road networks, shipping routes, human and animal population density, and agricultural land use. The detailed methods are described in Crippa et al. (35).[19] We aggregate the data to total emissions within the 0.5° × 0.5° grid cells. From the database, we use CO2 emissions from fossil fuel combustion and chemical processes (e.g. cement production) as well as CH4 and NO2 emissions. Although these data are currently state of the art, we are less confident that they can precisely measure changes in emissions from changes in the activity of MNEs while keeping general economic activity constant. We mainly include these data for completeness.

Governance: Governance has several dimensions. Here, we focus on 1) the ability of MNEs to influence the local regulator in the country of the affiliate and 2) the stringency of environmental regulation in the country of the MNE headquarters. In reality, these two dimensions are highly correlated, and most of the variation in our study results from differences between the country of the headquarters and the country of the affiliate. We therefore use the Rule of Law (ROL) index from the World Bank Worldwide Governance Indicators for both dimensions, primarily because of data quality, measurement consistency across countries, and because it is widely used in similar contexts (e.g., Nunn (52) or Michalopoulos and Papaioannou (53)). While this index is not specific to corruption, it measures whether individuals and firms have confidence in and follow the rules of society. The methods to construct the index are described in Kaufmann et al.

[19]The data are available in 0.1° × 0.1° spatial and yearly temporal resolution on `https://edgar.jrc.ec.europa.eu/dataset_ghg60`.

(54). The country-level data from 1996 to 2019 are standardized around zero, with higher values indicating higher ROL levels. We use the version provided by (55). In addition to this general index, we use two indices specific to corruption and the stringency of environmental regulations in robustness tests.

To measure specifically corruption, we use the Corruption Perceptions Index from Transparency International. The index measures the abuse of public power for private gain based on a large survey. The index is defined from 0 (highly corrupt) to 100 (clean) and spans the years from 2012 to 2020 (earlier years are removed because of a change in methodology). We use the version provided by (55).

Our main specific measure of environmental stringency is the "Stringency of environmental regulations" index from the World Economic Forum (56). The index is based on a survey of more than 10,000 business leaders in 124 countries. The survey asks the respondents to rank the outcomes on a scale from one (very lax, among the worst in the world) to seven (among the world's most rigorous).

A main concern is that multinational activity affects corruption and environmental regulation in the affiliates' countries. We, therefore, use the country-specific time constant mean across our study period (2007 to 2018).

All indices increase in governance quality but use different scales. Therefore, we rescale all indices so that zero is the lowest value while one is the highest value in the complete dataset (including all countries). After rescaling, zero indicates (almost) complete lawlessness, corruption, and the absence of any environmental regulation, while one indicates the opposite.

Each grid cell has two indices associated with it. The index of the country where the cell is located and the index of the parent corporation of the affiliates in that cell. We use the weighted mean of the parent corporations' regulatory environment using the share of affiliates as weights.

Night lights: We control for general economic activity in robustness tests using log night lights and log night lights squared to account for non-linearities. Night lights have been used to successfully predict economic growth (57) and other aspects of economic activity (58). We use the harmonized global nighttime light dataset (59). The authors generate an integrated and consistent nightlight dataset on a global scale by harmonizing the observations from different datasets.

Weather: Weather is likely to directly impact all of our dependent variables. Hence, we control for weather in all of our specifications, despite the exogeneity of our treatment variable. Here, we use the monthly Berkeley Earth surface temperature data (60) in 1° resolution, as well as the monthly Global Precipitation Climatology Project (GCPC) data in 2.5° resolution for precipi-

tation (61). Although the GCPC data have a low spatial resolution, they use a combination of rain gauge stations, satellites, and sounding observations, which is especially important for Africa (with only a few direct measurements). We aggregate precipitation to the annual level by summing across all months. Further, we use the mean annual temperatures.

Estimation

Our research question focuses on the impact of MNE activity on the key environmental variables discussed above (deforestation, forest cover, crop diversity, air pollution, and greenhouse gas emissions). To benchmark the investigation, we start with a two-way fixed effects Ordinary Least Squares (OLS) regression, corresponding to the following specification:

$$y_{krt} = \beta \, \textit{affiliates}_{krt} + \gamma_k + \theta_{rt} + \mu_{krt} \tag{1}$$

where y_{krt} is our outcome variable in cell *k* in region *r* in year *t*, $\textit{affiliates}_{krt}$ is the number of MNE affiliates, and μ_{krt} is the error term. One feature of the MNE data is that its distribution is highly skewed to the right, with very few cells displaying a very high number of affiliates. For this reason, the independent variable is winsorized at the top percentile. γ_k and θ_{rt} are cell and region $\times$ year fixed effects (dummies or intercepts), respectively. These constant terms filter out time-invariant spatial heterogeneity (e.g., altitude, distance from the sea, latitude, etc.), as well as region-specific shocks (e.g., country or province-level elections or conflict). Note that our 755 regions are political units at the sub-national level. This specification implies that β is estimated from changes in the number of affiliates within the same cell over time relative to the changes in all other cells within the same region. Following convention, we cluster the standard errors at the country level.[20] We further transform air pollution and greenhouse gas emissions using log transformations.

Several environmental outcomes are related to the weather, which could also affect the activities of MNEs. We, therefore, control for mean temperature and annual precipitation levels in all specifications. Our major concern is, however, that MNE activity is correlated with economic activity in general. If this were the case, our estimates would be affected by omitted variable bias. We address this concern in three ways. First, we include lagged night lights as a proxy for gen-

[20] Our standard errors are rather conservative, which typically –if anything– leads to an underestimation of the precision of our findings. Abadie et al. (62) suggest that clustering is stricto sensu only necessary if the sampling procedure or the treatment itself is clustered, which is not the case in our analysis. Still, following convention, we adopt a clustering strategy that is quite demanding.

eral economic activity (e.g. 57) as controls in the first robustness tests. Second, we include the number of domestic firms in the previous year as controls in a second robustness test. The interpretation of the coefficients differs between these two robustness tests. While the coefficient in the first robustness tests estimates the impact of affiliates on the environment *in addition* to general economic activity, the coefficient of affiliates in the second specification quantifies the impact of affiliates on the environment while *holding the number of domestic firms constant*. The first robustness test, therefore, also provides an initial answer to the question of whether MNEs are worse for the environment than normal economic activity. Below, we outline our approach to comparing the environmental impact of multinational and domestic firms. The third way in which we address concerns about potential statistical biases arising from the non-random (i.e. endogenous) location of MNEs is an instrumental variable (IV) approach. We further describe this approach below.

Impact by Sector: The impact of economic activity on the environment may differ by sector. For example, a logging company may impact deforestation differently than a bank. Although this comparison is intuitive, it becomes muddied by possible supply and demand spillovers. For example, a multinational bank could lend money to domestic firms in the primary sector and thus increase logging indirectly. Alternatively, they could increase local incomes and the consumption of goods with high environmental externalities, such as meat (see, e.g., Alix-Garcia et al. (63)). Similar to our previous estimation strategy, we estimate equation (1) but using the sector-specific number of affiliates in an OLS and an IV approach. The sector-specific IV approach follows the main IV approach but uses a sector-specific instrument based only on firms in this sector. We report a joint estimation of domestic and MNE firms in all sectors in a robustness test. We cannot use an IV approach for the joint estimation because our instrument relies on the ownership structure of multinationals and, therefore, cannot be applied to domestic firms. It is also correlated across sectors, reducing its strength in a joint estimation for MNEs.

Comparing Multinationals and Domestic Firms: While quantifying the impact of multinationals on the environment is important, here we explore the more nuanced question of whether MNEs are more damaging to the environment than similar domestic firms. In one of our baseline specifications, we control for the lagged number of domestic firms in each grid cell. However, multinationals and domestic firms may differ in more respects than their ownership structure, including size and sector composition. A major concern is that MNE affiliates are larger than domestic firms. Indeed, the summary statistics in the SI suggest that MNE affiliates are more than four times larger than domestic firms when comparing mean sales or capital and about ten times larger than domestic firms when using the median for comparison. Different effects of

an additional affiliate and domestic firm on the environment could simply result from their size differences. To compare MNE affiliates and domestic firms, we, therefore, measure MNE and domestic firm activity by using their aggregate sales and, in an alternative specification, their aggregate capital per grid cell. In addition, MNEs and domestic firms are active in different sectors (see summary statistics in the SI). While the share of domestic firms in the primary sector is 20 %, it is only 11 % for MNE affiliates. We, therefore, also control for the share of domestic firms and affiliates in the primary and secondary sectors. The estimation of this approach is exclusively based on OLS estimations to make the estimates for the MNEs and the domestic firms directly comparable.[21] We, therefore, interpret only the relative magnitude of both estimates.

Regulation: The pollution haven literature suggests that pollution is relocated from countries with strict regulations to countries with less stringent environmental rules. We, therefore, expect that the expansion of MNEs from strictly regulated countries to countries with lax environmental regulations is especially damaging. Further, we discussed the possibility that powerful MNEs influence the regulator to lower the environmental standards. We, therefore, also expect more environmental damage in countries with weak regulators.

To test these hypotheses, we use the governance indicators described in the Data section in the country of the affiliate (ROL^a) and the country of the MNE's parent corporation (ROL^p). To recap, we use the weighted mean of the parent corporation governance indicators if several MNEs from different countries operate in a cell with the share of affiliates as weights. Specifically, we estimate

$$\begin{aligned} y_{krt} =& \beta_1 \, \textit{affiliates}_{krt} + \beta_2 \, \textit{affiliates}_{krt} \times ROL_k^a + \beta_3 \, \textit{affiliates}_{krt} \times ROL_k^p \\ &+ \gamma_k + \theta_{rt} + \mu_{krt} \end{aligned} \tag{2}$$

where ROL_k^a is the affiliate's (or grid cell k's) governance and ROL_k^p is the weighted mean of the parent corporations governance. As discussed above, we use time-constant governance indicators to avoid reverse causality. Because we normalized both indicators between zero and one, the direct effect (β_1) is the impact of an additional affiliate in the absence of governance in both countries.

IV Specification: A potential concern with the estimates of the model (1) is that the MNE location may not be random, potentially generating a bias in the estimates of model parameters. For example, it could be the case that MNEs deliberately develop and expand activities in locations on a positive or negative environmental trajectory. Second, and maybe more importantly,

[21] Note that the instrument does not predict the number of the domestic firms because it is based on the ownership structure of MNEs.

we are concerned that MNE activity is correlated with general economic development. To address this concern, we run two-stage least square (2SLS) estimations using the IV strategy proposed in (36), based on the notion that shocks to the parent corporation affect the expansion or contraction of its affiliates independently of their local environmental conditions. More specifically, we use the pre-period parent corporations' dependence on external credit in combination with international credit shocks and the location's initial composition of MNE affiliates to predict the expansion or contraction of MNEs' activity (measured by the number of affiliates) in the first stage.

The fundamental assumption that underlies our approach is that the affiliates' activities depend on the parent company's performance through e.g., the constraint on the amount of borrowing or any general financial help by the parent company. This thesis has found extensive support in the internal capital market literature (see, for example, (64)). It is also reflected in the sizeable F statistic of our first stage.

In the second stage, we use the predicted number of affiliates to quantify the causal impact of MNEs on environmental outcomes. The direct impact of the global credit shocks on environmental outcomes is absorbed by the region-year fixed effects. Our main concern is that the initial composition of the affiliates predicts the changes in the environmental outcome. We follow the approach suggested by Borusyak et al. (65) to show that our shocks are as good as randomly distributed conditional on the fixed effects and, therefore, cannot capture spurious correlations of the baseline MNEs' composition and a possible trend in environmental outcomes. Below, we discuss our IV strategy in more detail below.

As mentioned earlier, we need to determine the number of affiliates for each cell and year. To obtain it, we follow the strategy proposed by (36), who uses a classic shift-share approach. The methodology is carried out in three phases. Initially, we assess the influence of each parent company within individual cells for the base year, 2007. This involves evaluating the proportion of each parent company's m's subsidiaries within a specific cell. To illustrate, $w^m_{k,c,2007}$ denotes the fraction of subsidiaries belonging to parent m in cell k for the year 2007.[22] This forms the share component of the instrument. Next, the dependence of the parent company on external financing over the past decade (1997-2006) is calculated, represented by dep^m_{97-06}.[23] Finally, this company-specific (time-invariant) variable is combined with metrics of global credit accessibility,

[22] This proportion is calculated as the number of m's subsidiaries in cell k for the year 2007 relative to the total subsidiaries in the same cell during the same year.

[23] This is quantified using the parent's total (non-equity) liability-to-asset ratio, as discussed in sources such as 66.

denoted by cre_{t-1}.[24] The interaction $dep^{m}_{97-06} \times cre_{t-1}$ represents the shift component. For each cell-year, therefore, we obtain an instrument z for the number of MNE affiliates:

$$z_{k,c,t} = \sum_{m} w^{m}_{k,c,2007} \left(dep^{m}_{97-06} \times cre_{t-1} \right) \tag{3}$$

where we keep as constant the initial share of multinationals in each cell ($w^{m}_{k,c,2007}$) as weighting strategy for exogeneity. Consistency of the 2SLS estimates relies on the assumption that, other than multinationals' activity, non-African shocks to credit given to the private sector will – conditional on controls, cell and country×year fixed effects – impact environmental outcomes in a given African cell k only through affiliates of multinational groups present in the cell.

[24] World Bank data: worldwide domestic credit to the private sector (financial resources provided to the private sector), excluding African countries.

As a robustness test, we also use domestic credit provided by the financial sector.

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Supplementary Materials

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1 Summary Statistics

Table 3: Summary Statistics of all Grid Cells

Statistic	N	Mean	Min	Pctl(25)	Median	Pctl(75)	Max
Deforestation [km2]	124,452	35.145	0.000	0.000	0.204	28.812	1,491.760
Forest Cover [%]	125,076	10.890	0.000	0.00002	2.485	15.706	83.151
Crop Diversity [SDI]	20,846	1.327	0.000	0.000	0.000	2.573	11.869
Log(PM2.5)	125,076	1.100	−0.126	0.956	1.188	1.275	1.592
Log(CH4)	106,368	1.154	−10.285	0.971	1.435	1.646	2.298
Log(N2O)	67,926	0.066	−11.130	−0.273	0.312	0.686	1.749
Log(CO2)	123,076	1.727	−6.604	1.471	1.763	2.014	2.671
Number Affiliates	125,076	0.389	0	0	0	0	377
Number Domestic Firms	125,076	9.838	0	0	0	0	6,165
Night lights	125,076	1.092	0.000	0.000	0.005	0.769	61.256

Table 4: MNE Affiliate Size and Sector of Grid Cells with MNE Affiliates

Statistic	N	Mean	Min	Pctl(25)	Median	Pctl(75)	Max
Sales MNE Affiliates [Million USD]	524	6.153	0.000	2.612	5.102	9.373	20.585
Capital MNE Affiliates [Million USD]	521	1.048	−0.121	0.226	0.822	1.427	5.000
MNE Affiliates Primary Sector [%]	524	11.421	0.000	0.000	2.840	13.202	100.000
MNE Affiliates Secondary Sector [%]	524	45.444	0.000	24.384	38.889	66.667	100.000

The unit of observation is a grid cell-year combination. Only grid cells with non-missing capital and sales data are included.

Table 5: Domestic Firm Size and Sector of Grid Cells with Domestic Firms

Statistic	N	Mean	Min	Pctl(25)	Median	Pctl(75)	Max
Sales Domestic Firms [Million USD]	2,203	1.391	0.000	0.262	0.547	0.908	20.472
Capital Domestic Firms [Million USD]	2,198	0.182	−0.038	0.030	0.080	0.150	4.366
Domestic Firms Primary Sector [%]	2,203	20.803	0.000	3.475	15.333	29.328	100.000
Domestic Firms Secondary Sector [%]	2,203	31.403	0.000	20.530	31.613	41.486	100.000

The unit of observation is a grid cell-year combination. Only grid cells with non-missing capital and sales data are included.

2 Instrument Validity

Our 2SLS strategy is based on a shift-share instrument. This instrument combines a general shock (the volume of global credit) with two exposure variables: the credit dependency of the parent corporation in a pre-period (1997 to 2006) and the composition of affiliates from different parent corporations in the baseline period (2007). The direct effect of global credit shocks on the environment is captured by our region $\times$ year fixed effects while the cell fixed effects capture the time-constant differences in environmental outcomes that are correlated with the affiliate composition. Our main concern is, however, that the affiliate composition may be correlated with the environmental dynamics in the cells, even in the absence of multinational expansions. Examples may include a high concentration of affiliates in the primary sector, which could be indicative of environmental destruction from large-scale mining, forestry, or industrial agricultural activity in general. Here, we follow the strategy of Borusyak et al. (65), who show that the instruments are valid even if the exposure variables were to be non-random (i.e. endogenous) as long as the shocks are as-good-as randomly assigned. First, we display the distribution of the shock and the exposure variables before we introduce a falsification test.

2.1 Distribution of shock and exposure variables

In this section, we follow the approach of the first part of Table 1 of Borusyak et al. (65), section 6.2.2. First, in Table 6 we show the distribution of the shock variable $\left(dep^{m}_{97-06} \times cre_{t-1}\right)$. In particular, in column 1 mean, standard deviation and interquantile range of the distribution of the shock variable at the headquarter level are presented. In column 2, we present the same statistics after residualizing it on year fixed effects. The shock presents a standard deviation around 250 with or without controlling for year fixed effects, while the interquartile range remains well above 300 in both cases. These statistics show a significant degree of variation of the shock, a key requirement highlighted by the authors to ensure the robustness and unbiasedness of the results.

Second, we display the inverse of the Herfindahl-Hirschman Index (HHI) of shock-level average exposure as a simple way of describing the effective sample size. Table 7 shows the 1/HHI of the exposure variable ($w^{m}_{k,c,2007}$), i.e. the share of affiliates from one parent corporation within each cell. Reassuringly, this number is particularly high, as recommended by the authors.

Table 6: Distribution of shock variable

	(1)	(2)
Mean	659.5	0
Standard deviation	255.82	248.75
Interquartile range	331.37	316.52
Specification		
Residualizing on year FE	No	Yes

Notes: This table replicates for our data the first part of Table 1 of Borusyak et al. (65), section 6.2.2. Columns 1 and 2 show the mean, standard deviation, and interquartile range of the distribution of the shock variable, without (column 1) and with (column 2) residualizing it on year-fixed effects, as requested by the authors.

Table 7: Distribution of exposure variable

	Year 2007
Effective sample size (1/HHI of weights)	158

Notes: This table presents the inverse of the HHI of shock-level average exposure, to depict in a simple way the effective sample size, as suggested by (65).

2.2 Falsification test

Here, we display the correlation of potential confounders with our affiliate weighted shocks (see Borusyak et al. (65), pages 206-207). Validity requires that locations are uncorrelated with our instrument, i.e. shocks to MNEs. To test this, we use the pre-period credit exposure (dep^{m}_{97-06}) and correlate it with the MNE share weighted cell characteristics. In other terms, we correlate the MNEs' pre-period credit exposure with the MNEs' share weighted cell characteristics for all outcomes (e.g. the average forest cover for each MNE at the beginning of the period, using the number of MNEs in each grid cell). Results are presented in Table 8, where we can see that, reassuringly, we do not find any significant correlation.

Table 8: Falsification test

Estimation	OLS						
Dependent Variable	Credit Dependence						
Average Deforestation	0.0232						
	(0.0203)						
Average Forest Cover		0.00166					
		(0.00117)					
Average Crop Diversity			-0.00867				
			(0.00579)				
Average Log(PM2.5)				0.00853			
				(0.0137)			
Average Log(CH4)					0.00936		
					(0.00925)		
Average Ln(N2O)						-0.00367	
						(0.00656)	
Average Log(CO2)							0.00220
							(0.00606)
Observations	846	865	865	865	865	865	865

Notes: In this table, following Borusyak et al. (2022, pages 206-207), we show the correlation of potential confounders with our affiliate weighted shocks. Dependent variable: pre-period credit exposure (dep^{m}_{97-06}). Independent variables: multinationals' share weighted cell characteristics for environmental outcomes; in other words, the average outcome (depending on the column, i.e. deforestation for columns 1, tree coverage for column 2, etc) for each multinational at the beginning of the period, using the number of multinationals in each grid cell as weights.

3 Main OLS Results - Regression Tables

Here, we present the regression tables for our main results.

Table 9: Main OLS results

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.005***	-0.002**	0.00004	0.0008**	0.0005***	-0.00009
	(0.0008)	(0.0008)	(0.0010)	(0.00003)	(0.0003)	(0.00004)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: Main OLS results. The independent variable is the current number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 10: Main OLS results with night lights as control

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.005***	-0.003**	0.00003	0.0007**	0.0005***	0.00003
	(0.0006)	(0.0010)	(0.001)	(0.00003)	(0.0003)	(0.00005)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: Main OLS results with night lights as control. The independent variable is the current number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged night lights and lagged night lights squared as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 11: Main OLS results with lagged domestic firms as control

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.004***	-0.002**	0.00003	0.0008**	0.0005***	-0.00005
	(0.0007)	(0.0008)	(0.001)	(0.00003)	(0.0003)	(0.00004)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: Main OLS results with lagged domestic firms as control. The independent variable is the current number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged domestic firms as control. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 12: Main OLS results with lagged affiliates as independent variable

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.004***	-0.002***	-0.00003	0.0008**	0.0003***	-0.0002
	(0.0008)	(0.001)	(0.0009)	(0.00004)	(0.0003)	(0.00006)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356

Notes: Main OLS results with lagged affiliates as independent variable. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 13: Main OLS results with lagged affiliates as independent variable and night lights as control

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.004***	-0.003***	-0.00005	0.0007**	0.0003***	-0.00006
	(0.0006)	(0.001)	(0.001)	(0.00004)	(0.0003)	(0.00008)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356

Notes: Main OLS results with lagged affiliates as independent variable and night lights as control. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged night lights and lagged night lights squared as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 14: Main OLS results with lagged affiliates as independent variable and lagged domestic firms as control

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.003***	-0.002***	-0.00005*	0.0008**	0.0003***	-0.0001
	(0.0007)	(0.001)	(0.0009)	(0.00003)	(0.0003)	(0.00006)	(0.0005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356

Notes: Main OLS results with lagged affiliates as independent variable and lagged domestic firms as control. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged domestic firms as control. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

4 Main IV Results - Regression Tables

Here, we present the regression tables for our main results.

Table 15: Main IV results

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.020***	-0.034**	-0.019**	0.0002	0.005*	0.001*	-0.002
	(0.007)	(0.014)	(0.008)	(0.0005)	(0.003)	(0.0007)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	22.9	23.7	21.1	23.7	23.7	23.7	23.7

Notes: Main IV results with lagged affiliates as independent variable and lagged domestic firms as control. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged domestic firms as control. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 16: Main IV results with night lights as control

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.023***	-0.040**	-0.022**	0.0002	0.004	0.001*	-0.003
	(0.009)	(0.017)	(0.010)	(0.0006)	(0.003)	(0.0008)	(0.005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	32.7	33.2	28.6	33.2	33.2	33.2	33.2

Notes: Main IV results with night lights as control. The independent variable is the current number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged night lights and lagged night lights squared as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 17: Main IV results with lagged domestic firms as control

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.021***	-0.034**	-0.022**	0.0002	0.006*	0.001*	-0.002
	(0.007)	(0.015)	(0.010)	(0.0005)	(0.003)	(0.0008)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	21.0	21.8	15.1	21.8	21.8	21.8	21.9

Notes: Main IV results with lagged domestic firms as control. The independent variable is the current number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged domestic firms as control. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 18: Main IV results with lagged affiliates as independent variable

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.020***	-0.035**	-0.021**	0.0004	0.006**	0.002**	-0.002
	(0.007)	(0.015)	(0.009)	(0.0006)	(0.003)	(0.0007)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356
Wald (1st stage), Affiliates	25.3	26.4	28.6	26.4	26.4	26.4	26.4

Notes: Main IV results with lagged affiliates as independent variable. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 19: Main IV results with lagged affiliates as independent variable and night lights as control

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.023**	-0.042**	-0.023**	0.0003	0.005*	0.002**	-0.003
	(0.009)	(0.019)	(0.010)	(0.0007)	(0.003)	(0.0007)	(0.005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356
Wald (1st stage), Affiliates	37.6	38.4	38.6	38.4	38.4	38.4	38.4

Notes: Main IV results with lagged affiliates as independent variable and night lights as control. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged night lights and lagged night lights squared as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 20: Main IV results with lagged affiliates as independent variable and lagged domestic firms as control

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.021***	-0.036**	-0.024**	0.0004	0.006**	0.002**	-0.002
	(0.007)	(0.016)	(0.010)	(0.0006)	(0.003)	(0.0007)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,081	114,653	20,846	114,653	114,435	114,653	113,356
Wald (1st stage), Affiliates	23.5	24.5	19.1	24.5	24.5	24.5	24.5

Notes: Main IV results with lagged affiliates as independent variable and lagged domestic firms as control. The independent variable is the lagged number of affiliates per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. In addition, it includes lagged domestic firms as control. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

5 Sample Restrictions

In a robustness test, we restrict the sample to cells with A) tree cover, B) night lights, and C) regions with MNE affiliates in at least one year of the sample period (2007 to 2018). Figure 6 shows the sample maps. The sample restrictions create several reduced balanced panel datsets. The results are reported in the main article.

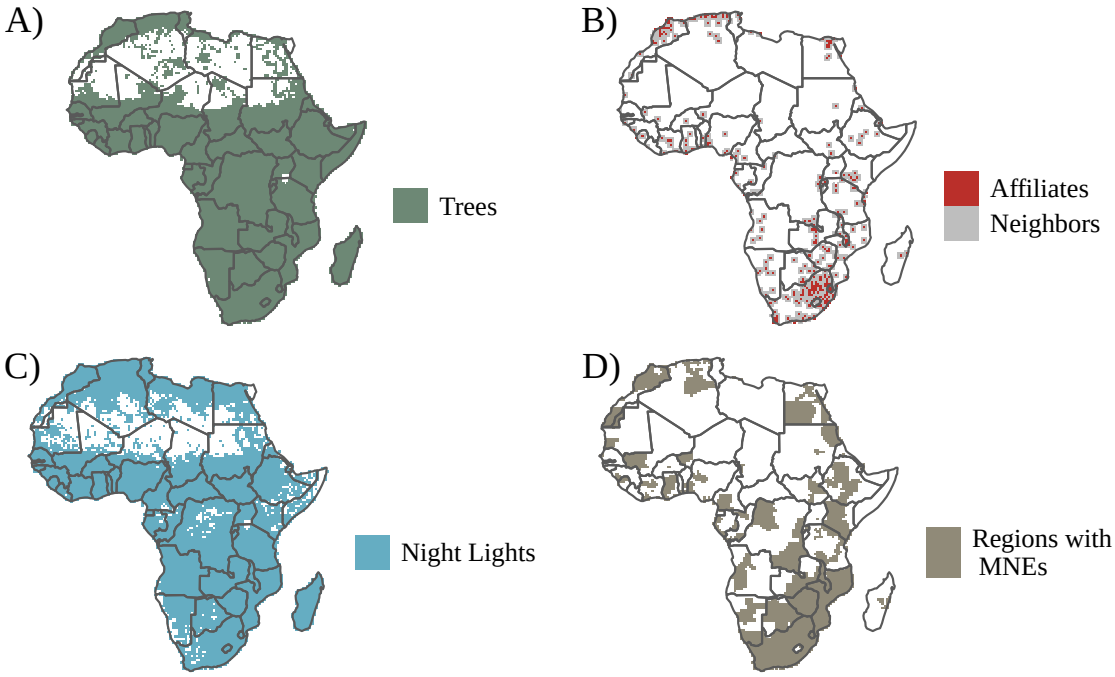


Figure 6: Subsamples: Cells with A) tree cover, B) affiliates and their neighboring cells, c) night lights, D) cropland.

6 Results with Spillovers

Here, we present the OLS regression results of our main approach but with the number of the MNE affiliates in all eight neighboring grid cells of the focal grid cell as an additional control (Spillover). We compare the estimates to the baseline specification (Baseline).

In particular, in Figure 7, we display first the estimate of the previous baseline estimation (labeled "Baseline – Affiliates"). We then compare those estimates with the estimates of an alternative "Spillover" specification that contains two variables of interest: the number of affiliates in a given cell as well as the number of affiliates in the eight neighboring cells. In this specification, the number of affiliates is labeled "Spillover – Affiliates," while the number of affiliates in the eight neighboring cells is labeled "Spillover – Neighboring Affiliates." As expected, we find that the number of MNE affiliates in the neighboring cells does impact environmental outcomes in a given cell, but to a smaller extent than the affiliates operating directly in this cell.

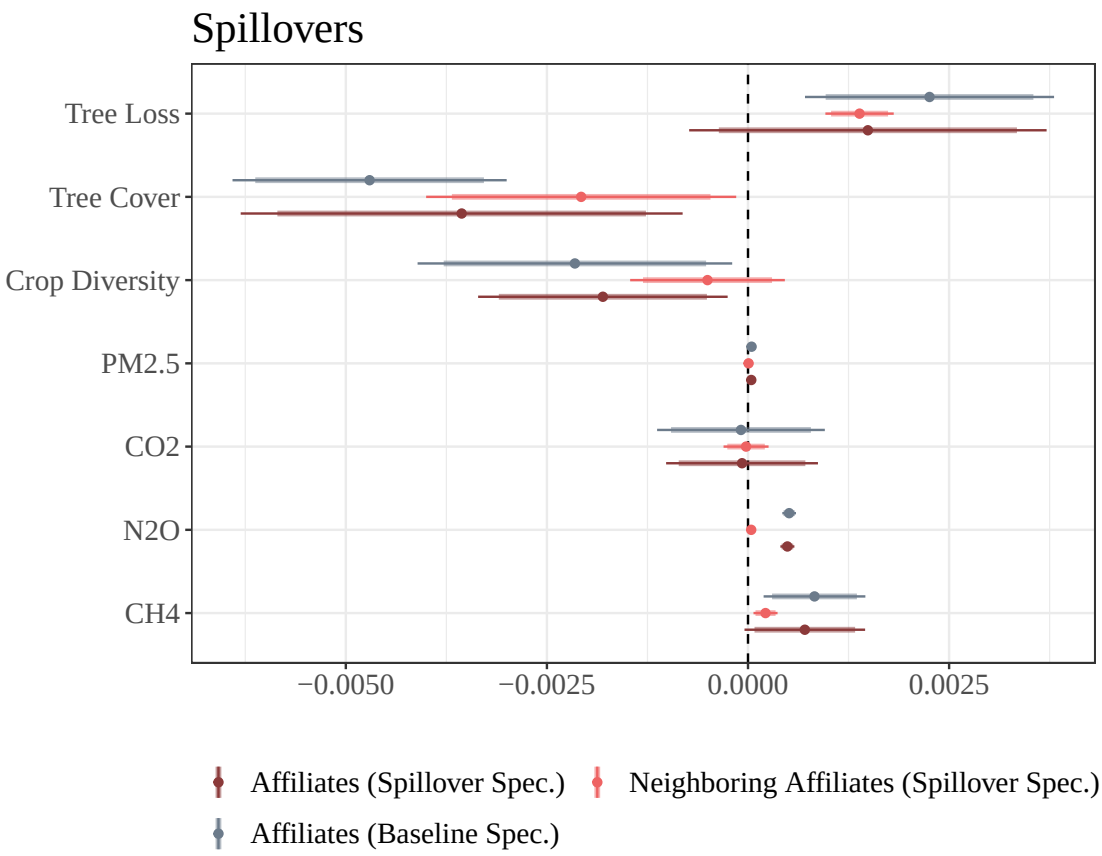


Figure 7: The direct and spillover effect of MNEs on the environment: The 'Baseline' specification is equivalent to the 'Current' specification in the main results. The 'Spillover' specification includes the number of the MNE affiliates in the focal grid cell and, **in addition**, the affiliates in all eight neighboring grid cells 'Neighboring Affiliates'. The figure shows the point estimates as well as the 90 % confidence intervals (thick lines) and 95 % confidence intervals (thin lines). All specifications include year-region and cell fixed effects as well as mean precipitation and temperature levels as controls. The environmental outcomes are tree cover loss in 100 km^2 (Deforestation), tree cover in percent (Forest Cover), crop diversity measured as effective species numbers (Crop Diversity), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). Standard errors are clustered at the country level.

7 Results by Sector - Regression Tables

Here, we present the regression tables for our OLS and IV results by sector. We run individual regressions for each sector.

Table 21: OLS Results: Primary Sector

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.006	-0.007**	-0.004	-0.00005	0.001	-0.0010***	0.0006
	(0.003)	(0.003)	(0.006)	(0.0002)	(0.002)	(0.0004)	(0.002)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: OLS results by sector with affiliates in the primary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 22: OLS Results: Secondary Sector

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.008**	-0.011***	-0.005	0.0001	0.003**	0.0008**	-0.0002
	(0.003)	(0.004)	(0.007)	(0.0001)	(0.001)	(0.0004)	(0.002)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: OLS results by sector with affiliates in the secondary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 23: OLS Results: Tertiary Sector

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.002***	-0.005***	-0.002***	0.00003	0.0008***	0.0006***	-0.0002
	(0.0008)	(0.0008)	(0.0007)	(0.00002)	(0.0003)	(0.00004)	(0.0004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: OLS results by sector with affiliates in the tertiary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 24: IV Results: Primary Sector

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.077	-0.194	-0.098*	0.002	0.017	0.010*	-0.007
	(0.050)	(0.117)	(0.057)	(0.003)	(0.025)	(0.006)	(0.022)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	10.7	10.5	8.79	10.5	10.5	10.5	10.5

Notes: IV results by sector with affiliates in the primary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 25: IV Results: Secondary Sector

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.049	-0.130***	-0.068	-0.00004	0.019**	0.006**	0.003
	(0.035)	(0.039)	(0.042)	(0.002)	(0.008)	(0.003)	(0.018)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	21.6	23.3	21.1	23.3	23.3	23.3	23.3

Notes: IV results by sector with affiliates in the secondary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 26: IV Results: Tertiary Sector

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.026***	-0.040***	-0.011*	0.0004	0.007**	0.002*	-0.001
	(0.005)	(0.013)	(0.006)	(0.0004)	(0.004)	(0.001)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662
Wald (1st stage), Affiliates	16.9	17.7	17.5	17.7	17.7	17.7	17.7

Notes: IV results by sector with affiliates in the tertiary sector as independent variable. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

8 Results by Sector (Joint Estimation) - Regression Tables

Here, we present the regression tables for our joint OLS estimation of the impact of MNE affiliates and domestic firms by sector.

Table 27: OLS Results by Sector: Joint Estimation

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.001	-0.009***	-0.004**	0.00003	0.00002	0.0002	-0.0008
	(0.001)	(0.002)	(0.002)	(0.00007)	(0.0004)	(0.0002)	(0.0005)
Affiliates × Share Primary (A)	0.021	0.008	-0.026	-0.0006	0.007	0.0008	0.007
	(0.020)	(0.020)	(0.036)	(0.001)	(0.005)	(0.001)	(0.007)
Affiliates × Share Secondary (A)	-0.002	0.018*	0.018	0.0004	0.002	0.002	0.002
	(0.006)	(0.009)	(0.019)	(0.0003)	(0.002)	(0.001)	(0.003)
Domestic	0.00003	-0.0001*	-0.0001***	-0.00001	0.00001***	-0.000004	-0.000002
	(0.00002)	(0.00007)	(0.00002)	(0.000009)	(0.000004)	(0.000003)	(0.000005)
Domestic × Share Primary (D)	-0.00009	-0.0002	0.0002	-0.00004	0.0003	-0.00004**	0.0002
	(0.00007)	(0.0002)	(0.0002)	(0.00003)	(0.0004)	(0.00002)	(0.0002)
Domestic × Share Secondary (D)	-0.00007	0.0004**	0.0003***	0.00004	-0.00005	0.00001	-0.00005***
	(0.00005)	(0.0002)	(0.00005)	(0.00003)	(0.00003)	(0.000008)	(0.00002)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: Joint OLS results by sector. The independent variables are the number of affiliates (Affiiates), the number of domestic firms (Domestic), and the interaction terms with the share of affiliates (A) and domestic firms (D) in the primary and secondary sector respectively. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

9 Results for Domestic and Multinational Firms - Regression Tables

Here, we present the regression tables for our joint OLS estimation of the impact of MNE affiliates and domestic firms. We express the activity as the number of firms as well as their aggregate size in a robustness test while controlling for the sector of both MNEs and domestic firms.

Table 28: Multinational and Domestic Firms (Numbers)

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.002***	-0.005***	-0.002	0.00007*	0.0008**	0.0005***	-0.00004
	(0.0007)	(0.0009)	(0.001)	(0.00003)	(0.0003)	(0.00004)	(0.0005)
Domestic	0.00001	-0.00003	-0.00003	-0.000004	0.000009*	-0.000002	-0.000008
	(0.00001)	(0.00005)	(0.00003)	(0.000004)	(0.000005)	(0.000002)	(0.000006)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: Main OLS results. The independent variables are the current number of affiliates and the current number of domestic firms per cell. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Additinally, we include the share of affiliates in the primary and secondary sector as well as the share of domestic firms in the primary and secondary sector as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 29: Multinational and Domestic Firms (Capital-Cell)

	Deforestation (1)	Forest Cover (2)	Crop Diversity (3)	Log(PM2.5) (4)	Log(CH4) (5)	Log(N2O) (6)	Log(CO2) (7)
Affiliates	0.001***	-0.007***	-0.003***	0.00007***	0.0003***	0.0003***	-0.00004
	(0.0003)	(0.0004)	(0.0002)	(0.00001)	(0.00005)	(0.00002)	(0.0001)
Domestic	0.000008	0.0002	0.0003**	0.00001*	0.00008*	0.0000007	-0.00004
	(0.00002)	(0.0002)	(0.0001)	(0.000007)	(0.00004)	(0.00001)	(0.00006)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120,824	121,363	20,098	121,363	121,124	121,363	119,949

Notes: Main OLS results. The independent variables are the aggregate size of affiliates and domestic firms per cell. Here, we use the cell-ownership-specific mean capital to measure firm size. We drop cells with missing size information. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Additinally, we include the share of affiliates in the primary and secondary sector as well as the share of domestic firms in the primary and secondary sector as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 30: Multinational and Domestic Firms (Capital-Country-Sector)

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.002***	-0.008***	-0.004***	0.00006***	0.0008***	0.0006***	-0.0003
	(0.0005)	(0.002)	(0.0003)	(0.00002)	(0.0003)	(0.00004)	(0.0002)
Domestic	-0.00002*	0.0003***	0.0001	0.000007	0.00004	-0.00002	-0.00008
	(0.00001)	(0.00008)	(0.0002)	(0.000008)	(0.00005)	(0.00001)	(0.00007)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,419	124,039	20,628	124,039	123,800	124,039	122,625

Notes: Main OLS results. The independent variables are the aggregate size of affiliates and domestic firms per cell. Here, we use the onwership-sector-country-specific mean capital to measure firm size. We drop cells with missing size information. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Additinally, we include the share of affiliates in the primary and secondary sector as well as the share of domestic firms in the primary and secondary sector as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 31: Multinational and Domestic Firms (Sales-Cell)

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.0002***	-0.0005**	0.001	0.00002**	0.00006**	0.00005***	-0.00002
	(0.00004)	(0.0002)	(0.001)	(0.000008)	(0.00002)	(0.000009)	(0.00004)
Domestic	0.00003***	-0.00002***	0.00002	-0.0000004**	0.000005	-0.000002	-0.000003**
	(0.000004)	(0.000007)	(0.00001)	(0.0000002)	(0.000004)	(0.000002)	(0.000001)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,659	120,110	19,716	120,110	119,871	120,110	118,696

Notes: Main OLS results. The independent variables are the aggregate size of affiliates and domestic firms per cell. Here, we use the cell-ownership-specific mean sales to measure firm size. We drop cells with missing size information. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Additinally, we include the share of affiliates in the primary and secondary sector as well as the share of domestic firms in the primary and secondary sector as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

Table 32: Multinational and Domestic Firms (Sales-Country-Sector)

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.0001***	-0.0005**	-0.0003**	0.0000007	0.00007***	0.00007***	0.00004
	(0.00004)	(0.0002)	(0.0001)	(0.000006)	(0.000009)	(0.00001)	(0.00009)
Domestic	0.000004	-0.000009*	-0.000002***	-0.0000002	0.0000008***	-0.0000002	-0.000002***
	(0.000004)	(0.000005)	(0.0000007)	(0.0000004)	(0.0000002)	(0.0000002)	(0.0000006)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,973	119,479	19,557	119,479	119,240	119,479	118,065

Notes: Main OLS results. The independent variables are the aggregate size of affiliates and domestic firms per cell. Here, we use the onwership-sector-country-specific mean sales to measure firm size. We drop cells with missing size information. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects as well as precipitation and temperature as controls. Additinally, we include the share of affiliates in the primary and secondary sector as well as the share of domestic firms in the primary and secondary sector as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

10 Alternative Governance Indicators - Regression Tables

Here, we present the results on governance but using the "Stringency of Environmental Regulations" index from the World Economic Forum to measure environmental regulation in the country of the MNE headquarters and the Corruption Perceptions Index from Transparency International to measure corruption in the affiliate's country.

Table 33: Regulation in the Parent Corporations' and Affiliates' Countries

	Deforestation	Forest Cover	Crop Diversity	Log(PM2.5)	Log(CH4)	Log(N2O)	Log(CO2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affiliates	0.007	0.029***	0.017	-0.0008***	-0.002	0.00006	0.009***
	(0.006)	(0.006)	(0.010)	(0.0003)	(0.003)	(0.0006)	(0.003)
Affiliates × SER Parent	-0.004	-0.074***	-0.031*	0.001**	0.014*	0.004**	-0.008
	(0.013)	(0.017)	(0.018)	(0.0005)	(0.008)	(0.002)	(0.007)
Affiliates × CC Affiliate	-0.004	0.026**	0.003	0.0002	-0.011*	-0.003**	-0.006
	(0.010)	(0.012)	(0.013)	(0.0003)	(0.006)	(0.002)	(0.005)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,452	125,076	20,846	125,076	124,837	125,076	123,662

Notes: OLS results for the impact of regulation in the parent corporations' and affiliates' countries. The independent variables are the number of affiliates non-interacted and interacted with the Stringency of Environmental Regulations (SER) index in the parent corporation's country and Corruption Control Index (CC) in the affiliate's country. Both indices are normalized between 0 and 1 with higer values indicating better governance. The environmental outcomes are deforestation in 100 km^2, forest cover in percent, crop diversity measured as effective species numbers (Inverse Simpson index), Log(PM2.5), Log(CO2), Log(N2O), and Log(CH4). All specifications include year-region and cell fixed effects, as well as precipitation and temperature as controls. Standard errors are clustered at the country level. Significance codes are * 10 %, ** 5 %, *** 1 %

11 Biases from Satellite Data

Results based on data derived from satellite images may suffer from measurement error (49, 47, 67). This problem is less concerning in our case because 1) the satellite data are highly aggregated, which reduces potential biases (49, 47) and 2) the satellite data of interest are used as outcome variables, thus reducing the problem to differential measurement error, i.e. the problem that the measurement error could be correlated with our treatment.

A growing literature suggests solutions to the problems of measurement error in satellite-derived data products (49, 47, 67). However, most of these approaches rely on a panel of ground truth observations. These panel data do not exist for many regions. Here, we leverage the ground truth data from Stanimirova et al. (68) in combination with an approach related to König et al. (69) and Proctor et al. (48) to explore potential biases from differential measurement error. In particular, we first investigate whether measurement error is correlated with our main explanatory variable and then, in a second step, tackle potential measurement error directly by implementing imputation methods.

A key challenge for our endeavor is related to data availability. Specifically, we have ground truth observations for only 0.0014 % of all locations across Africa, and out of those ground truth observations, only 0.006 % have repeated observations with forest cover change. These constraints are typical for many developing countries and restrict our ability to perform the full corrections suggested by the literature. Further, we focus on implementing the approach for the Global Forest Change (GFC) data (15) because ground truth data at the resolution of the Vegetation Continuous Field data and for air pollution across a larger geographic range are unavailable for Africa. In contrast to our main analysis, we use the non-aggregated 30m pixel-level GFC data for this section.

Table 34 reports the results for the correlation of ground truth forest cover from Stanimirova et al. (68) (henceforward GTF) and the GFC data. We convert GFC data to forest cover data by defining a pixel as forested if it had forest cover >30 % in the year 2000 and either never experienced forest loss or before it experienced forest loss. This method underestimates forest cover because it neglects reforestation. This is well illustrated in the first column, which yields a very strong correlation between the GTF and GFC measures, but slightly below 1. This bears two lessons: First of all, it is reassuring that the two variables are highly correlated, which supports confidence in the accuracy of the measures. Second, the fact that the coefficient falls short of reaching 1 means that GFC may typically slightly underestimate forest cover, as explained above.

The specification of column two introduces the cell and region-by-year fixed effects from our

main regression specification. This specification uses the variation of the GTF data over time and within our $0.5°$ grid cell. The third specification additionally introduces the independent variables from our main regressions. Strikingly, when controlling for GFC Tree cover, the affiliates is not correlated with the residual variation in the GTF measure, highlighting the absence of non-classical measurement error in the dimension of interest.

The last specification of column (4) is similar to the third specification, but uses the measurement error (GTF - GFC) as an outcome. It again suggests that the measurement error is not correlated with our independent variables. In other words, there is little concern for differential measurement error.

Despite these reassuring diagnostics, we explore the topic further using multiple imputations, which works even with many missing ground truth observations (48). However, the results should be viewed with caution because 1) we are unable to residualize the data (see above), and 2) our outcome is binary. We, therefore, rely largely on cross-sectional variation in ground truth and satellite-based forest cover to correct for measurement error. We implement the process using the "mice" package (70).

Table 34: Ground Truth and Satellite Data of Forest Cover

Dependent Variables:	Tree Cover GTF			Measurement Error
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	0.061***			
	(0.010)			
Tree Cover GFC	0.856***	0.573***	0.573***	
	(0.050)	(0.023)	(0.023)	
Affiliates			0.0001	0.0001
			(0.0002)	(0.0001)
Local Firms			6.56×10^{-6}	4.25×10^{-6}
			(5.36×10^{-6})	(5.74×10^{-6})
Temperature			0.0003	-0.005
			(0.016)	(0.016)
Log Precipitation			-0.013	-0.011
			(0.012)	(0.012)
Fixed-effects				
Cell FE		Yes	Yes	Yes
Region × Year FE		Yes	Yes	Yes
Fit statistics				
Observations	362,180	362,180	362,180	362,180
R^2	0.694	0.848	0.848	0.387
Within R^2		0.363	0.363	1.05×10^{-5}

Standard-errors are clustered at the country level (in parentheses)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 35 reports the results using multiple imputations to correct for potential bias from classical and differential measurement error (48). Column (1) of Table 35 reports the naive regression of forest cover using satellite data and the number of multinational affiliates. The results deviate from our main results for several reasons. First, the forest data are on 30m resolution while the affiliates data are on $0.5°$ resolution, as in our main regression. Second, the sample differs because we only include forest pixels that have ground truth data for at least one point in time. Third, the

outcome is binary (forest or no forest per 30m pixel) in this analysis, while it is continuous (area deforested per $0.5°$ grid cell) in our main analysis. The second column replaces the cell-fixed effects for the large grid cells with the pixel-level fixed effects from the GTF/GFC data. The results remain unchanged. The last column reports the results with predicted tree cover using multiple imputations. Although the magnitude differs, the qualitative impact remains unchanged, and it becomes marginally statistically insignificant (p = 0.15).

Table 35: Multiple Imputation Results

Dependent Variables:	Tree Cover GFC		Tree Cover Imputed
Model:	(1)	(2)	(3)
Variables			
Affiliates	-0.00002*	-0.00002*	-0.00006
	(0.00001)	(0.00001)	(0.00004)
Fixed-effects			
Cell FE	Yes		Yes
Region × Year FE	Yes	Yes	Yes
Pixel FE		Yes	
Fit statistics			
Observations	3,001,214	3,001,214	2,975,419
R^2	0.72557	0.98279	0.99306
Within R^2	0.00000	0.00005	0.00005

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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