The Origins and Control of Forest Fires in the Tropics

Clare Balboni, Robin Burgess, and Benjamin A. Olken *

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Abstract

Environmental externalities – uncompensated damages imposed on others – lie at the root of climate change, pollution, deforestation and biodiversity loss. Empirical evidence is limited, however, as to how externalities drive private decision making. We study one such behavior, illegal tropical forest fires, using 15 years of daily satellite data covering over 107,000 fires across Indonesia. Weather-induced variation in fire spread risk and variation in who owns surrounding land allow us to identify how far externalities influence the decision to use fire. Relative to when all spread risks are internalized, we find that firms overuse fire when surrounded by unleased government lands where property rights are weak. In contrast, and consistent with Coase, firms treat risks to nearby private concessions similarly to risks to their own land. Government sanctions, concentrated on fires spreading to populated areas, also deter fires, consistent with Pigouvian deterrence.

Keywords: externalities, Indonesia, forest fires, wildfires, deforestation, environment, conservation, remote sensing, climate change

*Balboni: MIT Department of Economics, Cambridge, MA 02142, cbalboni@mit.edu. Burgess: LSE Department of Economics, London WC2A 2AE, United Kingdom, r.burgess@lse.ac.uk. Olken: MIT Department of Economics, Cambridge, MA 02142, bolken@mit.edu. We thank Michael Greenstone, Bard Harstad, Kelsey Jack, Matthew Kotchen, Mushfiq Mobarak, Joe Shapiro, Reed Walker and numerous seminar participants for helpful comments. We thank Menna Bishop, Helen Gu, Anton Heil, Shofwan Hidayat, Amri Ilmma, David Laszlo, Alyssa Lawther, Thuy (Peter) Le, Rishabh Malhotra, Jonathan Old, Victor Quintas-Martinez, Donata Schilling and Sam Solomon for outstanding research assistance. Burgess thanks European Research Council Advanced Grant 743278 and Balboni thanks Conservation International's Seligmann Innovation Fund for financial support.

1 Introduction

Environmental economics is rooted in the study of externalities. Early forerunners of the modern field (e.g., Marshall 1890, Pareto 1909, and Pigou 1920) highlighted the failure of market economies to properly account for the environmental consequences of economic activity. These ideas were then developed theoretically, with a focus on developing a consistent framework to analyze market failures as well as to design corrective policies. For example, Pigou (1920)'s discussion of corrective taxes and subsidies was succeeded by theoretical contributions relating to tradable permits (Dales 1968) and the possibility that an efficient solution to externalities may, under certain circumstances, be achieved by private negotiations (Coase 1960) or decentralized self-regulation (Ostrom 1990).

Empirical evidence is limited, however, on how externalities drive private decision making. Understanding the degree to which individuals and firms actually change their actions depending on whether the environmental damages they cause represent an externality – and what approaches are most effective in mitigating these externalities – is important as this will affect how climate change, pollution, deforestation and biodiversity loss unfold.[1]

To look at this, we study one type of such behavior – tropical forest fires used for land clearance – using 15 years of daily satellite data covering over 107,000 fires across Indonesia. Fires are used in many tropical countries, including Indonesia, as a cheap – though illegal – means of land clearance by firms but pose the risk that, once set, they burn out of control and damage nearby land. Firms, in effect, face the choice between a cheap but risky technology (fire) and a safer but more expensive technology (mechanical clearance) when readying land to grow plantation crops such as oil palm or wood fiber.[2]

Fires are most prevalent in forests located in low income parts of the globe (Appendix Figure A.1). Understanding why tropical forest fires start and how they might be controlled is important in its own right, as they represent a significant source of local, national and global externalities. Indonesian fires are an important contributor to this phenomenon, with tens of thousands of square kilometers of forest burned in recent years. While we focus on local externalities due to fire spread, more broadly, the externalities generated by these fires are manifold, including significant health impacts (Frankenberg et al. 2005, Jayachandran

[1] Important empirical contributions in this area include the literature on the political economy drivers of environmental externalities (Burgess et al. 2012, Kahn et al. 2015, Lipscomb and Mobarak 2017, Dipoppa and Gulzar 2022). Other work has explored the degree to which external actors can alter private decision making through payments for ecosystem services (e.g., Jayachandran et al. 2017) and improved auditing (e.g., Duflo et al. 2013), but does not study changes in the degree to which the behavior in question is, in itself, an externality.

[2] Mechanical clearance using bulldozers and other heavy equipment is estimated to cost 44-70% more than using fire (Simorangkir 2007). This trade-off between private benefit and the extent of the externality also lies at the core of other environmental phenomena, such as illegal fishing and release of effluents.

2009, Kim et al. 2017), ecosystem loss (Yule 2010) and global warming (Page et al. 2002). For example, the major 2015 Indonesian fires alone released about 400 megatons of CO_2 equivalent (Van Der Werf et al. 2017), at their peak emitting more daily greenhouse gases than all US economic activity, and are estimated to have caused over 100,000 excess deaths across Indonesia, Malaysia and Singapore (Koplitz et al. 2016).

To understand what affects the decision to set fires, we created a novel fire dataset on fire ignitions and spread. We begin with 15 years of daily hotspot data from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellites, which record – for every one square kilometer pixel, each day – whether there is a fire in that pixel or not. We merge this data across time and space to trace the likely path of each fire. This allows us to determine the most likely location where each fire started and the area over which it ultimately spread.

This procedure yields over 107,000 unique fires in our data that were started in Indonesia's forest estate for the period October 2000 to January 2016. We merge these data with detailed geospatial data on boundaries for the Indonesian national forest estate, protected forest areas, and every logging, wood fiber and palm oil concession in the Indonesian national forest system. Any uncompensated burning of land outside of a concession is an externality, but we are also interested in whether fire setters take into account the *type* of land that fires may spread to when making the ignition decision as these likely carry different social costs.

These data confirm that fire spread is a tail risk event – and that these risks entail an important local externality. The vast majority of fires burn for a single day (87% of all fires in the forest estate) and do not spread beyond their initial ignition area (89%), defined in our data as the pixels that are alight on the fire's first day. But fires that do spread can become enormous: the largest fire in our data spread to cover 466 times its initial area, and the largest single fire in our data burned 764 square kilometers. A substantial part of fire spread damage is borne by others – across all multi-day fires started in concessions, 28% of land burned outside the initial ignition area is outside the concession where the fire began.

The data reveal that fires do not occur randomly but rather are associated with human activity and appear to be used systematically as part of the clearing process by firms, consistent with the qualitative evidence (e.g., Cossar-Gilbert and Sam 2015; Mahomed 2019; Mellen 2019). We show that fires are eight times more likely (per square kilometer) to occur in oil palm or wood fiber concessions – for which land is cleared completely and then replanted – compared to logging concessions, which are selectively logged rather than clear-cut. Since we focus on firms' incentives to start fires as a cheap means of land clearance for conversion to industrial plantations, we concentrate our analysis of externalities and the control of forest fires on the 39,189 fires started inside wood fiber and palm oil concessions in the forest estate on the main forested islands of Indonesia across the study period. We investigate the links between land clearing and fires further by combining our fires data with annual satellite data on deforestation from Hansen et al. (2013). We find that fires are vastly more likely to occur immediately following recent deforestation: increasing the share of a pixel deforested from 0 to 100 percent leads to a 285 percent increase in the probability of fire in that pixel in the subsequent year.

Having documented the human origins of many of these fires, we then turn to the central question of how externalities play into the decision to use fire. To do so, for each of the more than 220,000 1km^2 pixels inside palm oil and wood fiber concessions in our data, we calculate what share of the nearby land – i.e. of all pixels within a 6km radius – are part of the same forest concession as that pixel. For those outside the concession, we further categorize the surrounding areas into four key types of land: other private concessions, protected areas (i.e. national parks and watershed protected areas), areas outside the national forest system (i.e. normal private land, which contains the vast bulk of the population), and unleased productive forest (i.e. areas that could be assigned as future concessions but have not been assigned to date). We also calculate the average population density in the surrounding area.

We examine how surrounding land composition affects the decision to use fire and find two main results. First, compared to pixels surrounded entirely by land controlled by the same owner, fires are used much more when the spread risk is to unleased, government-owned productive forest. This unleased land tends to be largely unprotected by the government (or anyone else) and therefore enjoys the weakest property rights. Second, fires are much less likely to be used when the surrounding land is outside the forest estate (i.e. inhabited private land). But of course, the areas surrounded by others' lands may be different in ways beyond those we can control for directly. To isolate the extent of the externality per se, we use the fact that weather – wind speed, precipitation, and temperature – influences the likelihood that fires spread, and that the degree to which the costs of a spreading fire are borne by others depends on how much surrounding land is part of the owner's parcel or belongs to someone else. We first show empirically that all three of these weather variables do indeed predict the degree of fire spread. We then compare how fire ignitions change on particularly risky days (i.e., windy, dry and hot days when fires are especially likely to spread) depending on what kinds of land are nearby.

Combining variation in weather-induced spread risk over time and space with the cross-sectional variation in who owns surrounding land, we show that externalities do influence fire-setting behavior, similar to the results in the cross-section. Specifically, we find that fires are substantially less likely to be started on days when the weather is conducive to fire spread in areas where the fire would be more likely to spread inside the same concession compared to when it would spread to unleased, government-owned land. Conversely, fires are even less likely to be started on risky days when the spread risk is to private land outside the forest estate where the population lives. Our estimates imply that the magnitude of the externality is substantial: if firms treated all surrounding land the way they do land outside the forest estate – the category of land they appear to be most concerned about – ignitions would decline by 55-58 percent.

Our analysis then enables us to look at whether private and public solutions can limit these externalities. Coase (1960) famously argued that, in the presence of externalities but in the absence of transaction costs, two private parties can bargain to the efficient outcome. To test this, we focus on cases where there are only two private parties – i.e. the area surrounding the pixel of interest consists either of land in the concession itself or land on a single, privately managed other concession. We find no evidence of an externality in this case: the risk of fire spread onto one's own land is treated identically to the risk of spread onto a neighbor's concession. Moreover, when we subdivide land based on whether it has been recently deforested or not, we find the same patterns. Firms make particular efforts to avoid fires that risk spreading to valuable, non-deforested land – but they do so identically regardless of whether this non-deforested land is in their own concession or their neighbor's. This is suggestive evidence for Coasian arrangements among private firms, with firms treating risks to nearby private concessions similarly to risks to their own land.

We find weaker evidence for the effectiveness of other private solutions to limit externalities. First, we explore the effect of reputations by looking at whether larger firms – measured either by the number of concessions or concession size – are less likely to exhibit externality-inducing behavior. We find that larger firms, while they do use fires less on average, are just as likely to discount the risk of spread onto unleased productive forest – where we saw externalities were most prevalent – as smaller firms. Second, we explore the impact of international certification by studying what happens when palm oil concessions become members of the Roundtable for Sustainable Palm Oil (RSPO), the leading international certification organization. Consistent with other research (Cattau et al. 2016; Carlson et al. 2018), we find weak evidence that RSPO membership reduces fires overall and, to the extent it does, that it may reduce fires primarily on low spread risk days. We then show that RSPO membership does not reduce the spread *externality* associated with fires: RSPO members are just as likely to discount the spread risk to unleased public lands as non-members.

On the public front, Pigou (1920) suggested that the government should levy taxes or other penalties to correct externalities. And indeed, fires for land clearing were illegal in Indonesia during the period we study, with substantial penalties including up to 15 years in jail and fines up to IDR 10 billion (about USD 1 million), although these are not always enforced. To quantify differential enforcement of penalties – and hence firms' potential expectations about the relative risks of being punished – we analyze data from large-scale government investigations into private firms for causing the devastating forest fires in 2015. The government published the initials of each firm they investigated, which we matched to firm names in our concession data to ask what types of fires were most likely to lead to government investigation. We find that the government is substantially more likely to investigate firms whose fires ended up burning land in protected areas and areas with high population density, which lines up with the types of land that firms avoid in their decisions of whether or not to use fire. This suggests that firms do behave as if they are responding to Pigouvian-style (1920) incentives. Even if the *level* of fire use is still excessive compared to the social optimum (given the regional and global externalities it creates), firms internalize which types of fires are *relatively* more costly.

Other public approaches have less of an impact. We show that public enforcement via government punishment of potentially corrupt local forest officials does not reduce fires. We also examine direct government ownership by identifying all concessions that are part of state-owned enterprises and find that, though these firms are, on average, 40 percent less likely than private firms to have fires start in their concessions, they do not differentially limit spread risk to unleased forest estate relative to their own land.

Firms are therefore strategic in that 1) they overuse fire relative to what they would do if all spread risks were internalized, 2) they can potentially bargain with other private firms to internalize private risks à la Coase, and 3) they do take into account the risks of government punishment à la Pigou.

The remainder of this paper is organized as follows. Section 2 describes the institutional setting and the datasets we use to study when and why forest fires are started. Section 3 describes the patterns of forest fires and examines their relationship with spatial land use and land clearance. Section 4 tests for and quantifies the externalities in fire-setting behavior. Section 5 tests for private solutions to externalities, and Section 6 tests for public solutions. Section 7 looks at robustness of results. Section 8 concludes.

2 Setting and Data

2.1 The forest sector

The Indonesian national forest system – known as the 'forest estate' (*kawasan hutan*) – is a vast system of national forest, covering over 1.3 million square kilometers, equivalent to about three quarters of the size of Western Europe. This comprises about 70% of Indonesia's total land area and is about double the size of the whole US Forest System.

While technically owned by the Indonesian central government, much of this land, in the so-called 'production' forest, has been leased out through long-term concessions for both logging and plantations. These two types of concession entail very different land-use patterns, which, as we will see below, lead to very different uses of fire. Logging concessions are required to sustainably manage the forest through selective logging. Plantations, by contrast, are typically clear-cut (harvesting the valuable timber and clearing the rest) and, after having been cleared, are planted either with fast-growing species used for paper pulp (wood fiber plantations) or for oil palm. These plantation sectors are vast. For example, pulping from two of Indonesia's largest firms is estimated to have been responsible for the deforestation of over 25 thousand square kilometers.[3] Indonesia is also the world's largest producer of palm oil (Hsiao 2022), the world's most commonly used vegetable oil. Oil palm plantations have grown fourfold since 2000 and now occupy 7% of Indonesia's land area (Edwards 2019).

The remaining national forest land falls into two categories. The Indonesian government has designated 43% of the national forest as 'protected' forest estate for watershed and biodiversity protection, including national parks, with logging and other extractive activities prohibited.[4] The remaining unleased production forest we refer to as a 'no man's land', with unclear ownership and extraction rights. Thus although all the land in the forest estate is owned by the central government, there is a continuum of areas, from those leased out for commercial exploitation by private companies to areas strictly protected by the government.

Other than some scattered squatter settlements, human populations live largely outside the forest estate on privately owned land. The history of land zoning in Indonesia thus means there is a patchwork of property right regimes across space that may carry different costs of fires spreading into them. We can exploit this variation to see whether firms take into account the externalities they might impose on others in their fire-starting decisions.

2.2 Use of fire for land clearing

Although illegal, fire is often used as a means of land clearance. After valuable timber has been harvested, land is burned to clear away the remaining debris prior to planting plantation crops. Fire is attractive to concession holders because it is cheap: for example, estimates from Riau province in 2000 suggest that alternative clearance methods (e.g. bulldozers) are 44% more expensive than burning primary forest for oil palm plantations, and 70% more expensive for wood fiber and timber plantations (Simorangkir 2007). Other benefits of fires

[3] See discussion by WWF at https://wwf.panda.org/our_work/our_focus/forests_practice/ forest_sector_transformation_updated/app_april_updated/deforestation_updated/.

[4] Despite the existence of legislation regarding forest clearing and zoning, adherence to these laws is imperfect (see, for example, Resosudarmo et al. 2006 and Casson 2001). Incomplete documentation of land ownership also renders the legitimacy of some land-clearing activities unclear.

for concession holders in this context have also been documented, including rapid nutrient release and inhibiting the spread of plant diseases.

2.3 Policies to prevent forest fires

Policies to control fires in Indonesia center on two main branches: zoning and penalties for using fires as a means of clearing land.[5] On zoning, the 1967 Basic Forestry Law gave the national government the exclusive right of forest exploitation in the forest estate (ROI 1967). This law centralized government control over the forest, with the zoning of land into protection and production forest in part designed to protect sections of the forest estate from deforestation and hence also from the use of fire in the conversion process. The 1999 Forestry Law, which updated the 1967 Law, has become the main legal instrument against forest fires by setting out principles for forest management and prohibiting the burning of any part of the forest estate.[6] Controls on the conversion of land have also been used, including a 2011 temporary moratorium on new concessions in primary natural forest and peatland areas (Murdiyarso et al. 2011).

Zoning policies have been supplemented by policies that impose penalties on those that set fires to clear forested land. In the aftermath of the enormous 1997 fires, the 1999 Forestry Law increased anti-fire efforts, stipulating fines and imprisonment for up to 15 years for burning forests, as well as requiring individuals and businesses in fire-prone areas to prevent environmental degradation and pollution caused by wildfires. This regulation was used, most notably, for a string of prosecutions against oil palm and timber companies for their role in the 2015 fires. Some of these prosecutions resulted in high-profile court decisions mandating hundred-billion Rupiah fines. However, around three trillion rupiahs (220 million USD) in fines from ten companies had still not been paid by 2019 (Greenpeace Indonesia 2019).

Indonesia's forest fire policies are characterized by two main challenges. First, political decentralization at the end of the 1990s created a complex relationship between central and district-level policymaking, which created political incentives for increasing deforestation and lax implementation of existing regulations (Burgess et al. 2012). Second, enforcement of policies aiming to control forest fires is often weak, from regulations granting concession rights through to punishment for offenders.[7]

[5] Detailed sources relating to all policies described in this section are described in Appendix K.

[6] All burning of forests was prohibited without exception in 1999, pursuant to Article 50, Law No. 41/1999. The 2009 Environmental Protection and Management Law (No. 32/2009) allows the burning of 20 thousand square meters of land per family head for the planting of local varieties; this excludes oil palm and timber and should not affect fires in the large-scale concessions we study here. It also reduced the maximum punishment for burning forests.

[7] Licenses being granted often contradict official forest area designations, such as when mining concessions are granted in protected forest areas (Enrici and Hubacek 2016). Oil palm companies charged with setting

2.4 Data

2.4.1 Identifying fire ignition and spread from fire hotspots

To create data on fires, we begin with data on fire hotspots. We use the MODIS Terra daily Level 3 fire product, a 1km gridded composite of fire pixels detected in each grid cell over each 24-hour period (Giglio and Justice 2015) from October 2000 to January 2016. This is derived from NASA's MODIS satellites, which collectively take 4 images of virtually the entire planet each day. MODIS routinely detects flaming and smoldering fires with a size of 1000m^2 and, under optimal observation conditions, can detect fires as small as 50m^2 (Giglio et al. 2015).

We link daily MODIS observations over time in order to track the ignition and spread of individual fires. We create a 'fire' observation using an iterative procedure. This starts with an initial fire, denoted A_X, comprising a given pixel, or set of contiguous pixels, that is on fire on day X. A 1-pixel buffer is then created on each side of A_X, and if any pixel within this buffer is on fire on day $X+1$, we call this a continuation of fire A_X. If a contiguous set of pixels is on fire on day $X+1$, but only some of them intersect the buffer, all of them are classified as a continuation of fire A_X. A 1-pixel buffer is, in turn, created around the fire on day $X+1$, and this process is iterated forward over time. If a pixel is covered by clouds on a given day, the next day's observation is used instead.

An example of this procedure is shown in Figure 1. In the Figure, pixels outlined in black had a fire on Day 1 according to that day's MODIS hotspot data, and pixels colored red had a fire on Day 2 and subsequent consecutive days. The blue boxes A, B, C and D denote four fires that we classify as single fires, with ignition area as the black area and total spread extent as the union of the black and red areas.

This procedure yields a total of 176,855 fires across Indonesia from October 2000 to January 2016, with the strongest density of fires across the sample concentrated in Sumatra and Kalimantan as shown in Figure 2c. Restricting attention to Indonesia's major forested islands (excluding Java and the Lesser Sunda Islands) and to pixels inside the forest estate yields a total of 107,334 fires. Table 1 presents descriptive statistics for the 44,454 of these fires that are inside concessions. The focus of our study is a quantitative analysis of firms' incentives to start fires as a relatively cheap means of land clearance for conversion to industrial plantations. The majority of the paper's analysis therefore concentrates on the 39,189 fires started inside wood fiber and palm oil concessions across the study period, although we present robustness checks for alternative sample restrictions including logging concessions as

fires in 2015 have used lengthy court appeals and a lack of policy harmonization across different layers of government to avoid handing over fines (Greenpeace 2019).

well in Appendix H.

2.4.2 Land classification and concessions

We overlay the fire data with data on land classifications and forest concessions. First, land is divided into areas within and outside the forest estate. Second, within the forest estate, land is demarcated into conservation and protection zones (hereafter 'protected forest') or forest in which production can take place (hereafter 'productive forest'). The map of these zones across Indonesia, obtained from Global Forest Watch, is shown in Figure 2a.

We overlay these broad categorizations with concession boundaries of logging concessions (for the selective logging of natural forests), palm oil concessions (allocated for industrial-scale palm oil production) and wood fiber plantation concessions (allocated for the establishment of fast-growing tree plantations to produce timber and wood pulp for paper and paper products). The data are compiled by Global Forest Watch from government, NGO and other sources and include georeferenced shapefiles demarcating the extent of each concession as well as information on firm – and, in some cases, firm group – name. The data are imperfect but provide the best available data on concession boundaries in Indonesia during our study period. The data on concession boundaries are static and as such do not reflect any changes in concession status that may have occurred over time during our sample period. Figure 2b shows the distribution of concessions by concession type in our dataset. The majority of concession holdings are within the forest estate but outside protected forest. Summary statistics pertaining to these concessions are included in Table 1.

These classifications yield four land categories of interest for the analysis: protected forest, productive forest inside concessions, unleased productive forest (productive forest not inside concessions) and areas outside the forest estate.[8]

2.4.3 Deforestation data

We augment this data with data on deforestation. Annual deforestation data from 2001-2014 across Indonesia was extracted from the dataset described originally in Hansen et al. (2013) at a resolution of 1 arc-second (approximately 30m per pixel at the equator).[9] We calculate the area of each of the pixels used in our analysis that was deforested in a given year.

[8]There are two additional land categories which are not of interest for the analysis and which are therefore suppressed in the results. These are protected forest inside concessions (these areas comprise only 2% of the total land area and are likely due to mapping inaccuracies) and concession areas that fall outside the forest estate (5% of total land area).

[9]The updated data can be downloaded at https://glad.earthengine.app/view/global-forest-change.

2.4.4 Weather conditions data

Data on the vector components of daily wind at 297 grid points across Indonesia over our study period was downloaded from the National Oceanic and Atmospheric Administration's NCEP-DOE Reanalysis 2 Gaussian Grid.[10] This was used to calculate daily wind speed, from which monthly averages were calculated, at each of these 297 points. The inverse distance weighted interpolation tool in ArcGIS was used to interpolate this data in order to assign a wind speed to each of the 1km^2 pixels used in our analysis. Data on monthly total precipitation comes from GloH20's gauge-corrected reanalysis product, MSWEP V2.8, which captures precipitation on an approximately 11km^2 resolution grid. We mapped these values onto our 1km^2 grid by calculating, for each 1km^2 pixel, the area-weighted average value from the 11km^2 resolution pixels with which it overlaps. Data on monthly average temperature is based on the Climatic Research Unit gridded Time Series V4.06 data set. This is an approximately 60 km^2 resolution gridded database constructed by interpolating data from a network of weather stations using angular distance weighting. Temperature values were assigned to each of the 1km^2 pixels used in our analysis using the same interpolation tools as for the precipitation data. Summary statistics for all weather variables are in Table 1.

2.4.5 Data on public and private regulation

In late 2015, lists of firms investigated and sanctioned by the Indonesian government for starting forest fires throughout Sumatra and Kalimantan islands were released by the Ministry of Forestry and the Environment.[11] This followed a comprehensive investigation after the devastating fires of 2015. All firms identified in the initial list were investigated for possible administrative sanctions, including requiring firms to rehabilitate land, license suspensions, requirements of public apologies, and the possibility of having their concessions revoked. By the end of 2015, 56 firms had received sanctions of some form, including 23 firms whose licenses were revoked, suspended, or otherwise referred for government sanctions.

[10] https://esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.gaussian.html

[11] The list of investigated firms was released in September 2015 (http://www.mongabay.co.id/2015/09/18/inilah-ratusan-perusahaan-dengan-lahan-terbakar-yang-bakal-kena-sanksi/) and the list of sanctioned firms in December 2015 (http://www.mongabay.co.id/2015/12/22/baru-23-perusahaan-terindikasi-bakar-lahan-kena-sanksi-administrasi/). As described above, these lists include only the initials of investigated and sanctioned firms, not complete firm names.

3 The Origins of Forest Fires

We begin in Section 3.1 by describing the patterns of forest fires and their relationship with spatial land use throughout Indonesia. Section 3.2 examines the relationship between fire and land clearing by merging fire data with data on deforestation.

3.1 Descriptive statistics: fire and land-use

To illustrate the relationship between fires and land use, Figure 3 zooms in on the province of Riau in central Sumatra, an area of substantial forest activity, to show the distribution of fire ignitions in our data overlaid with the land classification and concessions data, at a fine geographic scale. Each 1km^2 red box represents a grid cell in which we detect at least one ignition. Concessions are outlined (yellow for wood fiber, orange for oil palm). Protected forest zones are shown in dark green, regular forest estate areas in light green, and areas outside the forest estate in white. Note that a substantial portion of the forest estate belongs to the unleased productive forest, or 'no man's land', category.

Several patterns are worth noting. First, there are a vast number of fires. The area shown in the map covers approximately 7,700 square kilometers, and has over 3,400 separate fire ignitions during the period of our study. Second, the spatial patterns of land use appear to be related to ignition patterns. A 'natural' rate of fire ignition across space would suggest that the shares of land area and fire ignitions by each forest zone should be approximately equivalent. Yet in this relatively high fire area, we observe almost no fires started in the preservation area (Zamrud National Park) shown in the middle-right of the map or in the area outside of the forest estate in the bottom left, which is a small town. Similar patterns emerge when we consider the entire dataset. Appendix Figure A.2(a) compares the share of Indonesia's land area by land use zone with the share of ignitions in each zone and shows that ignitions are disproportionately less likely to occur in protected areas and more likely to occur in areas zoned for productive use.

The pattern is even more striking when we look across different concession types. Figure 2b displays the distribution of different concession types across Indonesia. Comparing this to the distribution of fires across the study period in Figure 2c, fires appear to be most strongly concentrated in areas in and surrounding the types of concessions associated with land clearing. Indeed Appendix Figure A.2(b) shows that, among all fires started within concessions, 46% of fires are started in oil palm concessions – which drain and clear existing forest before planting oil palm – even though they comprise just 28% of total concession land area. Similarly, 42% of fires are started in wood fiber plantations – which clear land after wood is harvested before replanting – even though these comprise just 22% of land area. By contrast, logging concessions, which practice selective logging rather than clear cutting, have a much lower share of ignitions – just 12% of fires, even though they comprise 51% of total concession areas. This is consistent with evidence that fires are the most profitable form of land clearance in the 'first rotation' when clearing vegetation and converting forests to oil palm and wood fiber (Simorangkir 2007).

3.2 Fire as part of the land-clearing process

To establish this link between land clearing and fire setting more precisely, we can move to the pixel level and look at the relationship between deforestation and subsequent fires.

To do so, we use the Hansen et al. (2013) global deforestation dataset. Since this dataset is based on Landsat, it has a resolution of approximately 30m per pixel at the equator, which is much finer than the 1km resolution of the MODIS-based hotspot data. We therefore calculate, for each of the 1km pixels in our MODIS-based fire hotspot data, the share of that pixel that was deforested in year t based on the Hansen et al. (2013) data.

To illustrate these patterns, Figure 4 shows part of the same area of Riau province as Figure 3, zoomed in further given the high spatial resolution of the deforestation data. The map marks areas where ignitions were detected in 2013 with 1km boxes (the resolution of the MODIS fire data), while areas that were deforested in 2012 are marked with orange. It illustrates that, at least in this area, almost all of the ignitions took place in areas that had experienced deforestation the previous year. Across the sample, 25% of year-month-pixel observations have some forest loss unconditionally, while 46% of year-month-pixel observations in which fires were recorded had some forest loss in the preceding year.

To analyze this more formally across our entire data, we estimate a fixed effects Poisson panel regression of the form:

$$\begin{aligned} \mathbb{E}[Ignitions_{imt}] &= \gamma_i \exp(\beta_1 Forestloss_{it-1} + \beta_2 Forestloss_{it-2} \\ &\quad + \beta_3 Forestloss_{it-3} + \delta_m + \delta_t) \end{aligned} \tag{1}$$

where an observation is a MODIS-sized 1km pixel in a given month m and year t. In this specification, γ_i is a pixel fixed effect, δ_m are month fixed effects and δ_t are year fixed effects. Note that this is a count model since multiple fires can start in the same pixel within the same month, since fires are measured daily.[12] Robust standard errors (i.e. robust to arbitrary variance of the error term, as long as the expectation in (1) is correctly specified; see Wooldridge 1999), clustered using 50km x 50km grid cells, are shown in parentheses.

[12]We obtain very similar results when aggregating the data to the pixel-year level.

Two important aspects of this specification are worth noting. First, pixel fixed effects are important because they capture fixed differences in land use and characteristics over time. This nets out fixed differences that may lead some areas to be more vulnerable to fire than others. Second, time fixed effects capture the fact that some years are more likely to experience fires (due to drought, for example), which may happen to be correlated with previous deforestation patterns.

The results are shown in Table 2, focusing in on wood fiber and palm oil concessions. We find that fire ignition is more likely in recently deforested areas.[13] The magnitudes are substantial: a 1km pixel that was completely deforested is expected to have 285% percent more ignitions than it would have otherwise. Interestingly, subsequent lags of the deforestation variable are *negative.* This suggests that the timing between deforestation and fire use is quite tight, consistent with the use of fires as part of the land-clearing process, rather than recent deforestation simply making the land more flammable by natural causes (in which case one would expect subsequent lags to also be positive). The negative further lags may reflect the fact that, several years after deforestation, the land has perhaps been replanted for oil palm and other uses, and hence it is no longer desirable to burn it. Combined, these results suggest a clear picture: many of the fires we observe appear to be a systematic part of the land clearance process.

4 Externalities and fire setting

The evidence in Section 3 points to forest fires in Indonesia being driven by human activity. This section examines whether firms take the externalities from fire setting into account in their decision of whether to burn forest or not. Understanding this is critical to understanding whether and how forest fires might be controlled.

[13] Much of the fire setting that follows deforestation may occur within the same year as the forest clearing. Unfortunately, we are unable to observe within-year variation in deforestation as the forest loss data is only available at annual frequency. We exclude deforestation in the current year from this regression because including contemporaneous deforestation would confound fires that follow deforestation (our effect of interest) and recorded deforestation caused by the fires themselves. Appendix Table B.1 shows the results including forest loss in the same year as the ignition: this continues to show that fire ignition is more likely in recently deforested areas, but is more difficult to interpret than the central specification in Table 2 given the reverse causality concerns described here. Appendix Table B.2 shows a similar pattern when controlling for whether the pixel has been burnt previously. In these cases, the results continue to show that fire ignition is significantly more likely in recently deforested areas, though here subsequent lags are smaller in magnitude than the first lagged term but not negative.

4.1 Ignitions, weather conditions, and fire spread risks

4.1.1 The risk of fire spread

A key risk from using fire for land clearance is that the fire may spread beyond the initial ignition area. To quantify this risk, we use our processing of the MODIS hotspot data, which allows us to separate pixels of initial ignition and areas to which the fire subsequently spreads. Note that this procedure may underestimate spread – since we classify all adjacent pixels that have a hotspot on the same day as a single 'ignition', this procedure will define the area of fire spread to be those adjacent pixels that are alight on subsequent days, rather than capturing spread within a single day.

Our data reveal that there are tail risks associated with fire-setting behavior. Eighty-seven percent of the 107,334 fires in our sample burn for only one day, and 89% do not spread beyond their original ignition area. However, the long tails of these distributions reveal that there is a small chance that fires burn for much longer than this (up to a maximum of 36 days) and spread to cover an area much greater than their ignition area (up to a maximum of 466 times the ignition area) and very large areas in absolute terms (up to a maximum of 764 1km^2 pixels). The risk of fire spread also imposes a risk of externalities: across all multi-day fires started inside concessions, 28% of the total land burned is outside the concession in which the fire was ignited.

4.1.2 Is spread risk predictable?

The risks of fire spread may vary over time depending on weather conditions such as wind, precipitation and temperature. Greater winds can increase fire spread for several reasons: increased winds supply more oxygen, which increases the intensity of the fires and can exert pressure on the fire to move, igniting new areas.[14] Periods of low precipitation will result in lower moisture content of the air, fuel and soil and therefore support fire development and spread. Higher temperatures can influence fire intensity and spread risk through heating fuel and changing the moisture content of the air. To the extent fire spread risk is predictable, potential fire setters should be more concerned about external risks from fire spread during

[14]While we explore the impact of wind *speed* on fire spread, we do not use variation in wind *direction*, given that wind direction at the point of the fire is a complex function influenced by winds generated by the fire itself as well as local topography and prevailing local winds (e.g. Benson et al. 2008). As a result, it is difficult to predict tropical fire spread accurately based on average meteorological wind direction, especially when aggregated temporally as here (Shmuel and Heifetz 2022). Consistent with this, we do not find that monthly average wind direction predicts the average direction of fire spread in our sample. This is in contrast to the use of wind direction data in other contexts to study the direction of *smoke* spread from fires, which occurs at much higher altitudes and is hence influenced to a greater extent by prevailing higher-altitude wind directions (e.g. Rangel and Vogl 2019).

these particularly risky periods.

To investigate the predictability of fire spread in our data, we merge our fire data with data on monthly average prevailing wind speeds, temperature and total precipitation. To isolate the effect of weather conditions from other factors that may influence fire spread, we implement a fixed effects Poisson specification of the form:

$$\begin{aligned}\mathbb{E}[FireSpread_{imt}] &= \gamma_i exp(\beta_1 Windspeed_{imt} + \beta_2 Precipitation_{imt} \\ &\quad + \beta_3 Temperature_{imt} + \beta_4 Ignitions_{imt} + \delta_m + \delta_t)\end{aligned} \tag{2}$$

where $FireSpread_{imt}$ is a count of the average number of pixels of fire spread area (burned area minus ignition area) of all fires started in pixel i during month-year mt, $Windspeed_{imt}$ is the average wind speed in pixel i during month-year mt, $Precipitation_{imt}$ is the total precipitation in pixel i during month-year mt, $Temperature_{imt}$ is the average temperature in pixel i during month-year mt, $Ignitions_{imt}$ is the number of ignitions in pixel i during month-year mt, γ_i are pixel fixed effects and δ_m and δ_t are month and year fixed effects. As above, we use robust standard errors to allow for arbitrary distributions of the error term.

The results are shown in Table 3 and demonstrate that an ignited fire is more likely to spread to a larger area when prevailing winds are strong, temperatures are higher, or precipitation is lower. Pixel fixed effects are included to capture fixed differences in spread risks across different soil types and other fixed land characteristics. The results suggest not only that fire is risky due to the risk that it spreads, but that this risk is predictable based on local weather conditions.[15] The time-varying but predictable risk of fire spread forms the basis of our empirical test for externalities in the next section.

4.2 Externalities in fire spread

The use of fire entails a risk of spread, but the degree to which spread risk is costly depends on what type of land it could spread to. One could imagine, for example, that a fire spreading into unoccupied forest land, where no one is likely to object, may be of less concern to a landowner than a fire that spreads into a city, town or protected national park, which may

[15] Local news reporting suggests that land owners are aware of the importance of weather conditions as a risk factor for fire spread and take this into account in their burning decisions. For instance, police reporting of burning suspected to have been undertaken professionally for land clearance in Pelalawan Regency referred to the perpetrators having taken wind conditions into account (https://www.liputan6.com/regional/read/2531132/tutupi-jejak-perusahaan-pembakar-lahan-catut-nama-kelompok-tani); media reporting refers to farmers in South Lampung taking rainfall and temperature into account in burning decisions (https://www.cendananews.com/2020/10/petani-di-lamsel-pertahankan-bersihkan-lahan-sistem-tebas-bakar.html); and recommendations relating to the use of fire for forest clearance among the Serawai people include consideration of wind strength (https://www.viva.co.id/berita/nasional/706170-belajar-dari-mereka-yang-membakar-hutan).

provoke a substantial backlash.

We examine the evidence for such deterrent effects of surrounding land types in two ways. First, we consider the impact of different types of land surrounding each pixel on ignitions in that pixel. Second, to further improve identification, we use the interaction of time-varying riskiness of fire spread, which is a function of recent weather conditions (as shown in the previous section), with the surrounding land type. This second specification uses the product of two factors which together create riskiness of starting a particular fire, which varies across both time and locations. This allows for more robust identification of the degree to which potential fire users are deterred by the externalities they may cause, because we can control flexibly for fixed attributes of a given pixel that make fire use more or less likely.

4.2.1 Cross-sectional variation in neighboring land-type

To examine the impact of surrounding land type on pixel-level ignitions, we use the following specification:

$$\begin{aligned} \mathbb{E}[Ignitions_{imt}] \quad = \quad & \exp(\textstyle\sum_j \beta_1^j NeighborLandType_i^j + \\ & +\beta_2 X_i + \delta_m + \delta_t) \end{aligned} \tag{3}$$

where $NeighborLandType_i^j$ is the share of land in the 6km radius buffer surrounding pixel i that is in land type j[16]; X_i are controls for island, concession type, the total size of the concession, baseline forest cover, and average population density in the 6km radius buffer surrounding pixel i[17]; and δ_m and δ_t are month and year fixed effects. We divide $NeighborLandType_i^j$ according to land type classifications that distinguish private land owned by the same concession-holder as the central pixel; private land owned by other concession-holders; national parks and conservation areas, which are explicitly protected by the government; land outside the national forest system, which is typically comprised of villages and smallholders; and unleased productive forest outside concession boundaries (as well as suppressed categories in the sea or neighboring countries). The variable $NeighborLandType_i^j$ is constant over time but varies across pixels in our dataset and yields within-concession variation in the share of land surrounding each pixel in different land types. An example of the construction of this variable is shown in Figure 5.

We benchmark the degree to which property owners avoid damaging other types of land to the way they behave vis-a-vis their own land by assigning the share of buffer pixels in

[16] A radius of 6km was chosen to estimate the area at risk of fire spread. This is the 90th percentile of the distribution of the maximum distance between fire ignition centroids and the boundary of extents burned for multi-day fires.

[17] This is calculated by (i) assigning a population density to each 1km grid cell based on the population density of the desa in which the grid cell centroid lies; and (ii) finding the average population density of the grid cell centroid points that lie within each pixel's 6km buffer.

the same concession as the central pixel to be the omitted category. The coefficients thus capture whether you are more or less likely to start fires when they might spread into your own land versus that of others; that is, whether or not you take into account the externality you might impose on others.

The results, shown in Table 4, panel (A), reveal that ignitions are more likely in areas neighboring unleased productive forest (i.e. "productive forest outside concessions") - relative to those neighboring the central concession holder's own land. This is the land where there is no one with a strong vested interest in protecting it - it is (largely) uninhabited, no one has a formal claim to be able to use its proceeds, and it is not a priority for forest protection by the government.

Conversely, ignitions are less likely in areas neighbouring land outside the forest estate relative to own concession land. Because the 1966 Forest Law banned human settlement within the forest estate, it is land outside that is most populated and hence where damages from fire spread will be particularly high. Fire setters seem to take this into account in their decisions of whether or not to use fire.

Neighboring land of all other types – other concession holders' land and protected forest – also appear to have a deterrent effect on fire setting relative to own concession land, though these results are not always significant. Taken together, these results suggest that fire setters are taking into account where fires might spread to and the costs of the damages they might cause.

4.2.2 Identifying externalities using time-varying fire spread risk

One potential concern with the previous specification is that there may be differences across areas in their propensity to use fires that may be correlated with the classification of neighboring land. To further pin down whether externalities affect the decision to use fire, we refine our analysis using both temporal and spatial variation.

To do so, we consider how fire-setting behavior is influenced by the interaction of local variation in the cost of fire spread (driven by the types of land surrounding each pixel) with spatial and temporal variation in the probability of fire spread (driven by the weather). The risk of fire spread is constructed as:

$$\begin{aligned} Weather\widehat{SpreadRisk}_{imt} &= \hat{\beta}_{wind}.Windspeed_{imt} + \hat{\beta}_{precip}.Precipitation_{imt} \\ &\quad + \hat{\beta}_{temp}.Temperature_{imt} \end{aligned} \tag{4}$$

where the estimated $\hat{\beta}$ coefficients are those obtained in Table 3 estimated on the sample in all concessions.[18] The expected external cost of starting a fire in a particular pixel in a particular month depends on the product of these two factors – the weather-induced spread risk in that pixel in that month and the composition of the types of land that surround the pixel.

We use the following specification to investigate whether external costs influence the decision to use fire:

$$\begin{aligned}\mathbb{E}[Ignitions_{imt}] \quad = \quad & \gamma_i \exp(\beta_1 \widehat{WeatherSpreadRisk}_{imt} + \\ & \textstyle\sum_j \beta_2^j NeighborLandType_i^j \times \widehat{WeatherSpreadRisk}_{imt} \\ & + \beta_3 X_i \times \widehat{WeatherSpreadRisk}_{imt} + \delta_m + \delta_t)\end{aligned} \tag{5}$$

Here the coefficients on the interaction terms, β_2, capture whether potential fire setters differentially use fires depending on the magnitude of their expected externality. In addition to time fixed effects (δ_m, δ_t) which absorb common time shocks, equation (5) includes pixel fixed effects (γ_i), which absorb fixed pixel characteristics and therefore rule out effects driven by, for instance, differential flammability on different land types. We also include interactions of the weather index with island, concession type, the total size of the concession (to account for the fact that in larger concessions, more pixels will mechanically have smaller shares of pixels outside the concession), baseline forest cover, and average population density in the 6km radius buffer. The identification thus rests on comparing areas surrounded by different land types on days when the weather makes fire spread more versus less likely.[19]

The results of this exercise are shown in panel (B) of Table 4. The results are broadly consistent with the cross-sectional results shown in panel (A).

Several results stand out. First, there is a clear externality with respect to unleased productive forest. To see this, note the positive coefficient on the interaction of $\widehat{WeatherSpreadRisk}$ with productive forest outside concession. This implies that concession owners are much less attentive to avoiding fires that would spread to unleased productive forest relative to fires that would spread to their own land.

Second, there is a notable contrast between the way forest owners treat neighboring unleased land and the way they treat land owned by other private concession owners. Indeed, the coefficients on land owned by other private concession owners are substantially smaller,

[18]This measure is normalized using the standard deviation calculated across the full set of pixel-month-year observations in our analysis sample (i.e. pixels in concession land inside the forest estate, excluding Java and the Lesser Sunda Islands).

[19]This identification strategy abstracts from inter-temporal substitution of ignitions in light of positive though imperfect serial correlation of the fire spread weather index across months (month-to-month serial correlation in the index is 0.26; see Appendix Table C.1). Given this, it is likely that the costs of waiting for a period when weather conditions are less conducive to spread to start a fire for land clearing may be non-trivial (at least a few months) once the land is ready to be cleared for planting.

and once we include the full set of controls (column (6)), the results suggest that in fact concession owners treat land owned by other private firms similarly to their own land. We explore this in more detail in Section 5 below.

Third, and conversely, there is some land that concession owners seem to clearly avoid burning: populated land outside the forest estate. Specifically, concession owners make more of an effort on days when the weather is conducive to fire spread to avoid starting fires that risk spreading into land outside the forest estate, i.e. to populated areas, even relative to their own lands. This can be seen from the negative coefficient on the interaction of $\widehat{WeatherSpreadRisk}$ with the number of pixels in the buffer area outside the forest estate.[20]

The evidence in Table 4 thus shows that potential fire setters are sophisticated in their choice to use fire – they are much less worried about the use of fire when the spread risk is to unleased productive forest than to their own land – but also avoid starting fires on windy days in locations where they could spread to population centers. On risky days and relative to their own land, the proximity of low-cost, unregulated land encourages fire use, whereas the proximity of high-cost, populated land discourages it.[21]

4.2.3 Quantifying the magnitude of the externality

To help quantify the magnitude of the externalities identified in the previous section, we consider how far ignitions would be reduced if agents treated all surrounding land (within the 6km radius we consider empirically) as if it were land outside the forest estate – the surrounding land type that has the strongest deterrent effect on fire setting as shown in Table 4. We estimate this by taking the estimated coefficients from Table 4 and simulating the value of the dependent variable in equations (3) and (5) under counterfactual scenarios that set $NeighborLandType_i$ to be entirely outside the forest estate, keeping all other covariates unchanged.

We do these calculations in two ways – first considering the cross-sectional estimates of the effect of nearby land type from panel (A) of Table 4, and then separately using the

[20]The positive direct effect of the weather-based spread risk index does not detract from this negative interaction; this positive main effect is driven by the fact that natural ignitions are more likely under windier, drier and warmer conditions, which increase the probability that a spark results in a fire that is detectable in our data.

[21]In addition to studying the impacts on fire ignitions, in Appendix D.1, we also investigate whether, conditional on a fire starting, it is differentially likely to spread depending on neighboring land types. Efforts to reduce fire spread may reflect actions taken either prior to a fire starting (such as building in fire breaks), or actions taken after the fire starts (i.e. firefighting effort), or a combination thereof. Importantly, actions to reduce fire spread once a fire has started might be undertaken by the government or other private actors, so that externality-containing (or inducing) behavior is more difficult to attribute to the owner of the concession in which the fire starts in this case. The results of these specifications suggest that, conditional on a fire starting, it is less likely to spread if surrounded by areas of higher population density.

interactions with spread risk in panel (B). To start, we use the panel (A) estimates and simulate the total number of ignitions when $NeighborLandType_i$ in equation (3) is set to be entirely outside the forest estate. Using this approach, we find that the number of ignitions inside wood fiber and palm oil concessions within the forest estate would decline by 55% if concession-holders treated all land in each buffer as if it were outside the forest estate. We perform a similar exercise using the estimates in panel (B) of Table 4, which estimate the externality by using the interaction of weather-induced spread risk with surrounding land type. We find a similar result: on net, we conclude that there would be a 58% reduction in the number of ignitions if concession owners treated the risk of any spread in the same way as they currently treat the risk of spread to land outside the forest estate.

Our key finding therefore is that externalities affect private decision making. This, in turn, opens up the space to think about how both private and public approaches which alter the costs of fire spread may be effective in reducing the uncompensated damages caused by forest fires. These two approaches are covered in Sections 5 and 6 respectively.

5 Private approaches to reducing externalities

In this and the subsequent section, we consider two alternative approaches to reducing externalities. First, in Section 5, we consider private market solutions - Coasian solutions among private firms, reputation effects, and voluntary organizations that certify firms as complying with environmental rules. Second, in Section 6, we consider public sector solutions – punishments for violations and direct government ownership of firms. We conclude that the problem is challenging but that the patterns we saw in Section 4 are consistent with elements of both approaches reducing externalities to some degree.

5.1 Private firms and the Coase Theorem

Coase (1960) famously argued that, in the presence of externalities but in the absence of transaction costs, two private parties can bargain to the efficient outcome. Can this work to prevent externalities in the context of fire setting?

To take this to the data, we need to narrow down our analysis to some degree. Specifically, we need to focus on cases where there are relatively clear property rights on both sides - that is, where the neighboring land is owned by a private party who could engage in Coasian bargaining. Furthermore, to approximate the Coase theorem's requirement that transaction costs are not too large, we focus on cases when there are at most two parties involved - that is, the entire 6km buffer consists either of your own land or of land controlled by at most one other private concession.

We also need to be precise about what the 'efficient' outcome looks like in our setting. Coase argued that the right solution to externalities is not necessarily the absence of the offending activity, but rather that the risk of damage is internalized. Put another way, firm boundaries should not matter – the damage done should be the same as if firm boundaries did not exist. We argue that, in our setting, the 'efficient' outcome would mean that firms would treat their neighbor's land the same as they treat their own land.

We examine this in the data in two ways. First, we re-estimate equations (3) and (5) focusing just on the cases where bargaining could most easily take place: when the surrounding land is controlled by at most one other concession. The results are presented in Table 5. Echoing the results in Table 4 above, the results here show that, once all controls are included, one's own land is treated no differently than others' land on risky days. This holds whether we use uninteracted surrounding land ownership (as per equation (3)) or its interaction with weather-derived fire spread risk (as per equation (5)).

But we can go further. To test this even more precisely, we separate out land that has been recently deforested from land that has not. Land that has recently been deforested is less valuable to protect – as shown in Table 2, this is the land that is typically cleared by fire – whereas land that has not been recently deforested is more valuable to protect, either because it has virgin timber or because it contains plantations or other crops. We therefore augment equation (5) by separately examining the effects of your own deforested and non-deforested pixels and neighboring concessions' own deforested and non-deforested pixels. In this case, we revert to using the full sample (rather than cases where the surrounding land is controlled by at most one other private firm) and use unleased productive forest as the omitted category in order to demonstrate clearly the effects of recent deforestation in both nearby land on your own concession and on that owned by others.

The results are presented in Table 6. The results suggest that firms try particularly hard to avoid setting fires that risk spreading to areas of either their own or others' concessions that have not recently been deforested. Most notably, they seem to avoid nearby land that has not recently been deforested in almost exactly the same way regardless of whether the land is elsewhere on your own concession or on someone else's concession – suggesting that own valuable land is treated the same as others' valuable land. Likewise, firms do not seem particularly perturbed about fire spreading to recently deforested land, treating this the same as unleased productive forest – but again, they do so similarly for land in their own concession and for land in neighboring concessions.

Taken together, these results suggest the possibility put forth by Coase: when there are a small number of private owners who can potentially bargain with one another, we do not detect externalities in fire-setting behavior.

5.2 Reputation effects

A second 'private' mechanism that could help limit externalities is reputations – firms with valuable reputations may be less likely to engage in damaging behavior. This could happen if, for example, a firm's brand name was sullied by its association with destructive forest practices. While we do not observe reputation directly, we can examine several proxies for this to see if firms that are likely to care more about these types of effects are less likely to engage in risky fire-setting behavior.

5.2.1 Firm size

The first characteristic we consider is the number of concessions owned by a firm, given the likelihood that firms with more concessions may be more concerned about reputational damage from their behavior in one concession affecting their other concessions. The second examines heterogeneity of the results according to the area of firm concessions, based on similar intuition that reputation concerns may loom largest for firms managing larger concession areas.[22]

The results are presented in Table 7. Columns (1) and (2) explore connections between fire setting and the number of concessions owned by the firm; columns (3) and (4) explore connections between fire setting and concession size. We focus on two specifications: columns (1) and (3) present results without controls (equivalent to column (1) in Table 4); columns (2) and (4) present results with the full set of controls (equivalent to column (6) in Table 4).

We begin in panel (A) by examining the cross-sectional relationship between firm size (i.e. number of concessions owned and concession size) and the overall number of ignitions. We find negative effects of both – larger firms, measured both in terms of the number of concessions owned and concession size, are significantly less likely to use fire.

We next turn to whether these larger firms engage in less *risky* fire-setting behavior. Specifically, in panel (B), we interact the risk index – i.e. $\widehat{WeatherSpreadRisk}$ – with a firm having more concessions or a concession having a larger size. We find no indication that firms with more *separate* concessions are differentially likely to use fire on risky days (columns (1) and (2)). We do, however, find that larger *concessions* are less likely to use fire on risky days, which is consistent with reputation concerns playing a role. This latter effect may, however, partially capture the effects of firms trying to minimize fire spread onto

[22]Qualitatively similar though weaker results are obtained when considering the total area of all concessions owned by a given firm, rather than concession area.

unintended areas of one's own concession (i.e. the effects explored in Table 4).

Third, we test whether these larger firms are less prone to lighting fires when the *externality* from doing so is high. To provide the cleanest test of this, we restrict attention to those cases where the concession is surrounded by unleased productive forest. This is the area identified in Table 4 as the area where the externality from fire setting is greatest. To confirm that indeed there is a strong externality present in this sample, Table 8 re-estimates equations (3) and (5) on this sample, considering only those pixel buffers that contain only own concession land or land in unleased productive forest. Table 8 confirms strong evidence for the externality in this sample of areas bordering unleased productive forest.

To test whether larger firms are less prone to using fires when there is a stronger externality, in panel (C) of Table 7, we restrict attention to this sample and augment our test for the externality in equation (5) by asking whether the externality-producing behavior – setting fires on risky days when surrounded by land outside your concession – is less pronounced for larger firms. That is, we estimate:

$$\begin{aligned}
\mathbb{E}[Ignitions_{imt}] \quad = \quad & \gamma_i \exp(\beta_1 Weather\widehat{Spread}Risk_{imt} + \\
& \beta_2 LandInsideConcession_i \times Weather\widehat{Spread}Risk_{imt} + \\
& \beta_3 LargeFirm_i \times Weather\widehat{Spread}Risk_{imt} + \\
& \beta_4 LargeFirm_i \times LandInsideConcession_i \times Weather\widehat{Spread}Risk_{imt} + \\
& + \beta_5 X_i \times Weather\widehat{Spread}Risk_{imt} + \delta_m + \delta_t)
\end{aligned} \tag{6}$$

where the key coefficient of interest is β_4, the coefficient on the triple interaction $LargeFirm_i \times LandInsideConcession_i \times Weather\widehat{Spread}Risk_{imt}$. This coefficient captures whether large firms are *differentially* less likely to exhibit the externality-inducing behavior we identified in Section 4.2.2, i.e. refraining from using fire on risky days more when the spread risk is to their own land versus when the risk is to unleased productive forest.

We find that they are not. Focusing on the specifications with controls (columns (2) and (4)), we find that while we see evidence of the externality – the coefficient β_2 on $LandInsideConcession_i \times Weather\widehat{Spread}Risk_{imt}$ is negative, indicating the presence of the externality – the triple interaction β_4 is small and statistically indistinguishable from zero using both measures of firm size.

Summing up, we find that, using both measures of firm size, large firms are less likely to use fire overall (panel (A)). There is some evidence that when spread risk is higher, firms with larger concession areas use fires less (panel (B)), but we find no evidence that larger firms internalize the spread risk to external land any more than small firms (panel (C)).

5.2.2 International certification: the Roundtable on Sustainable Palm Oil

One specific mechanism for enhancing a firm's reputation is through international certification of good behavior. By signing up with international certification organizations, firms can signal to buyers that their production processes do not involve illegal practices that damage others. Certification is now used in a wide variety of contexts as a private means of regulating practices such as illegal deforestation and burning, illegal fishing and the use of child labor.

In the context we study, the flagship certification policy is private regulation via membership of the Roundtable on Sustainable Palm Oil (RSPO). This is a multi-stakeholder not-for-profit organization founded in 2004 that encourages the production and trade of certified sustainable palm oil and, as part of this, promotes a zero-burning policy. Existing studies find muted evidence for reduced incidence of fires in RSPO-certified concessions: Carlson et al. (2018) find that RSPO certification reduced deforestation but not fire or peatland clearance, and Cattau et al. (2016) find that the prevalence of fires in Sumatra and Kalimantan from 2012-2015 was lower in RSPO-certified concessions only in areas and under climatic conditions when the likelihood of fire is relatively low.

We use our data to consider the impact of RSPO membership on overall ignitions, as well as on the externality-inducing behavior identified in Section 4.[23] We identify RSPO members in our concessions data, and their date of accession to the RSPO, by classifying a concession as an RSPO member if the concession name, or the company group to which the concession belongs, appears in the list of RSPO members published by the RSPO together with the date on which each member acceded to the RSPO.[24] Over our study period, 23% of company groups, owning 12% of palm oil concessions, became RSPO members.

It is worth noting that, on average, we find that the zero-burning policy promoted by the RSPO among its members was imperfectly enforced over the study period: fires started inside concessions owned by RSPO members at the time of ignition burned a total of 1648 km^2 , accounting for 2.1% of the total area burned by fires inside palm oil concessions.

We examine the impact of RSPO membership systematically in columns (5) and (6) of Table 7. The table shows that there is weak and statistically insignificant evidence that palm oil concessions owned by RSPO members may be associated with fewer ignitions - the point estimates do suggest a reduction of about 20 percent in ignitions when a firm joins the

[23]RSPO membership is the first step towards RSPO certification. While not an explicit pledge of zero burning, RSPO membership requires firms to work towards certification - which explicitly prohibits burning - and to provide annual progress reports and acknowledgment of the RSPO Statutes and Principle and Criteria. RSPO certification itself cannot be mapped directly to our concessions data since the unit of certification is an oil palm mill and its surrounding supply base.

[24]https://www.rspo.org/members/all

RSPO, but this is not statistically significant. But this masks important heterogeneity. Panel (B), columns (5) and (6), suggests that when the risk of spread is low, RSPO membership does reduce ignitions. But there is a positive interaction between $Weather\widehat{SpreadRisk}$ and $FirminRSPO$, suggesting that this reduction in fire use goes away when spread risk is high. This result echoes the findings of Cattau et al. (2016), which find reductions of fires in RSPO areas in wetter times (low risk) but not in dry times (high risk).

In panel (C), we then estimate whether RSPO membership is associated with a reduction in the *externality* associated with fire use by re-estimating equation (6) with RSPO membership as the interaction variable. We find that RSPO membership does not significantly affect the degree to which concession owners internalize the cost of fires on neighboring unleased productive forest.

These results together suggest that RSPO membership had limited success in reducing ignitions overall and was still more ineffective in reducing fires that impose particularly significant externalities, either those that occur at riskier times or those that are most likely to spread to unleased productive forest – the part of the forest estate where property rights are weakest.

The picture that emerges from this section is that private incentives clearly influence the use of fire. Firms are less likely to use fire if the adjoining land is either their own concession land or that of another firm. This is true in the cross-section but also when the risk of fire spread is higher. Interestingly firms also consider whether or not their own concession land or that of their neighbor is still forested or recently deforested. Our central result here – that treatment of own concession land, whether forested or not, is symmetric with adjoining concession land – suggests that strong private property rights can help limit but not eradicate the use of fire. Reputation concerns captured by firm size or private regulation via RSPO, in contrast, have much more muted effects. Taken together, these results suggest private approaches to limiting forest fire externalities can, at best, only be partially successful.

6 Public sector approaches to reducing externalities

The other, perhaps more conventional, approach to managing externalities is through government action. Pigou (1920), for example, argues that when the private and social benefits from an action differ, the solution is to levy a tax on the externality-generating activity so that the marginal benefits and costs are equated. Does that work in this context? Or would it be preferable if the government itself simply took over the production process? We explore these issues in this section.

6.1 Government sanctions

6.1.1 Penalties a la Pigou

Intentionally burning areas of the wood fiber and palm oil forest concessions we study was illegal throughout our study period, with substantial maximum penalties specified by law – up to 15 years imprisonment, fines up to IDR 10 billion (about USD 1 million during much of this period), and for corporate entities, a variety of financial penalties, sealing and loss of use of the concession, or even total guardianship of the company for up to three years (DLHK Provinsi Baten 2020).

But these are theoretical maximum penalties and, even if they are enforced, they may not be enforced *uniformly*. Indeed, the government may implicitly place different sanctions on different types of fires depending on what types of land are damaged and the amount of damage done. From the perspective of a firm considering using fire to clear land, what matters is the expectation about how different types of fire damage will result in different expected penalties (Becker 1968).

We cannot measure firms' expectations directly. But we can look at a period when the government of Indonesia initiated a large number of enforcement actions and estimate which types of fires are most likely to lead to crackdowns. To test whether firms are responding to these expected Pigouvian sanctions, we can then compare whether firms avoid the types of fires (i.e. from the estimates in Table 4) that the government is most likely to punish.

To look at what the government punishment function looks like, we can back out the government's implicit weights on different types of fire damage using data on firms investigated by the Indonesian government for forest fire violations following the devastating 2015 fires (see Section 2.4). Because the government released the province and firm initials of each firm being investigated, we can match investigations to specific firms in our concession data. We then use our data to investigate the relationship between the fires we detect that *originated* in each firm's concession and the associated risk of a subsequent government investigation.

Specifically, to estimate the government's decision rule, we estimate the following equation at the level of concessions c:

$$\begin{aligned} Pr(Punished_c) &= F(\textstyle\sum_{j\neq o} \beta_j BurnedArea_c^j + \gamma TotalBurnedArea_c \\ &\quad +\delta PopnBurnedArea_c + \eta X_c) \end{aligned} \tag{7}$$

where $F(\cdot)$ is the CDF of logistic distribution; $Punished_c$ is a dummy equal to 1 if concession c is owned by a firm that appeared on the list of investigated firms and in the province in which the firm was investigated; $BurnedArea_c^j$ is the number of pixels in land type j (excluding omitted category o) burned by fires started in concession c in the 12 months prior to the release of the investigated firm lists (September 2014 to August 2015); $TotalBurnedArea_c$ is the total area burned by fires started in concession c during that time; and $PopnBurnedArea_c$ is the population in areas burned by fires started in concession c during that time. The control variables X control for concession type and area; 2000 forest cover at the concession level; and island fixed effects.[25] Standard errors are clustered at the level of firm groups, defined according to firm group name where this is available and firm name otherwise. Note that the omitted category in equation (7) is pixels in the concession itself; so coefficients on other land types j are interpretable as the effect of burning land type j over and above the effect of burning land on your own concession.

The results are shown in Table 9. Focusing on the results with controls in column (2), a few patterns emerge. First, larger fires are clearly more likely to be punished. Second, the government is substantially more likely to punish those firms owning concessions whose fires spread into populated areas. Third, the government is also likely to target those firms owning concessions whose fires spread into protected zones. Pixels in unleased productive forest are treated no differently than land in the concession itself. On balance, the government therefore seems to care most about fires that burn in populated areas, and - among the lands owned by the government (unleased lands in the national forest) - it cares more about protected forest than it does about unleased productive forest.

These patterns are broadly similar to the patterns of avoidance behavior we saw in Table 4 – where concession owners appear to avoid risky fires that could spread into populated areas, and among government lands, they appear to care least about unleased productive forest. This suggests that firms do behave as if they are responding to Pigouvian (1920) style incentives, at least qualitatively – that is, they are avoiding fires that affect the types of lands that the government is most likely to investigate. These patterns, of course, do not speak to the *magnitude* of the Pigouvian response – and indeed, given that in many cases these investigations did not actually result in punishment or fines, there is reason to think that the magnitude is less than the Pigouvian optimum. But the fact that the patterns are broadly similar suggests the possibility that if the government were to increase the fines it levies, private actors would follow suit and reduce burning activity accordingly.

6.1.2 Criminal sanctions for collaborating government officials

Given that using fires for forest clearing is illegal, getting away with doing so may be easier if there are corrupt local officials who can be co-opted to look the other way. During the period we study, Indonesia's independent anti-corruption commission, the *Komisi Pemberantasan*

[25] The estimation sample includes only concessions in those provinces for which firm investigation lists were published and in which at least one fire was started between September 2014 and August 2015.

Korupsi (known as KPK), made investigations of corruption related to the forest sector a priority. Several provincial governors and district heads, as well as a number of officials in the district forest offices, were charged with and convicted of corruption related to the forest sector, and many were sentenced to jail.

We ask whether removing these corrupt officials from office affected the incidence of forest fires. To do so, we compiled information on all corruption cases related to forest fires that involved national, regional or local government officials and were sentenced by the courts over our study period. The primary source used for this was the annual reports of KPK[26] and the Indonesian Court System database[27], as well as supporting data from media reporting. This yielded data on 26 prosecutions over the study period across six distinct provinces and seven distinct regencies.

We examine the effects of prosecutions on subsequent fire-setting activity by marking pixels in regencies (provinces) in which regency-level (province-level) officials were prosecuted as treated after the announcement of the earliest prosecution in the sample. The specification used to test this is:

$$\mathbb{E}[Ignitions_{imt}] \quad = \gamma_i \quad exp(\beta Prosecuted_{imt} + \delta_{qmt}) \tag{8}$$

where $Prosecuted_{imt}$ is an indicator equal to one if pixel i is in a region where a prosecution has been announced prior to month-year mt; γ_i are pixel fixed effects; and δ_{qmt} are island-month-year fixed effects. Standard errors are clustered at the level of provinces.

This specification tests whether the prosecution of a local official reduces fire setting. The results, shown in column (1) of Table 10, suggest that on average prosecutions *do not* lead to lower levels of ignitions in the sample in subsequent periods. We next supplement the specification with weather conditions interactions to test whether prosecutions induce landowners to be more attentive to spread risk in their fire-setting behavior. The results in column (2) of Table 10 suggest that this is not the case: ignitions during times when the risk of spread is high do not fall differentially in regions where local officials have been prosecuted; if anything, the converse appears to be the case. Finally, we add interactions with the share of the pixel buffer that is in the same concession as the central pixel, in order to test whether local prosecutions ameliorate firms' propensity to impose externalities on their neighbors (i.e. to set fires differentially on riskier days when they are surrounded by more land owned by others). The results are shown in columns (3) (in the full sample) and (4) (restricting attention to those pixels whose buffers contain only own concession land and unleased productive forest, where externalities are highest as shown in Table 4; i.e. the

[26]These were accessed via the KPK's online archives at https://acch.kpk.go.id/id/berkas/penindakan/inkracht.
[27]https://putusan3.mahkamahagung.go.id/

sample used in Table 8) of Table 10 and suggest that local prosecutions are also ineffective in attenuating concession holders' externality-inducing behavior.

Taken together, these results suggest that prosecutions of officials for forestry corruption offences – which may be helpful for reducing corruption in the forest sector in other ways – appear to be ineffective at reducing fire setting overall, risky fire setting, or fire setting that imposes externalities on property owners' neighbors.

6.2 Government ownership

An alternative public approach to combating externalities is direct government ownership. In Indonesia, a substantial number of forest firms are, in fact, state-owned enterprises. Are these firms, owned by the government, better at internalizing externalities? To examine this, we identify concession names associated with the large state-owned plantation companies or which we could otherwise identify as government-owned[28], and examine whether government-owned concessions behave differently from privately-owned concessions.

The results are presented in Table 11. We find that, indeed, state-owned enterprises are substantially less likely to use forest fires than private concessions. Even with a robust series of controls – for concession type, concession area, baseline forest cover, and island dummies – government-owned concessions have about 40 percent (-0.49 log points) fewer fires than comparable privately-owned concessions. So at the broad level, government ownership is associated with being less likely to use fire than private ownership.

That said, panels (B) and (C) of Table 11 show no evidence that fire in government concessions is differentially sensitive to externalities than in private concessions. Panel (B) shows that there is no difference in the degree to which fire occurs on risky versus less-risky days in government versus private concessions. And panel (C) shows that, in both cases (government and private ownership), fire in concessions adjacent to unleased productive forest is less likely on risky days when more of the area that would be burned is in the own concession. So while we find that government ownership substantially reduces the use of fire overall, and hence the externality, it does not make it less sensitive to external risks.

[28]Specifically, we flagged two large state-owned plantation companies, Perhutani and Inhutani, and their subsidiaries; all companies who were explicitly identified as being state-owned enterprises in the name (either with a name including 'Persero' or 'PTP', which means state-owned enterprise); companies which were associated with a government department ('Ditjen'), or companies which included the name 'Perkebunan', which generically means plantation but in practice referred almost exclusively to another large state-owned plantation company (PT Perkebunan Nusantara).

7 Robustness and alternative explanations

7.1 Results using variation in other weather variables

As shown in Section 4.1, fire spread risk is predictable based on wind strength, precipitation and temperature. Appendix E presents the results of equivalent specifications where the combination of these three variables is replaced by each of them individually. These results demonstrate that spread risk may alternatively be predicted by individual components of local weather (Tables E.1 to E.3). This provides a useful opportunity to test whether concession-holders react in a similar way to variation in spread risk induced by different weather variables.

The results of our central specification (5), where the spread risk weather index is replaced by monthly average wind speed, total monthly precipitation, or monthly average temperature, are shown in Tables E.4 to E.6. These results show a very consistent pattern using variation in wind speed or precipitation alone: ignitions are intuitively higher in windier (Table E.4) or drier conditions (Table E.5), and concession-holders are less attentive to the weather-induced risk of fire spread when surrounded by unleased productive forest relative to being surrounded by their own land. The results using wind speed also demonstrate a somewhat stronger deterrent effect of surrounding land outside the forest estate, consistent with the main results. The more muted effects using variation in temperature alone (Table E.6) are unsurprising given that Indonesia is equatorial and as such experiences only modest variations in temperature. The consistency of the results across these specifications strengthens the interpretation of the results as being driven by concession holders' response to the externalities they may cause by starting a fire.

Our central specifications consider monthly average weather conditions given that there may be low costs to postponing fires to another day if weather is an important concern and daily weather data is used. Appendix F presents the results of robustness specifications using daily rather than monthly variation in wind speed and shows that our key results are robust in this case.

7.2 Results by concession type

The central specifications restrict attention to fires started inside wood fiber or palm oil concessions. Appendix G presents results separately for these two types of concessions. These show that the central results are consistent in the two types of concessions, with some differences in statistical significance given the smaller sample sizes in each regression but broadly similar qualitative findings when looking separately at palm oil and wood fiber concessions. Appendix H presents the results of the main specifications where fires started inside logging concessions are also included and finds qualitatively similar results.

7.3 Alternative fixed effects and clustering

The central results are robust to alternative clustering or fixed effects to those used in the baseline specifications. Appendix I presents results where clustering is at the level of 25km x 25km or 100km x 100km grid cells or at the level of concessions rather than 50km x 50km grid cells. We also find similar results replacing pixel, month and year fixed effects with pixel and month×year fixed effects or pixel and month×year×island fixed effects, which could potentially capture year-specific seasonality in addition to overall seasonality; see Appendix J for details. In an especially demanding specification including the risk index interacted with concession fixed effects (i.e. estimating separate coefficients on the risk index for every concession) (Table J.5), ignitions are again found to be more likely on days when weather conditions make spread more likely in areas where the fire would be more likely to spread to unleased productive forest compared to where spread would be internal.

8 Conclusions

Firms' decisions as to whether or not to impose uncompensated damages on others lie at the root of climate change, pollution, deforestation and biodiversity loss. We study what affects this decision in the case of forest fires in the tropics.

Novel satellite measurement of the ignition point and spread of over 107,000 fires enables us to establish that these are largely man-made, follow deforestation and are focused on clearing land for large-scale oil palm and wood fiber plantations. By combining our daily fire data with surrounding land zones and wind, temperature and precipitation drivers of fire spread, we analyze whether externalities influence fire-setting behavior. Across the 2000-2016 period, we find that this is the case – ignitions are significantly less likely on high spread risk days in areas where the fire would be more likely to spread inside the same concession versus cases in which spread would be to unoccupied, government-controlled land.

This analysis then opens up the possibility of looking at whether private and public solutions can limit these externalities. On the private front, we find that when we focus on cases where the spread risk would be limited to a single firm, firms treat the risks of spread to their own and the neighboring concession similarly. This suggests the possibility that under certain circumstances where transaction costs are limited, firms may be able to bargain among themselves to internalize these risks, as suggested by Coase.

On the public front, we investigate empirically which fires the government chooses to investigate and show that it is precisely these types of fires – particularly those that would spread into populated areas – that firms seem to avoid. This suggests the possibility of effective deterrence from government fines or punishment in the spirit of Pigou.

Two central conclusions emerge from our analysis. The first is that the value of making progress in limiting environmental externalities is enormous. We have only looked at the local externality of burning others' land, which abstracts from other externalities including health and economic costs of smoke and haze, ecosystem loss and global warming induced by greenhouse gas emissions. Based on the estimated wider impacts of forest fires in Indonesia[29], and assuming that impacts are directly proportional to the area burned, the estimated 55-58% reduction in fires associated with agents treating all land in each buffer as if it were outside the forest estate applied across all areas would have implied gains from reducing the damages from Indonesia's 2015 forest fires of up to 0.2% of Indonesia's 2015 GDP, global carbon emission reductions of up to 0.7 Gigatonnes (7.1% of the global carbon emissions from fossil fuels) and avoided the premature deaths of up to 14,630 adults and 4,226 children under three. The large size of these social costs relative to the small size of the benefits that accrue to private firms brings into sharp focus the large gains that are available from limiting environmental externalities.

The second conclusion is that we are very much in the infancy of working out how to limit environmental externalities. Three areas look important for making further progress. The first is political economy. If private benefits are small relative to social costs, how can the views of those that are damaged become represented? Our related work on political cycles in fires following deforestation demonstrates that electoral incentives matter in this context (Balboni et al. 2021), but we do not yet fully understand how popular dislike of fires can be better represented in policy making. The second is international policy. Citizens in many countries outside those where forest fires occur care about stopping them but have limited means of representing these preferences. There is now growing interest both in how policy instruments such as conservation-linked trade tariffs (e.g., Harstad 2022, Hsiao 2022) or REDD payments might fill the void left by weak domestic regulation, but limited evaluation of whether this works. The third is technology. Ultimately fire is a risky technology

[29]The most extensive literature quantifying the impacts of Indonesia's forest fires is based on the severe fires in 1997-1998, which resulted in the burning of over 50 thousand square kilometers of land (Varma 2003) and the vast spread of haze throughout Southeast Asia. Short-term costs and damages of the 1997-1998 fires for Indonesia and neighboring countries have been conservatively estimated at 4,475 million 1997 USD, mainly in medical costs, airport closures and tourism, and damages to ecosystems and biodiversity (Glover and Jessup 1999). Subsequent studies estimated the associated carbon emissions at 0.81–2.57 Gigatonnes (Page et al. 2002) and resulting premature deaths at 22,000–54,000 adults (Heil 2007) and 15,600 children under three (Jayachandran 2009).

for clearing land with many external harms, and there is a need to understand whether innovations or incentives can make cleaner alternatives more attractive.

This combination of empirical importance, limited evidence on what works and the sheer diversity of environmental externalities that we face makes this an area of research and policy where much greater investments will be needed going forward.

References

Balboni, Clare, Robin Burgess, Johannes Heil, Jonathan Old, and Benjamin A Olken (2021) "Cycles of Fire? Politics and Forest Burning in Indonesia," *American Economic Association: Papers and Proceedings*, 111, 415–19.

Becker, Gary S. (1968) "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76 (2), 169–217.

Benson, Randall P, John O Roads, and David R Weise (2008) "Climatic and weather factors affecting fire occurrence and behavior," *Developments in Environmental Science*, 8, 37–59.

Burgess, Robin, Matthew Hansen, Benjamin A Olken, Peter Potapov, and Stefanie Sieber (2012) "The Political Economy of Deforestation in the Tropics," *The Quarterly Journal of Economics*, 127 (4), 1707–1754.

Carlson, Kimberly M, Robert Heilmayr, Holly K Gibbs et al. (2018) "Effect of oil palm sustainability certification on deforestation and fire in Indonesia," *Proceedings of the National Academy of Sciences*, 115 (1), 121–126.

Casson, Anne (2001) *Decentralisation of policies affecting forests and estate crops in Kutai Barat District, East Kalimantan*, 4: CIFOR.

Cattau, Megan E, Miriam E Marlier, and Ruth DeFries (2016) "Effectiveness of Roundtable on Sustainable Palm Oil (RSPO) for reducing fires on oil palm concessions in Indonesia from 2012 to 2015," *Environmental Research Letters*, 11 (10), 105007.

Coase, R.H. (1960) "The Problem of Social Cost," *Journal of Law and Economics*, 3, 1–44.

Cossar-Gilbert, Irhash Ahmady and Sam (2015) "Setting a country alight: Indonesia's devastating forest fires are manmade," The Guardian, retrieved from theguardian.com/global-development-professionals-network/2015/nov/07/setting-a-country-alight-indonesias-devastating-forest-fires-are-manmade.

Dales, JH (1968) *Pollution Property and Prices*: University of Toronto Press.

Dipoppa, Gemma and Saad Gulzar (2022) "Administrative Incentives Impact Crop-Residue Burning and Health in South Asia," *Working Paper*.

DLHK Provinsi Baten (2020) "Pasal Sanksi Pidana Pelaku Pembakaran Hutan Atau Lahan (Criminal Sanctions Provisions for Actors Burning Forest Land)," Environment and Forestry Service of Banten Province, retrieved from dlhk.bantenprov.go.id/upload/article/2020/pasal_sanksi_pidana_pelaku_pembakaran.pdf.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan (2013) "Truth-telling by third-party auditors and the response of polluting firms: Experimental evidence from India," *The Quarterly Journal of Economics*, 128 (4), 1499–1545.

Edwards, Ryan B (2019) "Export agriculture and rural poverty: Evidence from Indonesian palm oil," *Working Paper*.

Enrici, Ashley and Klaus Hubacek (2016) "Business as usual in Indonesia: governance factors effecting the acceleration of the deforestation rate after the introduction of REDD+," *Energy, Ecology and Environment*, 1 (4), 183–196, 10.1007/s40974-016-0037-4.

Frankenberg, Elizabeth, Douglas McKee, and Duncan Thomas (2005) "Health consequences of forest fires in Indonesia," *Demography*, 42 (1), 109–129.

Giglio, Louis and Christopher Justice (2015) "MOD14A1 MODIS/Terra Thermal Anomalies/Fire Daily L3 Global 1km SIN Grid V006,"Technical report, NASA EOSDIS LP DAAC, 10.5067/MODIS/MOD14A1.006.

Giglio, Louis, Wilfrid Schroeder, Joanne V Hall, and Christopher O Justice (2015) "MODIS Collection 6 Active Fire Product User's Guide," *Department of Geographical Sciences. University of Maryland*.

Glover, David and Timothy (ed.) Jessup (1999) *Indonesia's fires and haze: The cost of catastrophe*: Institute of Southeast Asian Studies, Singapore.

Greenpeace (2019) "Indonesian Forest Fires Crisis: Palm oil and pulp companies with largest burned land areas are going unpunished," Greenpeace South Asia, retrieved from greenpeace.org/southeastasia/publication/3106/3106.

Greenpeace Indonesia (2019) "Ganti Rugi 18,9 Triliun Terkait Kasus Kebakaran dan Kerusakan Hutan Gagal Dibayar Sejumlah Perusahaan, Pemerintah Harus Mengambil Langkah Tegas," retrieved from greenpeace.org/indonesia/siaran-pers/1103/ganti-rugi-189-triliun-terkait-kasus-kebakaran-dan-kerusakan-hutan-gagal-dibayar-sejumlah-perusahaan-pemerintah-harus-mengambil-langkah-tegas/.

Hansen, Matthew C, Peter V Potapov, Rebecca Moore et al. (2013) "High-resolution global maps of 21st-century forest cover change," *Science*, 342 (6160), 850–853.

Harstad, Bård (2022) "Trade and Trees," *Working Paper*.

Heil, Angelika (2007) *Indonesian forest and peat fires: emissions, air quality, and human health* Ph.D. dissertation, University of Hamburg.

Hsiao, Allan (2022) "Coordination and Commitment in International Climate Action: Evidence from Palm Oil," *Working paper*.

Jayachandran, Seema (2009) "Air Quality and Early-Life Mortality: Evidence from Indonesia's Wildfires," *Journal of Human Resources*, 44 (4), 916–954.

Jayachandran, Seema, Joost De Laat, Eric F Lambin, Charlotte Y Stanton, Robin Audy, and Nancy E Thomas (2017) "Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation," *Science*, 357 (6348), 267–273.

Kahn, Matthew E., Pei Li, and Daxuan Zhao (2015) "Water Pollution Progress at Borders: The Role of Changes in China's Political Promotion Incentives," *American Economic Journal: Economic Policy*, 7 (4), 223–42.

Kim, Younoh, Scott Knowles, James Manley, and Vlad Radoias (2017) "Long-run health consequences of air pollution: Evidence from Indonesia's forest fires of 1997," *Economics & Human Biology*, 26, 186–198.

Koplitz, Shannon N, Loretta J Mickley, Miriam E Marlier et al. (2016) "Public health impacts of the severe haze in Equatorial Asia in September–October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure," *Environmental Research Letters*, 11 (9), 094023.

Lipscomb, Molly and Ahmed Mobarak (2017) "Decentralization and Pollution Spillovers: Evidence from the Re-drawing of County Borders in Brazil," *The Review of Economic Studies*, 84 (1), 464.

Mahomed, Raheela (2019) "Indonesia fires: Palm oil companies accused of starting blazes," Al Jazeera, retrieved from aljazeera.com/news/2019/09/indonesia-fires-palm-oil-companies-accused-starting-blazes-190919134146766.html, Sep.

Marshall, Alfred (1890) *Principles of economics*: Macmillan.

Mellen, Ruby (2019) "Wildfires in Indonesia have ravaged 800,000 acres. Palm oil farmers are mostly to blame.," The Washington Post, retrieved from washingtonpost.com/world/2019/09/18/wildfires-indonesia-have-ravaged-acres-palm-oil-farmers-are-blame/, Sep.

Murdiyarso, Daniel, Sonya Dewi, Deborah Lawrence, and Frances Seymour (2011) "Indonesia's forest moratorium: A stepping stone to better forest governance?" *CIFOR Working Paper*.

Ostrom, Elinor (1990) *Governing the commons: The evolution of institutions for collective action*: Cambridge University Press.

Page, Susan E, Florian Siegert, John O Rieley, Hans-Dieter V Boehm, Adi Jaya, and Suwido Limin (2002) "The amount of carbon released from peat and forest fires in Indonesia during 1997," *Nature*, 420 (6911), 61–65.

Pareto, Vilfredo (1909) *Manuel d'économie politique*, 38: Giard & Brière.

Pigou, A.C. (1920) *The Economics of Welfare*: Macmillan.

Rangel, Marcos A and Tom S Vogl (2019) "Agricultural fires and health at birth," *Review of Economics and Statistics*, 101 (4), 616–630.

Resosudarmo, Ida Daju, Christopher Barr, Ahmad Dermawan, Bambang Setiono et al. (2006) *Decentralization of forest administration in Indonesia: Implications for forest sustainability, economic development and community livelihoods*: CIFOR.

ROI (1967) "Undang Undang Nomor 5 Tahun 1967 tentang Pokok-pokok Kehutanan (Basic Forestry Law)," Republic of Indonesia.

Shmuel, Assaf and Eyal Heifetz (2022) "Re-examining the assumption of dominant regional wind and fire spread directions," *International Journal of Wildland Fire*, 35 (5), 480–491.

Simorangkir, Dicky (2007) "Fire use: Is it really the cheaper land preparation method for large-scale plantations?" *Mitigation and Adaptation Strategies for Global Change*, 12 (1), 147–164.

Van Der Werf, Guido R, James T Randerson, Louis Giglio et al. (2017) "Global fire emissions estimates during 1997–2016," *Earth System Science Data*, 9 (2), 697.

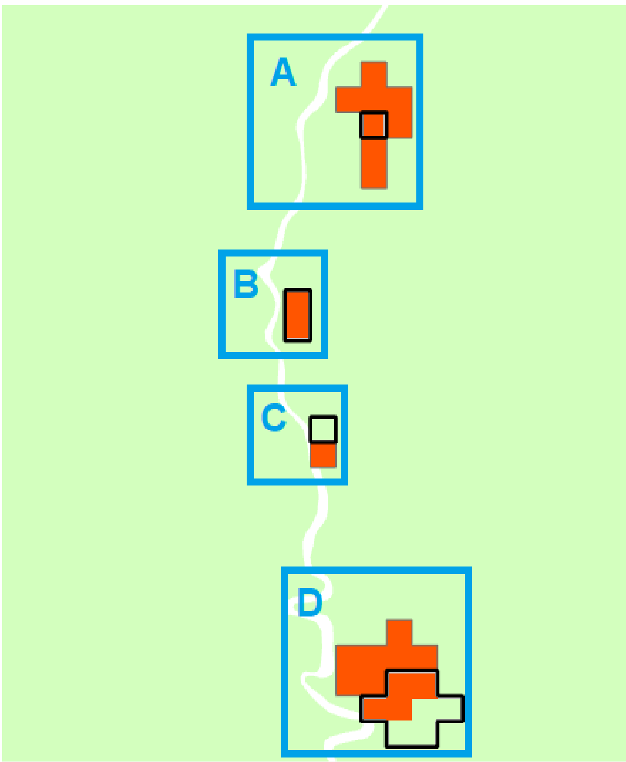
Varma, Anshuman (2003) "The economics of slash and burn: a case study of the 1997–1998 Indonesian forest fires," *Ecological Economics*, 46 (1), 159–171.

Wooldridge, Jeffrey M (1999) "Distribution-free estimation of some nonlinear panel data models," *Journal of Econometrics*, 90 (1), 77–97.

Yule, Catherine M (2010) "Loss of biodiversity and ecosystem functioning in Indo-Malayan peat swamp forests," *Biodiversity and Conservation*, 19 (2), 393–409.

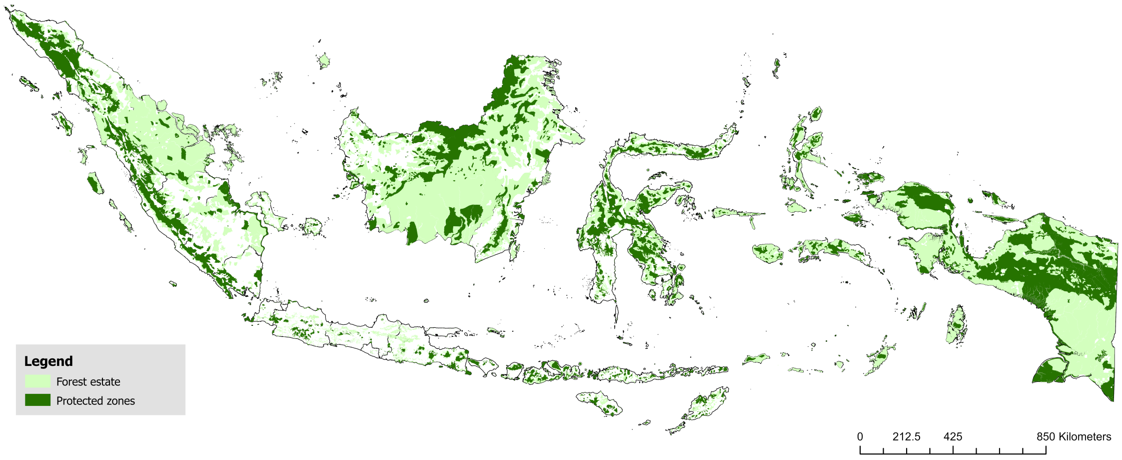
Figures and Tables

Figure 1: Example of Fire Identification Algorithm

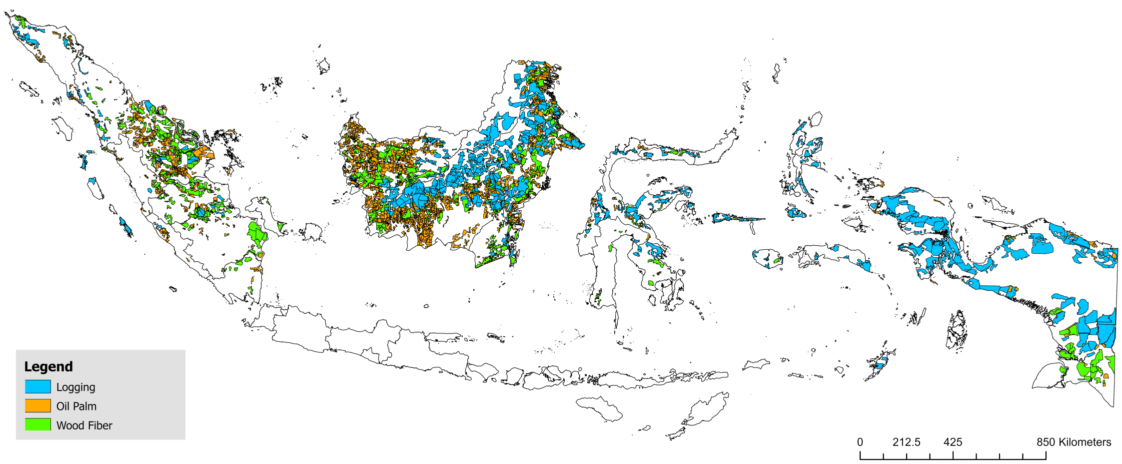


Notes: Example showing how we track contiguous "multi-day" fires. Pixels outlined in black are ignition pixels (has a fire on day 1), and the red pixels are spread areas (has a fire on day 2 onwards). This diagram shows 4 multi-day fires in blue boxes (starting on different dates). Total spread extent is the union of red and black-outlined pixels within each box.

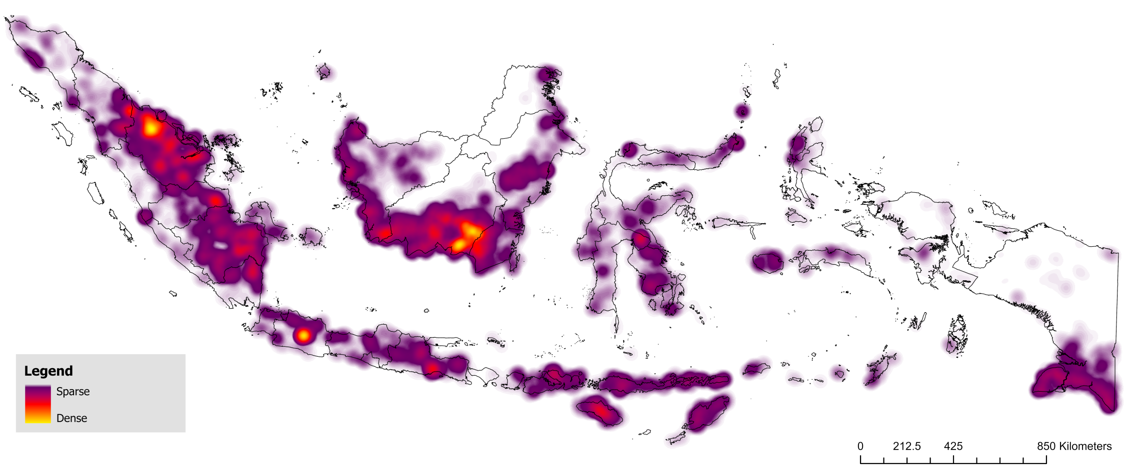
Figure 2: Indonesia Forest Estate, Concessions, and Fires Maps



a Forest estate and protected forest zones

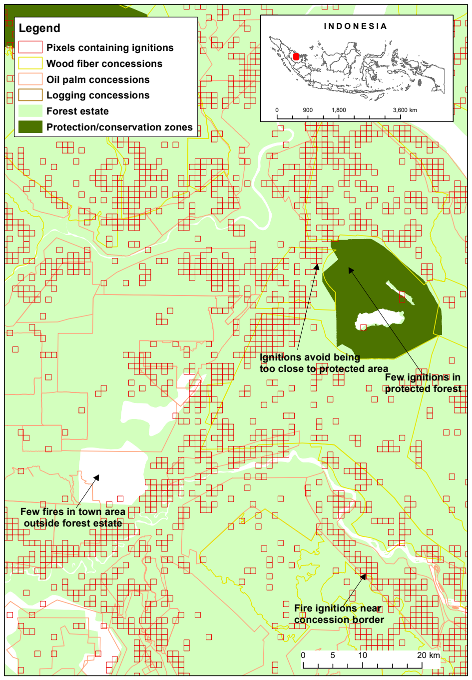


b Concessions (by type)



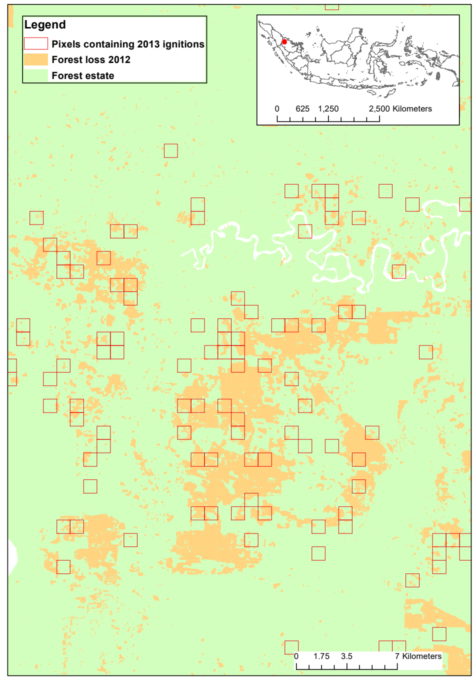
c Ignition Density (2000-2016)

Figure 3: Ignitions and concession areas in Riau province, Sumatra



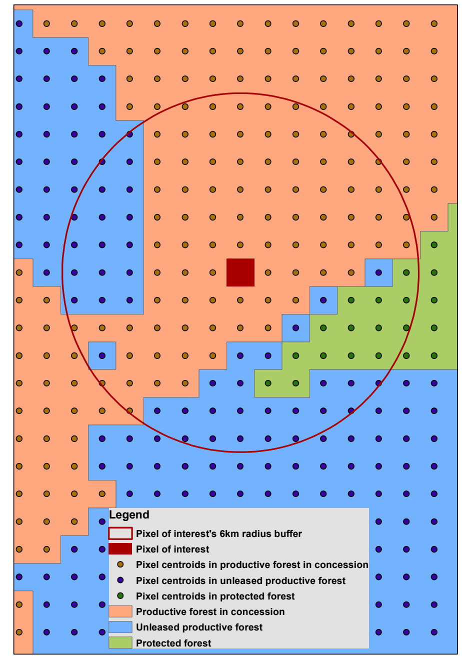
Notes: Each 1km^2 red grid cell is a pixel in which at least one ignition was detected during our sample period. Concessions are outlined (yellow for wood fiber; orange for oil palm). Protected forest zones are shown in dark green; regular forest estate areas are shown in light green; and areas outside the forest estate are shown in white.

Figure 4: 2012 deforestation and 2013 ignitions in Riau



Notes: Each 1km^2 red grid cell is a pixel in which any ignition was detected in 2013. Deforested areas in 2012 within the forest estate are shown in orange; (non-deforested) forest estate areas are shown in light green.

Figure 5: Illustration of pixel buffer classification



Notes: The central pixel of interest is shown in red, and its 6km buffer is outlined in red. Surrounding pixels are inside the buffer if its centroid (dots) lies within it. Orange pixels denote areas in concession and forest estate; blue pixels denote areas in unleased productive forest; green pixels denote areas in protected forest zones.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Median
Weather data:					
Precipitation (mm)	246	110	0	1,684	243
Wind speed (km/h)	6.1	4.3	.00047	34	4.8
Temperature (Celsius)	26	1.4	18	30	27
Fire data:					
Total area burned (1kmx1km pixels)	4.50	11.95	1.00	546.00	2.00
Total days burned	1.29	1.05	1.00	24.00	1.00
Number of ignitions	44,454				
Probability of ignition in pixel-month-year	.00037				
Share of pixels where ignition ever observed	.055				
Concession data:					
Concession area (1kmx1km pixels)	235	482			
Cumulative area - all concessions (1kmx1km pixels)	546,225				
Cumulative area - wood fiber concessions (1kmx1km pixels)	135,339				
Cumulative area - palm oil concessions (1kmx1km pixels)	86,890				
Cumulative area - logging concessions (1kmx1km pixels)	323,996				
Number of concessions	2,320				

Sample is restricted to pixels within all three concession types (logging, palm oil, wood fiber), within the forest estate, and on major forested islands (excluding Java and Lesser Sunda Islands). Weather variables summaries are further restricted to pixels where all three weather variables are available.

Table 2: Impact of Deforestation on Ignitions

Dependent variable = Number of fires in pixel*month*year	Pixel FE	Pixel Month & Year FE
Forest loss (km2) in year t-1	1.1119***	1.3472***
	(0.1251)	(0.1321)
Forest loss (km2) in year t-2	-0.3690***	-0.3081**
	(0.1328)	(0.1335)
Forest loss (km2) in year t-3	-0.5480***	-0.3492**
	(0.1811)	(0.1490)
Observations	3,235,680	3,235,680
Mean of Dep. Var.	0.0100	0.0100

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. All pixels inside wood fiber and palm oil concessions inside forest estate in Indonesia excl Java and Lesser Sunda Islands.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact of Wind Speed, Temperature and Precipitation on Fire Spread

Dependent variable = Average fire spread area (burned area minus ignition area)	Pixel FE	Pixel Month & Year FE
Wind speed in km/h	0.1466***	0.1510***
	(0.04407)	(0.04452)
Temperature (Celsius)	0.7767***	0.5700***
	(0.1598)	(0.1679)
Precipitation (mm)	-0.004932***	-0.006626***
	(0.0008665)	(0.0008751)
Observations	5,897	5,897
Mean of Dep. Var.	4.608	4.608

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. All regressions control for number of ignitions in pixel-month. All pixels inside wood fiber, palm oil, and logging concessions inside forest estate in Indonesia excl Java and Lesser Sunda Islands.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of Surrounding Land Type and Weather Spread Risk Index on Ignitions

Dependent variable = Number of fires in pixel*month*year	M & Y	M & Y	M & Y	M & Y	M & Y	M & Y
Panel A: Main Effects	FEs	FEs	FEs	FEs	FEs	FEs
Num pixels in 6km buffer in different concession from central pixel	-0.0005364	-0.001199	-0.001463	-0.0005091	-0.004285***	-0.003603***
	(0.001233)	(0.001231)	(0.001389)	(0.001192)	(0.001240)	(0.001362)
Num pixels in 6km buffer outside forest estate	-0.004221	-0.005263*	-0.003636	-0.004795*	-0.007181**	-0.006287**
	(0.002819)	(0.002773)	(0.002765)	(0.002776)	(0.002897)	(0.002718)
Num pixels in 6km buffer in protected forest	-0.003017	-0.002399	-0.003388	-0.002543	-0.006460*	-0.003699
	(0.003516)	(0.003389)	(0.003357)	(0.003554)	(0.003441)	(0.003310)
Num pixels in 6km buffer in productive forest outside concession	0.006851***	0.005740***	0.005894***	0.006899***	0.002998**	0.003119**
	(0.001388)	(0.001288)	(0.001503)	(0.001338)	(0.001319)	(0.001330)
Average population density in 6km buffer	-0.0002219	-0.003038***	-0.0005620	-0.001095	-0.001033	-0.004975***
	(0.0007267)	(0.001139)	(0.0007562)	(0.0008061)	(0.0008162)	(0.001236)
Control: Island	NO	YES	NO	NO	NO	YES
Control: Concession Type	NO	NO	YES	NO	NO	YES
Control: Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Concession Area	NO	NO	NO	NO	YES	YES
Observations	39889620	39889620	39889620	39852540	39889620	39852540
Mean of Dep. Var.	0.000972	0.000972	0.000972	0.000972	0.000972	0.000972
	Pixel	Pixel	Pixel	Pixel	Pixel	Pixel
Panel B: With Pixel FE and Risk Index	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Risk index in standard deviation units	1.4919***	1.5532***	1.6859***	1.2089***	1.7316***	1.6269***
	(0.1000)	(0.1313)	(0.1062)	(0.1324)	(0.09203)	(0.1488)
Risk index * Num pixels in 6km buffer in different concession from central pixel	0.003237**	0.002154*	0.002042	0.002922**	0.001323	0.0004953
	(0.001297)	(0.001215)	(0.001243)	(0.001282)	(0.001120)	(0.001042)
Risk index * Num pixels in 6km buffer outside forest estate	-0.005492***	-0.005403***	-0.005127***	-0.005434***	-0.006830***	-0.005808***
	(0.001934)	(0.001898)	(0.001964)	(0.001892)	(0.001887)	(0.001878)
Risk index * Num pixels in 6km buffer in protected forest	0.0001574	0.0002460	-0.0009392	0.0002413	-0.001484	-0.001045
	(0.001915)	(0.001670)	(0.001734)	(0.001858)	(0.001823)	(0.001590)
Risk index * Num pixels in 6km buffer in productive forest outside concession	0.006644***	0.006552***	0.005312***	0.006436***	0.004616***	0.004476***
	(0.001549)	(0.001586)	(0.001507)	(0.001500)	(0.001321)	(0.001282)
Risk index * Average population density in 6km buffer	0.001078	0.0008309	0.0007956	0.001112	0.0004371	0.0004254
	(0.001156)	(0.001180)	(0.001082)	(0.001185)	(0.001038)	(0.001084)
Control: Risk Index × Island	NO	YES	NO	NO	NO	YES
Control: Risk Index × Concession Type	NO	NO	YES	NO	NO	YES
Control: Risk Index × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Risk Index × Concession Area	NO	NO	NO	NO	YES	YES
Observations	4715100	4715100	4715100	4707360	4715100	4707360
Mean of Dep. Var.	0.00823	0.00823	0.00823	0.00823	0.00823	0.00823

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. All pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category: "Num pixels in 6km buffer in same concession as central pixel" and interaction with risk index (panel B). Suppressed categories: "Num pixels in 6km buffer in sea", "Num pixels in 6km buffer in Malaysia / PNG" and interactions with risk index (panel B) .

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Impact of Surrounding Land Ownership and Weather Spread Risk Index on Ignitions - Cases Involving Single Property Border

Dependent variable = Number of fires in pixel*month*year **Panel A: Main Effects**	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Num pixels in 6km buffer in same concession as central pixel	-0.003894	-0.002489	-0.002782	-0.003560	0.001046	-0.0002139
	(0.002895)	(0.002830)	(0.002648)	(0.002975)	(0.002379)	(0.003025)
Control: Island	NO	YES	NO	NO	NO	YES
Control: Concession Type	NO	NO	YES	NO	NO	YES
Control: Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Concession Area	NO	NO	NO	NO	YES	YES
Observations	4869720	4869360	4869720	4867200	4869720	4866840
Mean of Dep. Var.	0.000785	0.000785	0.000785	0.000785	0.000785	0.000785
Panel B: With Pixel FE and Risk Index	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs
Risk index in standard deviation units	2.2394***	1.9435***	2.5414***	2.0485***	2.1897***	2.0557***
	(0.2685)	(0.3003)	(0.2710)	(0.3244)	(0.2790)	(0.3758)
Risk index * Num pixels in 6km buffer in same concession as central pixel	-0.006056***	-0.004520**	-0.003581*	-0.006308***	-0.002858	-0.001183
	(0.002044)	(0.002071)	(0.001963)	(0.001983)	(0.002035)	(0.002058)
Control: Risk index × Island	NO	YES	NO	NO	NO	YES
Control: Risk index × Concession Type	NO	NO	YES	NO	NO	YES
Control: Risk index × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Risk index × Concession Area	NO	NO	NO	NO	YES	YES
Observations	478,980	478,980	478,980	478,440	478,980	478,440
Mean of Dep. Var.	0.00798	0.00798	0.00798	0.00798	0.00798	0.00798

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. Sample: Pixels whose buffer contains land in a single or at most two concessions pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category: "Num pixels in 6km buffer outside same concession as central pixel" and interaction with spread risk (Panel B).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Impact of Weather Spread Risk Index, Surrounding Land Type and Recent Deforestation on Ignitions

Dependent variable = Number of fires in pixel*month*year	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs
Risk index in standard deviation units	2.3950***	2.4417***	2.4073***	2.0974***	2.3569***	2.2521***
	(0.1558)	(0.1471)	(0.1560)	(0.1783)	(0.1455)	(0.1664)
Area (km2) in 6km buffer in same concession as central pixel deforested last year	0.01565***	0.01835***	0.01525**	0.01725***	0.01635***	0.01903***
	(0.006074)	(0.006083)	(0.006152)	(0.005997)	(0.006105)	(0.006082)
Risk index * Area (km2) in 6km buffer in same concession as central pixel deforested last year	-0.005190	-0.007564*	-0.003453	-0.006402	-0.003971	-0.005997
	(0.004772)	(0.004550)	(0.004833)	(0.004628)	(0.004695)	(0.004570)
Risk index * Area (km2) in 6km buffer in same concession as central pixel not deforested last year	-0.006558***	-0.006381***	-0.005171***	-0.006310***	-0.004438***	-0.004069***
	(0.001574)	(0.001627)	(0.001524)	(0.001523)	(0.001323)	(0.001280)
Area (km2) in 6km buffer in different concession as central pixel deforested last year	0.009449	0.008417	0.01010	0.009548	0.009448	0.009454
	(0.009939)	(0.009995)	(0.009926)	(0.009961)	(0.009941)	(0.009963)
Risk index * Area (km2) in 6km buffer in different concession as central pixel deforested last year	0.0001434	-0.00008361	-0.0002695	-0.0001663	0.0003910	-0.0004793
	(0.007915)	(0.007873)	(0.007916)	(0.007883)	(0.007911)	(0.007813)
Risk index * Area (km2) in 6km buffer in different concession as central pixel not deforested last year	-0.003348**	-0.004227***	-0.003187**	-0.003421**	-0.003241**	-0.003719***
	(0.001477)	(0.001405)	(0.001440)	(0.001429)	(0.001444)	(0.001333)
Area (km2) in central pixel deforested last year	1.4519***	1.4386***	1.4597***	1.4896***	1.4576***	1.4758***
	(0.1682)	(0.1689)	(0.1679)	(0.1719)	(0.1691)	(0.1732)
Risk index * Area (km2) in central pixel deforested last year	-0.2462**	-0.2341**	-0.2534**	-0.2797**	-0.2514**	-0.2676**
	(0.1194)	(0.1194)	(0.1184)	(0.1215)	(0.1195)	(0.1218)
Risk index * Num pixels in 6km buffer outside forest estate	-0.01200***	-0.01179***	-0.01023***	-0.01178***	-0.01129***	-0.009945***
	(0.001747)	(0.001730)	(0.001928)	(0.001718)	(0.001744)	(0.001915)
Risk index * Num pixels in 6km buffer in protected forest	-0.006447***	-0.006202***	-0.006188***	-0.006206***	-0.006059***	-0.005367***
	(0.002158)	(0.002068)	(0.002023)	(0.002042)	(0.002080)	(0.001879)
Risk index * Average population density in 6km buffer	0.001352	0.001114	0.001043	0.001371	0.0006507	0.0006086
	(0.001251)	(0.001279)	(0.001169)	(0.001275)	(0.001121)	(0.001148)
Control: Risk index × Island	NO	YES	NO	NO	NO	YES
Control: Risk index × Concession Type	NO	NO	YES	NO	NO	YES
Control: Risk index × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Risk index × Concession Area	NO	NO	NO	NO	YES	YES
Observations	4,286,520	4,286,520	4,286,520	4,279,800	4,286,520	4,279,800
Mean of Dep. Var.	0.00877	0.00877	0.00877	0.00877	0.00877	0.00877

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. Sample: All pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category: Area (km2) in 6km buffer in same concession as central pixel not deforested last year, area (km2) in 6km buffer in different concession as central pixel not deforested last year, interaction of risk index and "Num pixels in 6km buffer in productive forest outside concession". Suppressed categories: Interactions of risk index and "Num pixels in 6km buffer in sea", "Num pixels in 6km buffer in Malaysia / PNG".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Impact of Reputation Concerns on Ignitions and Externalities

Dependent Variable = Number of fires in pixel*month*year	(1)	(2)	(3)	(4)	(5)	(6)
					Pixel	Pixel
Panel A: Main Effects	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Num concessions owned by firm	-0.01071***	-0.008586***				
	(0.002540)	(0.002647)				
Concession Area		-0.0002418***	-0.0004523***	-0.0002321**		
		(0.00008805)	(0.0001060)	(0.00009220)		
Firm is RSPO member in month-year					-0.2294	-0.2283
					(0.2015)	(0.2019)
Control: Island	NO	YES	NO	YES	NO	YES
Control: Concession Type	NO	YES	NO	YES	-	-
Control: Forest Cover 2000	NO	YES	NO	YES	NO	YES
Control: Concession Area	NO	YES	-	-	NO	YES
Observations	39945420	39873060	39910140	39873060	2,063,700	2,048,940
Mean of Dep. Var.	0.000974	0.000971	0.000972	0.000971	0.00842	0.00842
	Pixel	Pixel	Pixel	Pixel	Pixel	Pixel
Panel B: With Risk Index	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Risk index in standard deviation units	1.7439***	1.7727***	1.8678***	1.7742***	1.8671***	2.0171***
	(0.06157)	(0.1076)	(0.06176)	(0.1041)	(0.07219)	(0.1322)
Risk Index * Num concessions owned by firm	-0.004282	0.0003321				
	(0.002703)	(0.003047)				
Risk Index * Concession Area		-0.0002395*	-0.0003804***	-0.0002412*		0.0003990**
		(0.0001393)	(0.0001044)	(0.0001395)		(0.0001824)
Firm is RSPO member in month-year					-0.6107***	-0.5955***
					(0.2028)	(0.2117)
Risk Index * Firm is RSPO member in month-year					0.2792*	0.2707*
					(0.1505)	(0.1528)
Control: Risk Index × Island	NO	YES	NO	YES	NO	YES
Control: Risk Index × Concession Type	NO	YES	NO	YES	-	-
Control: Risk Index × Forest Cover 2000	NO	YES	NO	YES	NO	YES
Control: Risk Index × Concession Area	NO	YES	-	-	NO	YES
Observations	4,731,300	4,709,160	4,716,900	4,709,160	2,063,700	2,048,940
Mean of Dep. Var.	0.00822	0.00823	0.00823	0.00823	0.00842	0.00842
	Pixel	Pixel	Pixel	Pixel	Pixel	Pixel
Panel C: With Surrounding Land Ownership, and Risk Index	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Risk index in standard deviation units	3.0736***	2.4482***	2.6038***	2.0499***	2.1183***	2.1801***
	(0.2816)	(0.2723)	(0.2336)	(0.2997)	(0.2530)	(0.4087)
Risk Index * Num pixels in 6km buffer in same concession as central pixel	-0.01290***	-0.005403***	-0.005759**	-0.004346**	-0.0004178	-0.001672
	(0.002802)	(0.001908)	(0.002412)	(0.002072)	(0.002154)	(0.002673)
Risk Index * Num concessions owned by firm	-0.04900***	-0.001881				
	(0.01826)	(0.01735)				
Risk Index * Num pixels in 6km buffer in same concession as central pixel * Num concessions owned by firm	0.0004226***	0.0001103				
	(0.0001567)	(0.0001601)				
Risk Index * Concession Area		-0.0004343**	-0.0004322	0.0007406**		0.0003806
		(0.0001768)	(0.0004158)	(0.0003323)		(0.0002843)
Risk Index * Num pixels in 6km buffer in same concession as central pixel * Concession Area			-2.869e-07	9.493e-07		
			(0.000003662)	(0.000002303)		
Firm is RSPO member in month-year					-1.5524	-0.1864
					(1.1198)	(2.2531)
Risk Index * Firm is RSPO member in month-year					0.6953	-0.06167
					(0.6109)	(1.8710)
Risk Index * Num pixels in 6km buffer in same concession as central pixel * Firm is RSPO member in month-year					-0.004442	-0.008386
					(0.004396)	(0.006146)
Control: Risk Index × Island × Num concessions owned by firm	NO	YES	NO	YES	NO	YES
Control: Risk Index × Concession Type × Num concessions owned by firm	NO	YES	NO	YES	-	-
Control: Risk Index × Forest Cover 2000 × Num concessions owned by firm	NO	YES	NO	YES	NO	YES
Control: Risk Index × Concession Area × Num concessions owned by firm	NO	YES	-	-	NO	YES
Observations	752,040	750,420	752,040	750,420	224,460	224,460
Mean of Dep. Var.	0.00824	0.00823	0.00824	0.00823	0.00891	0.00891

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. Panel (A), (B): all pixels inside concessions and forest estate, excl Java and Lesser Sunda Islands. Panel (C): pixels whose buffers contain only own concession land and unleased productive forest inside concessions and forest estate excl Java and Lesser Sunda Islands. Columns (1) to (4) includes wood fiber and palm oil concesions, column (5) and (6) restricts to only oil palm concessions. Omitted category for panel (C): "Num pixels in 6km buffer outside same concession as central pixel" and interactions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ newline * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Impact of Surrounding Land Ownership and Weather Spread Risk Index on Ignitions - Cases Where Buffer Contains Only Own Concession Land and Unleased Productive Forest

Dependent variable = Number of fires in pixel*month*year **Panel A: Main Effects**	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs	M & Y FEs
Num pixels in 6km buffer in same concession as central pixel	-0.01011***	-0.007907***	-0.008235***	-0.009935***	-0.003228	-0.005075**
	(0.002143)	(0.001867)	(0.002214)	(0.002092)	(0.002089)	(0.002194)
Control: Island	NO	YES	NO	NO	NO	YES
Control: Concession Type	NO	NO	YES	NO	NO	YES
Control: Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Concession Area	NO	NO	NO	NO	YES	YES
Observations	6193620	6193620	6193620	6188760	6193620	6188760
Mean of Dep. Var.	0.00100	0.00100	0.00100	0.000998	0.00100	0.000998
Panel B: With Pixel FE and Risk Index	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs
Risk index in standard deviation units	2.7996***	2.6652***	2.8292***	2.3350***	2.6173***	2.2344***
	(0.2490)	(0.2300)	(0.2561)	(0.3360)	(0.2089)	(0.2489)
Risk index * Num pixels in 6km buffer in same concession as central pixel	-0.01048***	-0.009411***	-0.007624***	-0.009993***	-0.005882***	-0.004393**
	(0.002466)	(0.002376)	(0.002337)	(0.002509)	(0.001929)	(0.001800)
Control: Risk index × Island	NO	YES	NO	NO	NO	YES
Control: Risk index × Concession Type	NO	NO	YES	NO	NO	YES
Control: Risk index × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Risk index × Concession Area	NO	NO	NO	NO	YES	YES
Observations	752,040	752,040	752,040	750,420	752,040	750,420
Mean of Dep. Var.	0.00824	0.00824	0.00824	0.00823	0.00824	0.00823

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. Sample: Pixels whose buffers contain only own concession land and unleased productive forest inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category: "Num pixels in 6km buffer outside same concession as central pixel" and interaction with spread risk (Panel B).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Government Punishment

Dummy = 1 if firm investigated	(1)	(2)
Pixels in productive forest in others' concessions burned by fire	-0.1255**	-0.1611
	(0.05849)	(0.1011)
Pixels outside forest estate burned by fire	-0.1395	-0.1819
	(0.09904)	(0.1175)
Pixels in unleased productive forest burned by fire	-0.09042***	-0.01750
	(0.01312)	(0.02587)
Pixels in protected forest burned by fire	0.03249	0.1345***
	(0.04482)	(0.04609)
Total area of fires burned Sep 2014-Aug 2015	0.02951***	0.01310*
	(0.005500)	(0.007483)
Population in fire extent	0.0006448***	0.0007288***
	(0.0001572)	(0.0001441)
Control: Islands	NO	YES
Control: Concession Type	NO	YES
Control: Forest Cover 2000	NO	YES
Control: Concession Area	NO	YES
Observations	600	599
Mean of Dep. Var.	0.157	0.157

Logit regressions. Robust standard errors clustered at level of firm groups. The sample includes only pixels in wood fiber and palm oil concessions in those provinces for which firm investigation lists were published and in which at least one fire was started between September 2014 and August 2015. Omitted category: "Pixels burned in productive forest in own concession burned by fire" . Suppressed categories "Pixels in Malaysia / PNG burned by fire", "Pixels in protected forest in others' concessions burned by fire", "Pixels outside forest in others' concessions burned by fire", "Pixels in protected forest in own concession burned by fire", "Pixels outside forest in own concession burned by fire".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of Proscecutions on Ignitions and Externalities

Dependent variable = Number of fires in pixel*month*year	Pixel Island x MY FEs	Pixel Island x MY FEs	Pixel Island x MY FEs	Pixel Island x MY FEs
Prosecuted region	0.1387			
	(0.2045)			
Risk index in standard deviation units		1.6378***	1.6555***	1.9505***
		(0.1216)	(0.1381)	(0.2796)
Risk index * Prosecuted region		0.2856***	0.8392***	1.6715***
		(0.06414)	(0.1976)	(0.1882)
Risk index * Num pixels in 6km buffer in same concession as central pixel			-0.0005426	-0.001124
			(0.0007773)	(0.0009959)
Num pixels in 6km buffer in same concession as central pixel * Prosecuted region			0.003302***	0.009764***
			(0.001264)	(0.001043)
Risk index * Num pixels in 6km buffer in same concession as central pixel * Prosecuted region			-0.001717**	-0.004645***
			(0.0007081)	(0.001212)
Observations	4,536,857	4,500,388	4,498,648	566,319
Control: Island interactions	NO	YES	YES	YES
Control: Concession Type interactions	NO	YES	YES	YES
Control: Forest Cover 2000 interactions	NO	YES	YES	YES
Control: Concession Area interactions	NO	YES	YES	YES
Mean of Dep. Var.	0.00858	0.00861	0.00861	0.0109

Poisson regressions. Robust standard errors clustered at level of provinces. Sample: Columns (1) to (3): All pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Columns (4): pixels whose buffers contain only own concession land and unleased productive forest inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category: Interaction of risk index and "Num pixels in 6km buffer outside same concession as central pixel".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Impact of Government Ownership on Ignitions and Externalities

Dependent variable = Number of fires in pixel*month*year	M & Y	M & Y
Panel A: Main Effects	FEs	FEs
Government owns concession	-0.3440**	-0.4911***
	(0.1487)	(0.1618)
Control: Island	NO	YES
Control: Concession Type	NO	YES
Control: Forest Cover 2000	NO	YES
Control: Concession Area	NO	YES
Observations	39945420	39873060
Mean of Dep. Var.	0.000974	0.000971
	Pixel	Pixel
Panel B: With Pixel FE and Risk Index	M & Y FEs	M & Y FEs
Risk index in standard deviation units	1.7169***	1.7749***
	(0.05611)	(0.1034)
Risk Index * Government owns concession	-0.1048	-0.007759
	(0.1469)	(0.1588)
Control: Risk Index × Island	NO	YES
Control: Risk Index × Concession Type	NO	YES
Control: Risk Index × Forest Cover 2000	NO	YES
Control: Risk Index × Concession Area	NO	YES
Observations	4,731,300	4,709,160
Mean of Dep. Var.	0.00822	0.00823
	Pixel	Pixel
Panel C: With Pixel FE, Surrounding Land Ownership, and Risk Index	M & Y FEs	M & Y FEs
Risk index in standard deviation units	2.8061***	2.2143***
	(0.2523)	(0.2503)
Risk Index * Num pixels in 6km buffer in same concession as central pixel	-0.01062***	-0.004289**
	(0.002529)	(0.001788)
Risk Index * Government owns concession	1.2389	1.1254
	(1.4612)	(1.3080)
Risk Index * Num pixels in 6km buffer in same concession as central pixel * Government owns concession	-0.007579	-0.003272
	(0.01228)	(0.01102)
Control: Risk Index × Island × Government owns concession	NO	YES
Control: Risk Index × Concession Type × Government owns concession	NO	YES
Control: Risk Index × Forest Cover 2000 × Government owns concession	NO	YES
Control: Risk Index × Concession Area × Government owns concession	NO	YES
Observations	752,040	750,420
Mean of Dep. Var.	0.00824	0.00823

Poisson regressions. Robust standard errors clustered at level of 50km2 grid cells. Panel (A), (B): all pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Panel (C): pixels whose buffers contain only own concession land and unleased productive forest inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category for panel (C): "Num pixels in 6km buffer outside same concession as central pixel" and interactions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$