The Origins and Control of Forest Fires in the Tropics

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Abstract

Pigou (1920) pointed to "uncompensated damage done to surrounding woods by sparks from railway engines" as the canonical example of an environmental externality. We study a modern corollary – illegal tropical forest fires used for clearing land – using 15 years of daily satellite data covering over 107,000 fires across Indonesia. We exploit variation in wind speed and in who owns surrounding land to generate variation in the degree to which the use of fire at a given time and place represents an externality. We find firms overuse fire relative to a case where all spread risks are internalized. However, firms appear partially sensitive to the risks of government punishment, which deters them from burning near protected forest or populated areas on particularly windy days. Counterfactuals suggest that if firms treated all surrounding land the way they treat neighboring populated areas, fires would be reduced by 80 percent.

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

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1 Introduction

Environmental economics is rooted in the study of environmental externalities. Early forerunners of the modern field (Marshall 1890, Pareto 1909, Pigou 1920) highlighted the failure of market economies to properly account for the environmental consequences of economic activity. This failure rests importantly on the possibility that one agent's utility or production function may depend directly on real variables chosen by another without an offer of compensation for their effect (see, for example, Salanié 2000). For example, Pigou (1920) pointed to the "uncompensated damage done to surrounding woods by sparks from railway engines" as the canonical example of an environmental externality.

Much of the early analysis of environmental externalities lay in the theoretical realm, with a focus on developing a consistent framework to analyze market failure as well as 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, Ostrom 1998). In the aftermath of the credibility revolution in economics (Angrist and Pischke 2010), a wave of empirical papers focused on estimating the health and other impacts of different types of environmental externalities, for example, pollution (Chay and Greenstone 2003, Deryugina et al. 2019, Currie et al. 2009), forest fires (Frankenberg et al. 2005, Jayachandran 2009, Koplitz et al. 2016, Kim et al. 2017) and emissions-induced climate change (Schlenker et al. 2005, Burke et al. 2009, Burgess et al. 2017).

By contrast, there has been comparatively less empirical attention given to the economic question of how externalities affect private decision making in the first place – that is, the degree to which private actors change their behavior depending on the extent to which the environmental damage they cause is an externality. This is an important question as the actions of private individuals and firms account for the bulk of environmental externalities we observe in the world and so understanding what drives their decisions is paramount (Greenstone and Jack 2015).[1] Whether

[1] Important 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) which investigates externalities in regulation across political jurisdictions. Other recent work has explored the degree to which external actors can alter private decision making through payments

or not they lessen actions that potentially damage others will largely affect how environmental change unfolds in the tropics, and more broadly.

In this paper, we study this question by examining a modern corollary of Pigou's "sparks from railway engines": tropical forest fires in 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. 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] The decision to ignite an illegal forest fire is *de facto* a decision not to use the safe technology for clearing land. There is a an extensive theoretical (Acemoglu et al. 2012, Acemoglu et al. 2016) and empirical (Aghion et al. 2016) literature looking at how firms choose between production technologies that do and do not have externalities (often in the context of pollution), but this has been less of a focus in the land use literature.

Many features make fires an almost ideal environment in which to analyze private agents' externality-generating activities and what incentivizes them to control how much they are used. Fires are observable from space, and using the data sets we have assembled, we can track their precise ignition point and daily spread. This daily fire data can be superimposed on geocoded maps of different types of land use zones, which vary from highly protected forest such as national parks to areas where property rights are less well defined. Finally, the riskiness of using fire depends on wind speed, which increases the probability a fire spreads to surrounding land. The combination of varying wind speeds over time and space, as well as differences in who owns surrounding land, generates variation in the degree to which the use of fire at a given time and place represents an externality (i.e., we focus on the degree to which landowners are more sensitive to spread risks induced by stronger winds when the area to which an ignited fire would spread is their own land versus owned by others). This

for ecosystem services (see, 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 release of effluents and illegal fishing. The degree to which the firm has to bear the cost of imposing these externalities on others may have a bearing on whether they choose the illegal action with external consequences over the legal alternative with fewer externalities.

enables us to discern the degree to which fire setters take into account the externality that their actions cause, and to consider how alternative policy environments may affect their decisions.

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 (Cochrane and Schulze 1998, Keeley et al. 2004, Gillett et al. 2004, Cruz et al. 2012, Kraaij et al. 2018) whose prevalence may worsen as the earth warms (Parry et al. 2007, Pitman et al. 2007, Abatzoglou and Williams 2016). Globally, fires are particularly prevalent in developing countries containing large stands of tropical forest with economic growth and trade liberalization often driving increased forest exploitation (Harstad 2020). In particular, when we pull together MODIS satellite data for detecting *all* fires across the world for the period 2003-2018, we find that the incidence of fires in heavily forested low-income countries is about four times higher than that in forested high-income countries (see Appendix Figure A.1). Indonesia, which along with Brazil and the Democratic Republic of Congo contains the bulk of the earth's tropical forests, is on the front line of the global fire problem.[3] The degradation of these forests affects the pace of *global* environmental change so how to conserve them has become an international policy concern (Harstad 2020, Hsiao 2020).

Indeed, vast systems of fires regularly erupt in Indonesia and have burned millions of hectares of forest in recent years. While we focus on local externalities due to fire spread in this paper, more broadly, the externalities generated by these fires are manifold and often extend beyond Indonesia's borders, including significant health impacts (Frankenberg et al. 2005, Jayachandran 2009, Koplitz et al. 2016, Kim et al. 2017), ecosystem loss (Yule 2010) and global warming (Page et al. 2002, Permadi and Oanh 2013). 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). Hsiao (2020) estimates that the palm oil industry in Indonesia and

[3]Indonesia is responsible for less than 1% of the global area burned, but accounts for 8% of carbon and almost a quarter of methane emissions from fires, due to the large amount of biomass burned in the tropical forest and peatlands (Van Der Werf et al., 2017). In 2019 alone, Indonesian forest fires emitted around twice the amount of carbon than fires in the Brazilian Amazon forest (Jong, 2019).

Malaysia, where fire is used extensively to clear forest land, accounted for 4.7% of global CO_2 emissions from 1986 to 2016 – more than all emissions from India. Forest fires are therefore among the most environmentally damaging illegal behaviors that firms in Indonesia engage in.

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 MODIS satellites, which record – for every one square km pixel, each day – whether there is a fire in that pixel or not, calculated from the four MODIS flyovers that occur each day (Giglio and Justice 2015). The MODIS datasets can detect quite small fires – as small as 50 m^2 – within each pixel. To track fire ignition and spread, we merge this data across time and space to trace the likely path of each fire; that is, we assign contiguous pixels burning on adjacent days to be part of the same fire. This allows us to determine the most likely location where each fire started and, for each ignition, the area over which it ultimately spread. This procedure yields over 107,000 unique fires in our data, covering all of the main forest islands of Indonesia 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 starters take into account the *type* of land that fires may spread to when making the ignition decision as these may 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) and do not spread beyond their initial ignition area (89%). But the 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. Twenty-nine percent of the total area burned by fires over our study period is outside the initial extent burned by the fires on the day they were ignited. Moreover, a substantial part of the damage from spreading fires is borne by others: across all multi-day fires, 32% 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 likely to be used systematically as part of the clearing process by firms, consistent with the qualitative evidence (Neslen 2016; Cossar-Gilbert and Sam 2015; BBC 2015; Mahomed 2019; Schlanger 2019; Mellen 2019; Karmini and NG 2019; Nicholas 2019). We show that fires are eight times more likely (per hectare) 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 39,077 fires started inside wood fiber and palm oil concessions 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). Doing so, we find that fires are vastly more likely to occur immediately following recent deforestation, consistent with the notion of 'slash and burn' but at an industrial scale. In particular, increasing the share of a pixel deforested from 0 to 100 percent leads to a 279 percent increase in the probability of fire in that pixel in the subsequent year. This is unlikely due to the fact that deforestation simply makes the land naturally more flammable: we find that the year after that – i.e. just two years after the deforestation event – the pixel is in fact less likely to burn than before deforestation took place. We also exploit this slash and burn cycle to see whether the likelihood of using fire post-deforestation varies with district electoral cycles and find that its use is suppressed in election years, when it might perhaps dent the incumbent district head's electoral chances.

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. We use the fact that wind 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 wind speed does, indeed, predict the degree of fire spread: one standard deviation higher wind speed (equivalent to about 5km/hr) increases the area of fire spread by 287 percent.[4]

Combining variation in wind speeds over time and space with cross-sectional vari-

[4] One might also expect wind to predict the *direction* of fire spread in addition to the overall likelihood of fire spread, but this does not appear to be true in the data. We discuss this in more detail below.

ation in who owns surrounding land, we show that fire setters do appear to take the externalities from fire setting into account. Specifically, we find that fires are substantially less likely to be started on windy days in areas where the fire would be more likely to spread inside the same concession compared to when it would spread to land owned by others. Landowners therefore disproportionately avoid burning their own land relative to that of others when fire is particularly risky, suggesting that a Coasian bargain has not been reached. This is interesting as, in theory, concession holders could arrive at agreements to bring forest burning down to an – at least locally – efficient level without the need for government intervention.

We then compare the degree to which firms avoid imposing externalities on adjacent private property depending on the costs doing so might incur, by examining how varying wind speeds interact with heterogeneity in what type of land lies just outside their borders. To do so, for each of the more than 300,000 1km^2 pixels inside palm oil and wood fiber concessions in our data, we calculate what share of the surrounding pixels are made up of different types of land. We focus on four 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 then compare how fire ignitions change on windy versus non-windy days – i.e. when spread risk is high versus when it is low – depending on what kinds of land are nearby.

By classifying land in this way, we can benchmark the degree to which property owners avoid damaging other types of land to the way they behave vis-a-vis unleased productive forest land, which tends to be largely unprotected by the government (or anyone else) and therefore enjoys the weakest property rights. In particular, we examine how landowners treat the risk of fire spread to national parks, which are explicitly protected by the government, and land outside the national forest system, which is typically comprised of villages and smallholders, in comparison to risk of spread to unleased and largely unprotected productive forest land.

As a benchmark, to quantify how government concerns with burning vary across land types, we analyze data from the first government investigations into private firms for causing forest fires in 2015. The haze from the 2015 fires enveloped Indonesia and several surrounding countries, led to a state of emergency of being declared in six

Indonesian provinces and prompted the government to take action. The government published the initials of each firm they investigated, which we match to firm names in our concession data. We can then ask what types of fires were most likely to lead to government investigation. We find that, conditional on the total area burned, the government is substantially more likely to investigate firms whose fires ended up burning land in protected areas and areas with high population density. By contrast, the government does not seem differentially likely to investigate cases where the fire damage is largely in concessions. A fraction of firms that were investigated suffered consequences – such as having their licenses revoked – which indicates some commitment of government to punish landholders whose fires end up burning national parks and populated lands.

We then bring in our data on fire externalities and compare how landholders treat externalities on the types of land for which the government is potentially a protector to how they treat externalities on other private lands. We show that, indeed, the relative weights on different types of fires the government appeared to use in these investigations line up with the relative weights on different types of risks that firms appear to use when deciding whether or not to use fires. 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 in terms of fire spread and local damage.

The results thus suggest that firms are strategic in two senses: 1) they overuse fire relative to what they would do if all spread risks were internalized, but 2) they do take into account the risks of government punishment and this deters them from burning near protected or highly populated areas. But on net, the social damages from fires still vastly exceed the likely private benefits – for example, the estimated external damages for the 1997/1998 Indonesian fires range from 1,286 (Glover and Jessup 1999) to 6,074 (Varma 2003) 2020 USD per ha burnt, while the average private benefits (difference in per ha cost of burning versus mechanical clearance) average around 52 2020 USD per ha after taking into account fertilizers and other costs (Guyon and Simorangkir 2002). Benefit cost ratios between 0.04 and 0.008, which lie well below 1, suggest that while qualitatively the government is deterring the fires that are relatively more costly, on net the government may wish to deter substantially more fires than it is currently doing.

Given this, the final part of the paper uses our analysis to derive some implications for the design of policies to better control these externalities, taking into account the responsiveness of private actors that we estimate here. Stopping fires and conserving tropical forests are now considered key nature-based solutions for confronting climate change, but how to design effective policies to achieve this remains a challenge (Girardin et al. 2021; Chausson et al. 2020; Seddon et al. 2020; Melo et al. 2021; Mori et al. 2021).[5] We find several results. First, we consider the scope of land zoning policies, which have been widely used by the Indonesian government in the past. We find that even if firms treated all surrounding land the way they treat their own land – i.e. a fully-Coasian solution where who owns the land does not matter for fire setting behavior – fires would only be reduced by 14%. This suggests that creating better property rights on unleased government land, and relying on private solutions à la Coase, will only have a relatively small effect on fires. Similarly, our counterfactuals suggest that a tort reform that allowed existing concessions to recover damages – i.e. so that land owners treated all surrounding existing land in other private concessions as if it was in their own – would only reduce fires by 6%.

Second, we consider stronger incentives generated by meting out punishments for setting fires – a policy in the spirit of Pigou. We simulate what would happen if enforcement were to increase such that existing property owners treated the risk of fire spread – anywhere – the same as they do that in the categories the government currently punishes most severely, i.e. populated areas and national parks. We find that this would have a substantial effect: if firms were as concerned about spread risks to surrounding lands as they are about spread to populated areas or protected forest, fires would be reduced by 80% or 67%, respectively. By comparison, an enforcement regime that prevented *any* fires from spreading outside the concession of ignition would result in an estimated 23% reduction in the area burned, while entirely preventing spread into protected and populated areas alone would result in only a 2% reduction in the area burned. These results are consistent with evidence in Souza-Rodrigues (2019), which estimates a model of demand for deforestation on private properties in the Brazilian Amazon and finds that counterfactual incentive-based

[5]This concern is both national and international. For example, in 2010 Norway and Indonesia entered into anagreement with Norway committing $1 billion dollars in exchange for reductions of deforestation in Indonesia. In this REDD+ (reducing emissions from deforestation and forest degradation) framework, payments would be made ex-post for achieved reductions in deforestation compared to the 'business-as-usual' rate.

policies may be very effective in reducing deforestation.

The remainder of this paper is organized as follows. Section 2 puts together the necessary data sets to look at when and why forest fires are started. Section 3 describes the patterns of forest fires in our empirical setting and examines their relationship with spatial land use and land clearance. Section 4 looks at results on factors that affect the propensity to start forest fires. A key finding is that both public and private regulation have not been effective in containing forest fire externalities. To gain insights into what policies might be effective, Section 5 considers how different policy counterfactuals would affect the extent to which forest fires are started and spread. Section 6 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 130 million hectares, equivalent to the size of the U.S. states of Texas, California, and Washington combined. This comprises about 70% of Indonesia's total land area, and is almost twice as large as the U.S. national 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, two very large pulp mills in Riau province have a combined capacity to process over six million tons of pulp and paper products annually and pulping from two of Indonesia's largest firms is estimated to have been responsible for the deforestation of over 2.5 million hectares.[6] Indonesia is

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

also the world's largest producer of palm oil (Hsiao 2020), 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 (i.e. the land not in a concession) 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. The remaining unleased production forest is considered to be 'no man's land', with unclear ownership and extraction rights. Thus though 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 that are strictly protected by 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.

Despite the existence of legislation regarding forest clearing and zoning, adherence to these laws is imperfect. For example, district heads (responsible for monitoring legal logging and controlling illegal logging since 1999) have been found to allow logging outside official concessions (Resosudarmo et al. 2006). They also facilitate the creation of new oil palm plantations inside national forest areas and sanction the transport and processing of illegally harvested logs (Casson 2001). Incomplete documentation of land ownership also renders the legitimacy of some land clearing activities unclear.

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. Fire is attractive to concession holders because it is cheap: for example, estimates from Riau province in 2000 suggest that burning primary forest is 44% cheaper than alternative clearance methods (e.g. bulldozers) for oil palm plantations, and 70% cheaper for wood fiber and timber plantations (Simorangkir 2007). Other benefits of fires 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.[7] On zoning, the 1967 Basic Forestry Law gave the national government the exclusive right of forest exploitation in the forest estate (ROI 1967, Barber 1990). This law centralized government control over the forest and enabled development of the oil palm, wood fiber, and timber sectors. The zoning of land into protection and production forest was 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 and gave district governments an important role in enforcing forest policy (Burgess et al. 2012), 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.[8]

In a similar vein, controls on conversion of land have also been used to try to prevent fires. To tackle fires associated with degraded peatlands, a temporary moratorium on granting permits to clear primary forests and peatlands for plantations or logging was instated in 2011. After being deemed relatively ineffective, peatland protection was strengthened in response to the 2015 fires by the removal of an exception for already existing concessions and the creation of a dedicated Peatland Restoration Agency.[9] In 2018, an additional three-year moratorium on new oil palm plantation licenses was issued, in combination with a call for regional governments and ministries to review existing licenses.

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,

[7] Detailed sources relating to all policies described in this section are described in Appendix J.

[8] 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 two hectares 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 forest.

[9] 2015 also saw a presidential instruction requiring all levels of government to develop land and forest fire management systems and to apply sanctions for businesses who do not implement fire management.

the 1999 Forestry Law increased anti-fire efforts, stipulating fines of up to 5 billion Rupiah and imprisonment for up to 15 years for burning forest, 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 creating the 2015 fires. Some of these prosecutions resulted in high-profile court decisions mandating hundred-billion Rupiah fines. However, over three trillion rupiah (220 million USD) in fines from ten companies had still not been paid by 2019.

Indonesia's forest fire policies, therefore, 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).[10] Second, enforcement of policies aiming to control forest fires is often weak, from regulations granting concession rights through to punishment for offenders.[11]

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 start with data collected by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). 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 the 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.

We link daily MODIS observations over time in order to track the ignition and spread of individual fires across Indonesia during our study period. We create a 'fire' observation using an iterative procedure. This starts with an initial fire, denoted A_X,

[10] While the Ministry of Forestry can rezone land to prevent uses that are likely to lead to fire, ambiguous land use planning, which is rife with overlapping tenure claims and conflicts, often makes this difficult.

[11] 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 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).

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 cloud 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. The white boxes A, B, and C denote three 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. Summary statistics are presented for all fires, but we restrict attention to Indonesia's major forested islands (excluding Java and the Lesser Sunda Islands) and to pixels inside the forest estate, yielding a total of 107,334 fires. 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 39,077 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 well in Appendix G.

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 referred to as 'protected forest', as opposed to forest in which production can take place. The map, which we obtained from Global Forest Watch, is shown in Figure 2, displaying forest estate and conservation/ protection zones across Indonesia. Third, we overlay these broad categorizations with concession boundaries. Data were obtained from Global Forest Watch on the location 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 from different 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.[12]

Figure 3 shows the distribution of concessions in Sumatra, alongside areas demarcating the forest estate and protection/ conservation zones. As shown in the Figure, the majority of concession holdings are within the forest estate but outside protection and conservation zones.

These classifications yield four land categories of interest for the analysis: protected forest, productive forest (land in the forest estate that is not in protected areas) inside concessions, unleased productive forest (land in the forest estate that is neither in protected areas nor inside concessions) and areas outside the forest estate.[13]

2.4.3 Deforestation data

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

2.4.4 Wind 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.[14] 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

[12] For instance, the data are known to be incomplete and subject to inaccuracies as a result of overlaps between different concession types where permits are issued by different ministries, out of date maps and different dates of data from different provenances (Greenpeace 2015).

[13] 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).

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

interpolate this data in order to assign a wind speed to each of the 1km^2 pixels used in our analysis.

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 was released by the Ministry of Forestry and the Environment.[15] This followed a comprehensive investigation to uncover the firms that had started the devastating fires of 2015 which led to thick smogs across Indonesia, Singapore and Malaysia. All firms identified in the initial investigative 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.

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 from previous years. Section 3.3 looks at whether the use of fire following deforestation varies across the district electoral cycle.

3.1 Descriptive statistics: fire and land-use

To illustrate the relationship between fires and land use, Figure 4 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 grid cell shown in Figure 4

[15] 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.

represents a grid cell in which we detect at least one fire ignition. 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. Note that not all of the regular forest estate is allocated to a concession; substantial parcels of the forest estate remain unallocated. We refer to these areas as unleased productive forest.

Several patterns are worth noting. First, there are a vast number of fires. The area shown in the map covers approximately 7,700 square km, slightly larger than the US state of Delaware, and has over 3,400 separate fire ignitions during the period of our study. The fires are clearly geographically clustered in areas of intense fire activity.

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, previously known as the Tasik Serkap Wildlife Reserve) shown in the middle-right of the map. Similarly, we see almost no fires 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 of over 100,000 fires.[16] 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. As in the example described above, ignitions are disproportionately less likely to occur in protected areas, and more likely to occur in production forest areas.

The pattern is even more striking when we look across different concession types in Appendix Figure A.2(b), which shows that fires are much more likely in the types of concessions associated with land-clearing. Specifically, 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 –

[16] As discussed above, we exclude Java and the Lesser Sunda Islands, which have relatively little forest, from our analysis.

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

The data above suggest that fires are more likely in the types of forest concessions – oil palm and wood fiber – where land is cleared and converted to alternate uses, rather than in logging concessions, which focus on selective logging. To establish this link more precisely, however, 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 5 shows part of the same area of Riau province as Figure 4, zoomed in further given the high spatial resolution of the deforestation data. The map shows ignition areas in 2013, with 1km boxes (the resolution of the MODIS fire data) illustrating all pixels where an ignition was detected in 2013. We overlay this with the fine-resolution deforestation data, showing in orange all deforestation that took place in 2012. The map illustrates that, at least in this area, almost all of the ignitions took place in areas that had experienced deforestation the previous year.

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

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

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.[17] 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.[18]

Two important aspects of this specification are worth noting. First, pixel fixed effects are important, because they capture fixed differences in land use (e.g. protection areas vs national park areas) and land 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 1, focusing in on wood fiber and palm oil concessions.[19] We find that fire ignition is more likely in recently deforested areas. The magnitudes are substantial: a 1km pixel that was completely deforested is expected to have 279% 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). Combined, these results suggest a clear picture: many of the fires we observe appear to be a systematic part of the land clearance process.

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3.3 Are fires responsive to government?

As power was decentralized after the fall of Soeharto, district governments were empowered to manage the natural resources within their jurisdictions (see Burgess et al. 2012). Democratic elections of district heads were asynchronous as they followed when terms of Soeharto-appointed heads came to an end (Skoufias et al. 2011; Martinez-Bravo et al. 2017).

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

[18]These and subsequent results are robust to clustering at 25km x 25km or 100km x 100km grid cells, see Appendix I.

[19]Appendix Table G.1 and G.2 show this for all concessions, and all forest land, and show similar patterns.

We can therefore exploit the slash and burn cycle portrayed in Table 1 to see whether the propensity to start fires in previously deforested pixels varies across the electoral cycle. This will give us insights both into whether district governments play a role in containing fires and whether that enforcement depends on political incentives. Forest fires (particularly when they run out of control) are both highly visible and potentially damaging to the local electorate and so political incentives to suppress them might vary across the electoral cycle. To the extent that we find that fires do follow the political cycle, it also reinforces the idea that these fires are set intentionally.

To look at this, we restrict the sample to pixels experiencing some deforestation in year $t-1$ and then estimate the incidence of fires depending on the location of a district in its 5-year election cycle. We also do this across different types of production and protected forest where the value of starting fires may vary (see Section 3.1). We estimate robust Poisson regressions with pixel-level fixed effects, thus restricting attention to pixels which experienced deforestation in multiple years.[20] This is possible because the deforestation data from Hansen et al. (2013) has a much finer spatial resolution than the MODIS fire data (30m×30m compared to 1km^2). We therefore exploit the fact that there are often multiple deforestation events in a given pixel in different years, which allows us to include pixel fixed effects and examine whether there are more fires in t conditional on a deforestation event in $t-1$, depending on position in the district election cycle, holding everything else about the pixel constant.

The results are shown in Table 2. In column 1 we see that for the whole forest estate we can reject the hypothesis that fire setting following deforestation is flat over the electoral cycle (p-value < 0.01). Relative to fires in the year prior to the election, there is a clear drop in fires in the year of an election. This pattern is driven by fires in productive forest (columns 2, 3, 4) with a drop in the incidence of fires being particularly sizeable for oil palm concessions. For oil palm concessions, we estimate that burning following deforestation is around 38% lower in the election year compared to the year prior to an election. We also find that the decline in fires is *only* in election years, bouncing back to pre-election levels in the year following the

[20] We model the conditional burning probability as $\mathbb{E}\left[y_{ijt}\right] = \gamma_i \exp(\sum_{\tau=-2}^{1} \beta_\tau \text{Election}_{j,t-\tau} + \delta_t)$ where y_{ijt} indicates the number of fires a pixel i in district j experiences in year t, after having been deforested in year t-1. γ_j and δ_t are fixed effects at the pixel and year level, respectively. Of the nearly 1.3 million pixels, 66,958 pixels with multiple deforestation events and some variation in slash-and-burn provide the variation used to estimate the model.

election (shown in the test of 'this vs. last' in the table.) In strict contrast, we do not observe electoral cycles where conversion of forested land to other uses is prohibited.

These results show that firms are least likely to use fire as a means of clearing recently deforested land when the electoral incentives for district governments to suppress fires are strongest.[21] This points to more stringent enforcement of forest fire regulations during election years when the smog and other damages they generate may dent the electoral chances of the district head. This is an important as it goes beyond establishing the presence of the slash and burn cycle in Section 3.2 to show that government policy affects the decision of what technology to use to clear land once a parcel of land has been deforested.

4 Externalities and the Control of Forest Fires

The three pieces of evidence from Section 3 on where fires are set, when they are set and whether they respond to electoral incentives all point 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.

4.1 Ignitions, wind speed, and fire spread risks

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 areas of initial ignition and areas of subsequent fire spread. 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 counts only spread occurring over multiple days, rather than spread within

[21] This result lines up with other work we have done looking at political cycles in *aggregate* ignitions and area burned, which considers political cycles in total ignitions each year at the district level (Balboni et al. 2021). Here, we are able to exploit recent deforestation as a trigger for fire (see 1) by focusing only on pixels deforested in $t-1$, and running regressions at the pixel level. The fine-grained approach here allows us to include pixel fixed effects, which capture factors such as soil types which may influence flammability. The analysis here also allows us to zero down on the oil palm and wood fiber areas of the productive forest that we know from Section 3.1 are the most prone to burning.

a single day.

Nevertheless, 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, 32% of the total land burned is outside the concession in which the fire was ignited.

The risks of fire spread may vary over time depending on wind speed. Greater winds can increase fire spread for several reasons. Increased winds supply more oxygen, which increases the intensity of the fires. Winds also exert pressure on the fire to move, igniting new areas, rather than simply burning existing areas.[22]

To investigate this in our data, we merge our fire data with data on average prevailing wind speeds in each month, obtained from the NOAA global wind speed model, as described above. To isolate the effect of windspeed from other factors that may influence fire spread, we implement a fixed effects Poisson specification of the form:

$$\mathbb{E}[FireSpread_{imt}] = \gamma_i exp(\beta_1 Windspeed_{imt} + \beta_2 Ignitions_{imt} + \delta_m + \delta_t) \tag{2}$$

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 (measured in standard deviation units), $Ignitions_{imt}$ 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.[23] As above, we use robust standard errors to allow for arbitrary distributions

[22]While intuitively one may expect the direction of the wind to influence the direction of fire spread, wind direction at the ground is very complex and influenced by the convection currents of the fire itself, and is notoriously hard to predict. In our data wind direction does not predict the direction of *fire spread*, although there is evidence from other contexts that wind direction may influence the direction of *smoke spread* from fires, which occurs at much higher altitudes and is hence more influenced by prevailing higher-altitude wind directions (e.g. Rangel and Vogl (2019)).

[23]We have also explored robustness to alternative fixed effects strategies. In particular, for all ensuing regressions including pixel, month and year fixed effects, we find similar results including pixel and month-year fixed effects or pixel and month-year-island fixed effects, which could potentially

of the error term.

The results are shown in Table 3 and demonstrate that an ignited fire is more likely to spread to cover a larger area when prevailing winds are strong. Column 1 shows the results with just pixel fixed effects, column 2 shows the results with both pixel and time fixed effects. Because these models include pixel fixed effects – which is important to capture fixed differences in spread risks across different soil types and other fixed land characteristics – this regression is identified on the 5,444 pixels for which we observe at least one spreading fire during our period.

The resulting magnitudes suggest that wind substantially increases the risk of fire spread. Focusing on the results in column 2, a one-standard deviation increase in wind speed – equivalent to about 5km/hr – increases the extent of fire spread by 287%. Combined, the results in this section suggest not only that fire is risky due to the risk that it spreads, but that that this risk is predictable – high winds substantially increase the risk of spread.

4.2 Externalities in fire spread and containment

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 may be of less concern to a landowner than a fire that spreads into a city or town. Similarly, fire spreading into a protected national park might be more of a concern than it spreading into unoccupied land.

To measure the degree to which potential fire users are deterred by the externalities they may cause, we use the product of two factors which together create riskiness of starting a particular fire that varies across time and locations. First, as described above, we use monthly data on wind speed at each pixel (as described in Section 2.4), which yields spatial and temporal variation in the probability of fire spread. Second, there is local variation in the cost of fire spread driven by the types of land that surround each pixel. To quantify the latter, for each pixel in our data, we construct the share of pixels by land category in a 6km radius surrounding each pixel, exemplified in Figure 6.[24] The expected external cost of starting a fire in a particular

capture year-specific seasonality in addition to overall seasonality; see Appendix H for details.

[24] 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.

pixel in a particular month depends on the product of these two factors – wind speed in that pixel in that month, and the composition of the types of land that surround the pixel.

We next consider whether fire-setting behavior is influenced by the likelihood of fires spreading to particular land types. We consider the effects of fires being differentially likely to spread to (i) land with the same versus different owners, and (ii) land types where there may be a differential threat of punishment. In both cases, we consider the impact on ignition probability and, conditional on a fire starting, on the probability of containment.

We investigate this with the following specification:

$$\begin{aligned} \mathbb{E}[Ignitions_{imt}] \quad = \quad & \gamma_i exp(\beta_1 WindSpeed_{imt} + \\ & \textstyle\sum_j \beta_2^j NeighborLandType_i^j \times WindSpeed_{imt} \\ & + \beta_3 X_i \times WindSpeed_{imt} + \delta_m + \delta_t) \end{aligned} \tag{3}$$

where $NeighborLandType_i^j$ is the share of land in the 6km radius buffer surrounding pixel i that is in land type j; the coefficient(s) on this interaction, β_2, capture(s) whether potential fire setters differentially use fires depending on the magnitude of their expected externality. Equation (3) includes pixel fixed effects (γ_i) and time fixed effects (δ_m, δ_t), which absorb fixed pixel characteristics and common time shocks. We also include interactions of wind speed 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), and with baseline forest cover. We consider specifications where $NeighborLandType_i^j$ is divided according to whether or not land in the 6km buffer surrounding pixel i is in the same concession as pixel i (for land inside concessions only), and where $NeighborLandType_i^j$ is divided according to land type classifications.

The identification thus rests on comparing areas surrounded by different land types on more versus less windy days. As such, it is important to consider the intertemporal dynamics of wind. In this context, wind is positively though imperfectly serially correlated across months.[25] Given this, it is likely that the costs of waiting for a non-windy period 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. This supports the identification strategy used, which abstracts from inter-temporal substitution of ignitions.

[25]Month-to-month serial correlation is 0.4; see Appendix Table B.1.

4.3 Magnitude of externalities: burning your own vs others' land

We begin by examining results where we split land surrounding each pixel based on what fraction is part of the concession in which the pixel is located, versus is 'external' to the concession owner. To do so, we estimate equation (3), using as the the key $NeighborLandType$ interaction the variable $FractionBufferOwn$, which calculates what share of the 6km buffer pixels is in the same concession as the central pixel.

The results, shown in Table 4, reveal that fire ignitions inside wood fiber and palm oil concessions are significantly less likely on windy days in areas where the fire would be more likely to spread inside the same concession compared to where spread would be external. Table 4 includes specifications including pixel, month and year fixed effects and successive controls for wind speed × island, wind speed × concession type, wind speed × 2000 forest cover and wind speed × concession area.[26,27]

The coefficients of interest are interactions, i.e. they estimate $\frac{\partial^2 \mathbb{E}[Ignitions_{imt}]}{\partial WindSpeed \partial FractionBufferOwn}$, and hence require some care to interpret. The negative coefficients we find says that land owners are more sensitive to spread risks (induced by stronger winds) when the area to which the fire would spread (i.e. the buffer zone) is largely their own land. To gauge magnitudes, we consider the semi-elasticity of ignitions with respect to the share of the buffer with the same owner as the central pixel. This can be interpreted as the percentage change in ignitions resulting from an additional buffer pixel in one's own land, for a given wind speed. Taking the derivative of the estimating equation 3 with respect to the fraction of the buffer in the same concession as the central pixel and re-arranging terms yields this semi-elasticity as:

$$\frac{\partial \mathbb{E}[Ignitions_{imt}]}{\partial FractionBufferOwn_i} / \mathbb{E}[Ignitions_{imt}] = \beta_2 WindSpeed_{imt} \tag{4}$$

where β_2 is the estimated interaction coefficient.

The estimated β_2 coefficients in Table 4 – i.e., the coefficients on $WindSpeed$

[26] In an especially demanding specification including concession fixed effects interacted with wind speed, fire ignitions inside concessions are again found to be less likely on windy days in areas where the fire would be more likely to spread inside the same concession compared to where spread would be external, although the results are no longer significant at conventional levels in this case (see Appendix Table C.1).

[27] Appendix tables F.1 and F.2 present results separately for wood fiber and palm oil concessions: while effects are stronger statistically in the case of the former, the point estimates are similar in both cases.

interacted with $FractionBufferOwn$ – range from -0.007766 to -0.002124. At the mean wind speed, these coefficients imply that one additional buffer pixel in one's own land decreases ignitions by 0.2%-0.7%. We next use these semi-elasticities to ask what the effect would be of a typical buffer being entirely owned by the same owner as the central pixel. Using the fact that the 6km buffers contain 137 pixels and that the mean number of buffer pixels in the same concession as the central pixel is 96, this suggests that a typical buffer being owned entirely by the same owner as the central pixel would reduce ignitions by 8% to 25% when the wind speed takes its mean value. An equivalent calculation when the wind speed is at the 95th percentile value suggests that this effect would be much larger – 22% to 61% – on very windy days.[28]

The central results in Table 4 thus reveal that fire setters do appear to take the externalities from fire-setting into account, suggesting a failure of Coasian (1960) bargaining to fully internalize externalities. In principle, part of the explanation for this might lie in the difficulty of contracting where pixel buffers contain land owned by several different parties. We do not, however, find significantly different results in specifications that restrict attention only to those pixels whose entire 6km buffer is in either the same concession as the central pixel or in a single other private party's concessions, suggesting that the externality is present even in cases involving only a single property border between two private firms (see Appendix Table D.1). This is a tighter test of Coase and suggests that multiple-party contracting issues alone are not necessarily driving the results. Appendix Table D.2 also presents results for the subset of buffers where pixels are either in the same concession as the central pixel or in unleased productive forest, where Coasian bargaining might be least likely given that property rights are least well defined in unleased productive forest. While the point estimates on the interaction terms are in general larger in this case, the results are not significantly different from those in the main specification in Table 4.[29] The fact that results for concessions surrounded by concessions look similar to those for concessions surrounded by unleased productive forest futher suggests that Coasian

[28]Note that direct (i.e., uninteracted) effects of $FractionBufferOwn$ are captured in the fixed effect of equation (3), and hence do not appear in equation (4). Presumably, one would expect these to be negative (more land in own buffer would lead to more caution about use of fire, even with little wind), in which case the estimates in this paragraph are a lower bound.

[29]We provide a formal statistical test of this in Table 6 below, which shows that nearby unleased productive forest is in fact treated no differently than nearby other private concessions.

bargaining is not playing a role in containing fires. This is worth noting, as with weak government enforcement one would hope that private interests might help to control the use of fire. This does not appear to be the case.[30]

It is possible that strategic interactions between neighbors may be important for the results if, for instance, neighbors have correlated incentives to start fires such that coordinated fires are started simultaneously by neighbors or fires are ignited with neighbors' acquiescence.The results in Table 4 demonstrate that being surrounded by one's own land has a deterrent effect on fire-setting on windy days, suggesting that it is unlikely that landowners wish to clear large areas of their concession at once (for instance to take advantage of economies of scale). If landowners do not aim to burn large swaths of their own land simultaneously, it seems less likely still that concession holders should necessarily want to burn their land at the same time as their neighbors. Instead, landowners may be expected to burn different plots at different times according to, for instance, whether the plot is still forested or whether and when it has been planted with plantation crops. Nevertheless, to investigate the possibility of strategic interactions between neighbors, we estimate the same specification restricting attention to situations where such effects may be less likely, namely (i) fires whose initial size is one pixel, and (ii) fires where no neighboring concession starts a fire in the same period. In both cases, the results are statistically indistinguishable from the main results (see Appendix Tables E.1 and E.2 respectively).

In addition to studying the impacts on fire ignitions, we also investigate whether, conditional on a fire starting, it is less likely to spread when the spread would be to neighbors' land. 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. We estimate this using the following OLS specification to determine how the spread of fire f ignited in pixel i at time t is influenced by the prevailing wind speed interacted with surrounding land type:

[30] We find weak evidence that single-concession firms may be those driving the finding that fire setters take the externalities from fire-setting into account. While this effect is attenuated for multi-concession firms, the attenuation is not driven by the largest firms (measured by the number of concessions held by the firm).

$$
\begin{aligned}
FireSpread_{fimt} \quad = \quad & \alpha + \gamma_i + \delta_m + \delta_t + \beta_1 WindSpeed_{imt} \\
& + \textstyle\sum_j \beta_2^j NeighborLandType_i^j \times WindSpeed_{imt} \\
& + \beta_3 X_i \times WindSpeed_{imt} + \epsilon_{fimt}
\end{aligned} \tag{5}
$$

The results of this analysis, shown in Table 5, reveal no significant effect in this case, suggesting that the main margin is the ignition of new fires, not fire-surpressing activity once fires are lit.

4.4 Does it matter who your neighbors are?

We next benchmark the degree to which property owners avoid damaging other types of land to the way they behave vis-a-vis unleased productive forest land, which tends to be largely unprotected by the government (or anyone else). We implement this by re-estimating equation (3), dividing $NeighborLandType_i^j$ 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 (which is the omitted category). We also examine the overall population density in the buffer area as a measure of the risk that fires would spread into populated areas.[31]

The results of this exercise are shown in Table 6 (ignitions) and 7 (spread). The results in Table 6 suggest that concession owners make more of an effort to avoid starting fires that risk spreading into their own land, protected forest or land outside the forest estate, relative to those that risk spreading into unleased productive forest. They appear to treat other firms' concessions similarly to land that lies in the unleased productive forest estate, suggesting that private party enforcement is not very strong in this context. We can again use the semi-elasticity of ignitions with respect to the share of the buffer that is comprised of different land types (e.g. equation (4)) to interpret the magnitude of these coefficients. The results suggest that one additional buffer pixel in protected forest versus unleased productive forest decreases ignitions by 0.9% at the mean wind speed and 2.7% when the wind speed is at the 95th percentile.

[31] 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 deterrent effect of surrounding land outside the forest estate is even stronger: in this case, these figures are 1.6% and 4.6% respectively.

The containment results broken down by land type in Table 7 again show little impact on fire spread based on nearby areas, suggesting that again ignitions are the main margin affected.

4.5 Do agents internalize government preferences?

Intentionally burning areas of the wood fiber and palm oil forest concessions we study was illegal throughout our study period, but the government may implicitly place different sanctions on different types of fires depending on what types of land are damaged. To back out the government's implicit weights on different types of fire damage, we use data on firms investigated by the Indonesian government for forest fire violations, as described in Section 2.4, to consider what the Government punishment function looks like. We then consider how aligned this is with the fire-setting behavior of concession holders.

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

$$\begin{aligned} Pr(Punished_c) &= F(\alpha + \textstyle\sum_{j \neq o} \beta_j BurnedArea_c^j + \gamma TotalBurnedArea_c \\ &\quad + \delta PopnBurnedArea_c + \eta ConcArea_c) \end{aligned} \tag{6}$$

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; $PopnBurnedArea_c$ is the population in areas burned by fires started in concession c during that time; and $ConcArea_c$ is the area of concession c. α captures island or province fixed effects.[32] Standard errors are clustered at the level of firm groups, defined according to firm group name where this is available and firm name otherwise.

The results are shown in Table 8. Larger fires are clearly more likely to be pun-

[32] 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.

ished; conditional on fire size, the government is also likely to target larger concessions. Looking in terms of the types of area burned suggests a few key patterns. First, the government is substantially more likely to punish those firms owning concessions whose fires spread into populated areas. Second, the government is also likely to target those firms owning concessions whose fires spread into protected zones (though the coefficient is statistically significant only in the specification with province fixed effects). Pixels in unleased productive forest are treated no differently than land in the concession itself. What is remarkable about these patterns is that they very much mirror the patterns of avoidance behavior we saw in Table 6, suggesting that concession owners substantially avoid the same types of land that trigger government investigations. This suggests that firms do behave as if they are responding to Pigouvian (1920) style incentives, and that these are stronger than the Coasian solution for burning other private lands.

5 Counterfactuals and Implications for Policy

In this section, we use our estimates to consider several counterfactual simulations in order to understand how changes in policies directed at containing forest fires would change the degree of fire use. As discussed in Section 2 the central government has far-reaching powers to control land allocations via land zoning policies and the issuing (and enforcement) of fines and other penalties for setting illegal forest fires within the forest estate. Given the important role of these two types of policies in controlling fires, we simulate the effect of hypothetical modifications of these policies which can, in principle, be enacted by the state.

Each simulation exercise is discussed in turn in the subsections below, and the full set of results is summarized in Table 9.

5.1 Counterfactual land zoning policies

The results in Section 4 indicate that a more spatially concentrated allocation of concession rights should reduce the incidence of fires. This arises because a more spatially concentrated allocation of concessions increases the likelihood that a given pixel's buffer has the same owner as the central pixel and, as shown in Table 4, this has a deterrent effect on externality-inducing fire-setting. We investigate this by using the coefficients estimated in Table 4, combined with a simulation exercise that achieves a more concentrated allocation of concession rights by assigning all concessions to have a single owner while keeping constant the total area allocated to concessions. It is worth noting that this counterfactual runs counter to current Indonesian policies, where bans on the transfer of concession rights as well as limits on the number of concessions held by a firm within a district effectively limit the spatial concentration of land.

The first step in the simulation exercise is to estimate the coefficients in equation (3), focusing on $FractionBufferOwn_i$:

$$\begin{aligned}\mathbb{E}[Ignition_{imt}] = \gamma_i exp(&\beta_1 WindSpeed_{imt} \\ &+ \beta_2 FractionBufferOwn_i \times WindSpeed_{imt} \\ &+ \beta_3 X_i \times WindSpeed_{imt} + \delta_m + \delta_t)\end{aligned} \tag{7}$$

We then simulate the value of the dependent variable under the counterfactual scenario by replacing $FractionBufferOwn_i$ with the number of buffer pixels in the same 'aggregate concession' as pixel i under this counterfactual, keeping all other covariates (including the pixel fixed effects) unchanged:[33]

$$\begin{aligned}\mathbb{E}[\hat{Ignition}_{imt}] = \hat{\gamma}_i exp(&\hat{\beta}_1 WindSpeed_{imt} \\ &+ \hat{\beta}_2 FractionBufferOwnAgg_i \times WindSpeed_{imt} \\ &+ \hat{\beta}_3 X_i \times WindSpeed_{imt} + \hat{\delta_m} + \hat{\delta}_t)\end{aligned} \tag{8}$$

This exercise suggests that assigning all concessions to have the same owner would result in a 6% reduction in ignitions inside wood fiber and palm oil concessions within the forest estate over our study period as a result of lower externality-inducing fire-setting.

The previous counterfactual experiment can also be extended to consider how far ignitions would be reduced if agents treated *all land* – including land not already allocated to concessions – as if it were their own concession land, using the same approach but setting $FractionBufferOwn_i$ to be equal to 100%. In this case, the simulations suggest that ignitions would instead be reduced by 14%.

[33]This implies that pixels in which no ignitions were observed over the study period will also contain no ignitions under the counterfactuals. While some covariates might also be expected to change under the counterfactuals, the key effect of interest is the change in incentives induced by the changing externality effect.

The results in Section 4 also indicate that fire-setters are deterred by the likelihood of a fire spreading into neighboring protected forest. This points to an alternative potential policy: namely, zoning more land to be designated as protected land. Such systematic zoning has been a regular policy tool since 1982, when the Indonesian government presented a national conservation plan which increased the protected area to around 10% of Indonesia's total land (Jepson et al. 2002).[34] One approach one could feasibly take is to zone all remaining land in the national forest that has not yet been leased out as protected forest, with concomitant enforcement of fires spreading into those areas. We calculate the implications of this through a similar approach, i.e. designating unleased productive forest to be protected forest land and using the estimated coefficients in Table 6. This exercise suggests that this alternative policy would result in a much larger decline in ignitions inside wood fiber and palm oil concessions within the forest estate over our study period, at 26%.

The results in Table 6 reveal that buffer land outside the forest estate – which is where the population lives – has the strongest deterrent effect on would-be fire-setters of all of the land types considered. The final counterfactual simulation examines the potential reduction in ignitions if agents acted as if all land in each buffer were in this land category. This may not be feasible, of course, but it is a useful counterfactual to illustrate the degree to which enhanced government enforcement could matter.[35] This counterfactual simulation results in a sharp 80% reduction in ignitions were agents to treat all land as if it were land outside the forest estate. A slightly smaller reduction of 67% would be achieved were agents to instead treat all land as if it were protected forest.[36]

The implementation of policies such as those described here would of course be

[34] Over the following decades, both new protected forests were designated, and large shares of existing protected forests were re-converted to production forest (Jong 2020). Recent court rulings have restricted the power of the central government to designate new protected areas (Enrici and Hubacek 2016).

[35] In this case, the counterfactual aims to capture only the deterrent effect of surrounding land associated with all buffer land being treated as if it were land outside the forest estate. Of course, reassigning buffer pixels inside concessions to be a different land type would mechanically also change the categorization of the central pixels, and therefore the sample of ignitions considered in the analysis, but given that this is not the effect of interest that we are aiming to consider with this counterfactual we abstract from this effect. This effect therefore captures the effect of increased enforcement as if all land outside a concession was in a particular land category.

[36] Note that this result is substantially higher than in the calculation in the previous subsection because we are now considering the counterfactual of treating all land as if it were protected, whereas the previous counterfactual only rezoned 'unleased forest estate land' as protected.

likely to give rise to general equilibrium effects and practical implementation challenges that complicate the interpretation of these estimates. For instance, designating more land as protected areas may lead to a reduction in the intensity of government enforcement; increasing land concentration might also have adverse economic and social consequences in the long run (see, e.g., Smith 2021); and political economy considerations would likely loom large in interactions between landowners and government in changing the distribution and concentration of land rights. The aim of the current exercise is to use the paper's estimates to investigate the potential efficacy of alternative land zoning and Pigouvian policies, such that a quantitative treatment of broader such effects is beyond the scope of this analysis, but such factors may be important in governing the impact of these policies in practice.

5.2 Counterfactual enforcement regimes

Next, we consider alternative policies targeted at more effective enforcement of existing regulations via Pigou-type fines incentivizing firms to prevent the spread of fires to surrounding land.

The first of these considers the impact of preventing the spread of fires started inside wood fiber and palm oil concessions from crossing property boundaries. Indonesian law requires concession holders to implement technical solutions that prevent the spread of fires outside of their concession boundaries. However, as we have seen, this policy is clearly not consistently enforced. We assume a scenario in which the government strictly enforces this regulation, and firms make associated technical investments to prevent fire spread outside their concession boundaries.[37] This can be estimated from our data by identifying the share of the burned area of each fire that falls outside the concession of ignition, and assuming that this share of the burning was prevented. This counterfactual simulates the effect of, for instance, effective regulation or enforcement of punishments for burning land owned by other concession holders or public lands. The results suggest that a total of 12.1 million hectares would have been burned by fires started inside wood fiber and palm oil concessions over our study period had these fires been prevented from crossing property boundaries. This

[37] The 1999 Forestry Law equips the Indonesian government with strong tools to fight the spread of fires into public lands, with the threat of up to 15 years of imprisonment or fines of up to 5 billion Rupiah for offending persons or businesses. As discussed in Section 2.3, even in cases where businesses have been ordered to pay high fines and reparations for infringements, such fines were often not paid.

represents a sizable reduction of 23% relative to the 15.6 million hectare total area that was burned over the period.

An alternative counterfactual considered is the effect of preventing the spread of fires started inside wood fiber and palm oil concessions into protected forest and populated areas only. This corresponds to, for instance, policies that implement effective enforcement of punishment for, or fire-fighting efforts to prevent, encroachment into public lands. The results suggest that in this case the total area burned would have been much closer to the level actually observed. The total burned area in this case is estimated to be 15.4 million hectares, which represents only a 2% reduction on the observed area burned.

An alternative form of regulation implemented over the period is private regulation via membership of the Roundtable on Sustainable Palm Oil (RSPO), a multi-stakeholder organization founded in 2003 that encourages the production and trade of certified sustainable palm oil and promotes a zero burning policy.[38] To consider the relative potential efficacy of this initiative compared to our counterfactuals, we simulate the effect of perfect enforcement of the zero burning policy promoted by the RSPO among its members. To do so, we simulate the area burned by fires started inside concessions owned by RSPO members at the time of ignition.[39] Removing the burned area from all of these fires from the total area burned by fires started inside wood fiber and palm oil concessions over our study period implies only a 3% reduction in the total area burned to 15.2 million hectares.

[38]Existing studies find muted evidence for reduced incidence of fires in RSPO-certified concessions. For example, 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. Consistent with this, in our data imprecisely estimated results suggest that palm oil concessions owned by RSPO members may be associated with fewer ignitions. We do not find that RSPO membership affects the degree to which concession owners internalize the costs of fires on neighbors.

[39]RSPO certification explicitly prohibits burning but the unit of certification is an oil palm mill and its surrounding supply base, which cannot be mapped directly to our concessions data. However, the first step towards RSPO certification is RSPO membership, which can be matched to our concessions data. While not an explicit pledge of zero burning, RSPO membership requires firms to work towards certification, to provide annual progress reports and acknowledgment of the RSPO Statutes and Principle and Criteria. RSPO members are matched to our concessions data 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 on the RSPO website (https://www.rspo.org/members/all). This list also includes the date on which each member acceded to the RSPO. Over our study period, 23% of company groups, owning 12% of palm oil concessions, became members of the RSPO.

6 Conclusions

Throughout the world there is a tension between firms trying to maximize private benefits and the environmental damages their actions impose on society. This tension is most keenly felt in developing countries where environmental externalities are less contained due to the imperfect enforcement of environmental regulations. The scale and growth of these damages within more weakly regulated developing countries has raised alarm, with the burning of vast tracts of tropical forests often topping the list of global environmental concerns.

This paper seeks to understand the degree to which these tropical fires are caused by firm behavior and, in particular, the extent to which fire is overused because firms do not internalize the risks that a fire, once ignited, can spread far beyond its initial area.

By tracking the daily spread of over 107,000 unique fires over a 15 year period we are able to show that they are concentrated in areas zoned for conversion to palm oil and wood fiber, tightly follow deforestation, and are suppressed in election years, all of which point to the human origins of these fires. This appears to be slash and burn on an enormous scale.

To make further progress, we then seek to understand whether firms take into account local externalities in their decision of whether to set fires. To do this we exploit the interaction between wind speed (a driver of spread risk) and land types that surround a concession pixel (that proxy for spread cost). Our results suggest that, over the period 2000-2016, fire setters do appear to take the externalities from fire setting into account. Ignitions are significantly less likely on windy days in areas where the fire would be more likely to spread inside the same concession versus cases in which spread would be to land with a different owner.

The analysis also considers how concession holders' fire-setting behavior is influenced by other types of neighboring land. The results suggest that surrounding land that lies in protected forest estate lands or populated areas outside the forest estate has a strong deterrent effect, consistent with these being the land types in which fires are most likely to lead to government sanctions.

The results thus suggest that firms are strategic in two senses: 1) they overuse fire relative to what they would do if all spread risks were internalized à la Coase, and 2) they do take into account the risks of government punishment à la Pigou, and this deters them from burning near protected or highly populated areas. The analysis therefore documents how government incentives shape the extent to which firms produce a negative environmental externality.

To quantify the magniudes of the externality, we build different policy counterfactuals to examine different routes into better controlling forest fires in the tropics. Our results from these policy counterfactuals suggest that relatively modest effects would result from either improving property rights and relying on Coasian private bargaining or from tort reform. In contrast, stronger Pigouvian incentives that encouraged property owners to treat the risk of any fire spread similarly to spread into land types that the government currently punishes most severely would achieve much stronger reductions. Indeed, if firms were as concerned about spread risks to surrounding lands as they are to protected forest or populated areas, fires would be reduced by 67% or 80%, respectively.

More generally, while economic theory suggests that private bargaining à la Coase and social pricing à la Pigou may under certain circumstances yield equivalent outcomes, our analysis suggests that private bargaining does not hold up to its promise in the context of this local externality. This is an important consideration not just for Indonesia, but more generally for other countries in the tropics where forest fires are major sources of local and global externalities.

Our analysis has considered a particular externality associated with forest fires, namely the local externality that arises if others own the land burned by a spreading fire. There are, however, a wide range of other local and global externalities associated with forest fires, including health and economic costs of smoke and haze, ecosystem loss and global warming induced by greenhouse gas emissions. We use our estimate of the reduction in the prevalence of forest fires were the damage risk to others' land to be treated equally to the damage risk to one's own property, together with the literature quantifying wider impacts of Indonesia's forest fires, to calculate a back-of-the-envelope estimate of the implied wider potential savings. Based on the estimated impacts of forest fires in Indonesia[40], and assuming that impacts are directly

[40]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 5 million hectares of land (Varma, 2003) and the vast spread of haze throughout Southeast Asia. While there are several reasons to expect that impacts may be heterogeneous across other fire episodes, this literature is helpful in considering the potential order of magnitude of wider effects. 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

proportional to the area burned, the estimated reductions in fires associated with the maximally effective policy we consider would have implied savings from Indonesia's 2015 forest fires[41] of 676 to 1,874 million 2015 USD (0.08–0.2% of Indonesia's 2015 GDP), global carbon emission reductions of 0.08 to 0.73 Gigatonnes (up to 7.5% of the global carbon emissions from fossil fuels) and avoided the premature deaths of up to 15,386 adults and 4,445 children under three. These figures suggest that the damages from failing to internalize local externalities can be substantial.

This paper has only broken the surface of the set of issues around how to control environmental externalities like tropical forest fires. Three areas look important for making further progress. The first is political economy. If private benefits are small relative to social costs then how can the views of those that are damaged become represented? Our work on political cycles in fires following deforestation demonstrate that electoral incentives bite 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 of the countries where the 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 2020, Hsiao 2020) 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 for clearing land with many external harms, and there is a need to understand whether innovations or incentives can make cleaner alternatives more attractive. The bottom line is that though the measurement revolution has made us better at monitoring forest fires in the tropics and understanding their origins, there are many avenues to pursue to better understand how to control them.

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 3 (Jayachandran, 2009).

[41] The 2015 fires burned an estimated 2.6 million hectares of land in Indonesia.

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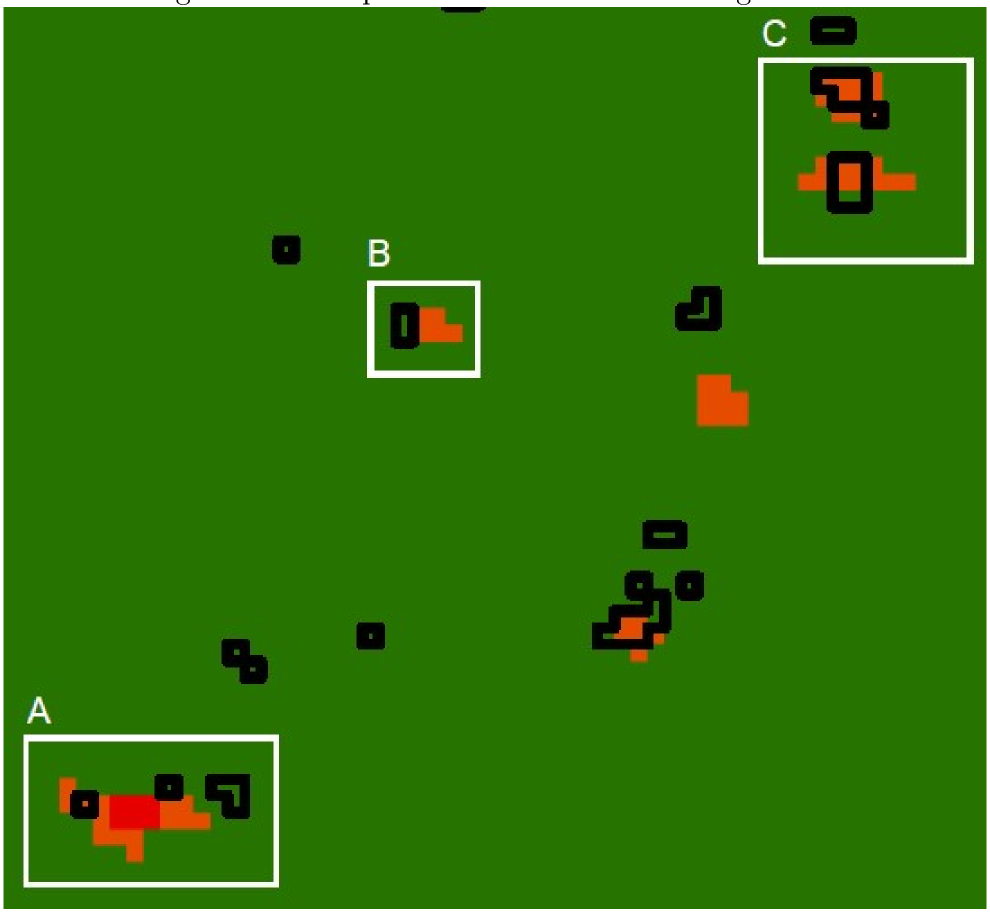
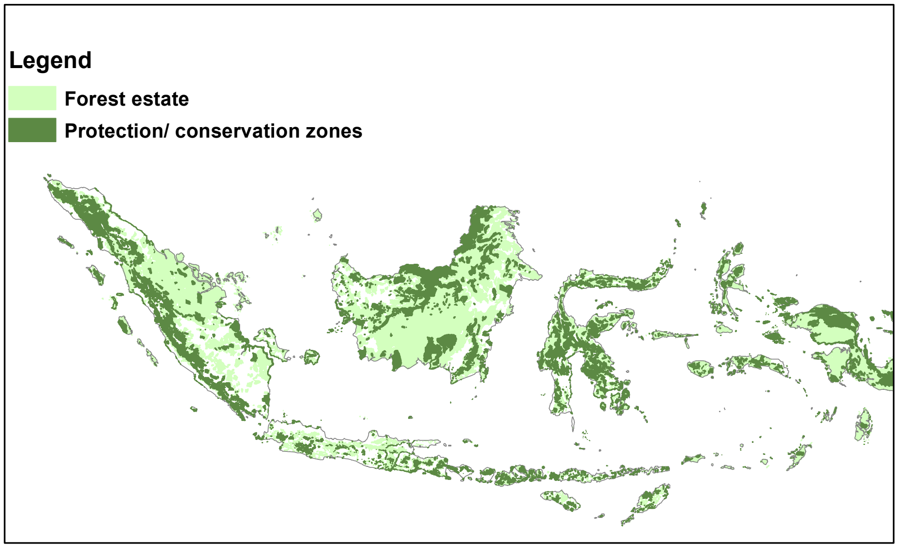
Figures and Tables

Figure 1: Example of Fire Identification Algorithm



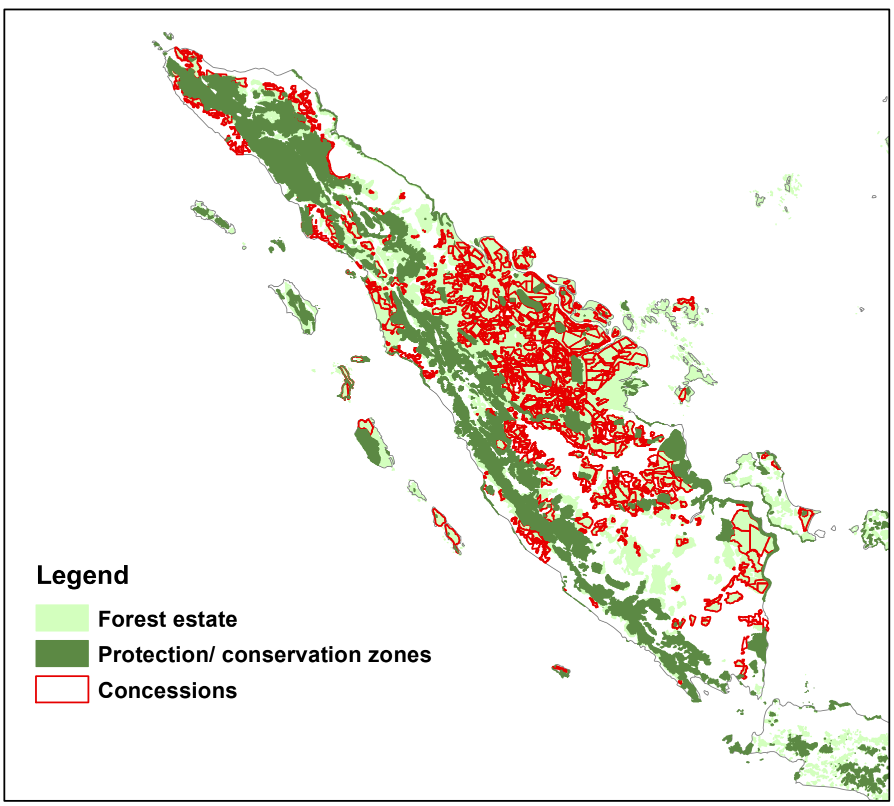
Notes: Example showing how we merge hotspots into contiguous multi-day 'fires'. In this example, Pixels outlined in black had a fire on Day 1 , and pixels colored red/orange/yellow had a fire on Day 2. The white boxes A, B, and C denote three fires that we classify as single fires, with ignition area as the black area and total spread extent as the union of the black and red areas.

Figure 2: Forest estate and protection/ conservation zones



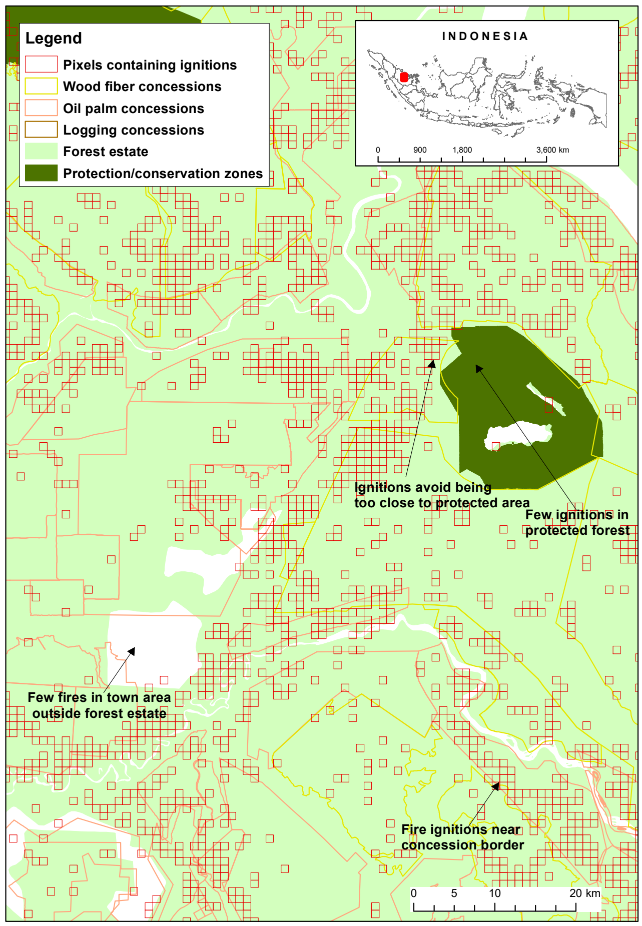
Notes: The Indonesian forest estate ('*kawasan hutan*') is shown in green. Within that, protected areas (watershed protection and conservation) are shown in dark green

Figure 3: Sumatra concessions, forest estate and protection/ conservation zones



Notes: The Indonesian forest estate ('*kawasan hutan*') is shown in green. Within that, protected areas (watershed protection and conservation) are shown in dark green. Concession boundaries are shown in red.

Figure 4: Fire ignitions and concession areas in an area of Riau province, Sumatra



Notes: Each 1km^2 grid cell in red shown represents a grid cell in which we detect at least one fire ignition. 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 5: Riau 2012 deforestation and 2013 ignitions

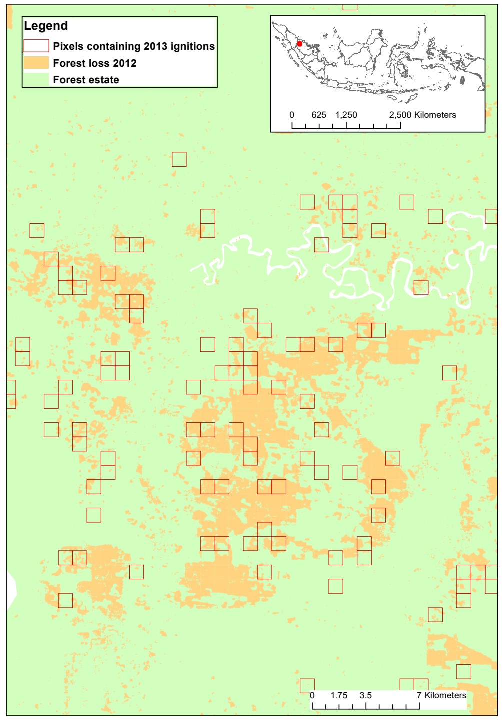


Figure 6: Illustration of pixel buffer classification

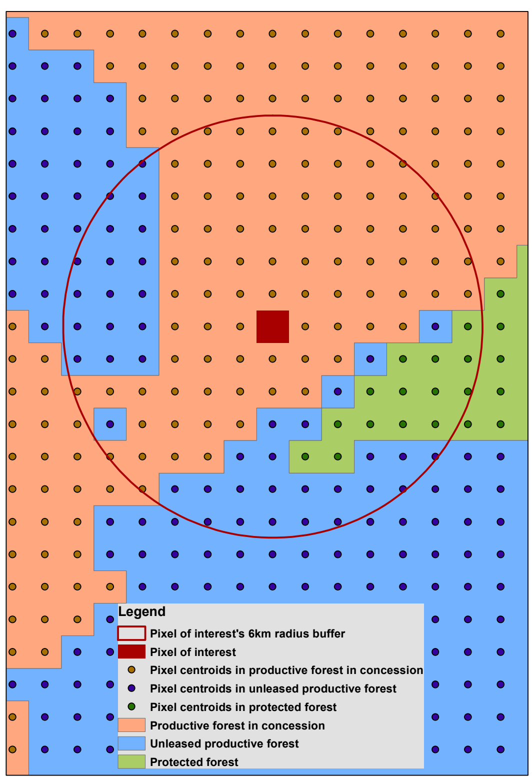


Table 1: Impact of Deforestation on Ignitions

Dependent variable = Number of fires in pixel*month*year	Pixel FE	Pixel Month & Year FE
Forest loss (km2) in year t-1	1.0898***	1.3314***
	(0.1241)	(0.1314)
Forest loss (km2) in year t-2	-0.3598***	-0.3056**
	(0.1335)	(0.1340)
Forest loss (km2) in year t-3	-0.5319***	-0.3432**
	(0.1804)	(0.1484)
Observations	3,224,160	3,224,160
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 2: Conditional burning and electoral cycles

	Entire forest (1)	Oil Palm (2)	Fibre (3)	Unleased (4)	Protected (5)
Election date:					
In 2 years	0.043	0.084	0.060	0.296	-0.389
	(0.114)	(0.181)	(0.171)	(0.221)	(0.310)
Next year	-0.003	0.066	-0.023	0.256	0.232
	(0.107)	(0.119)	(0.145)	(0.235)	(0.206)
This year	-0.358**	-0.480**	-0.275	-0.351	0.086
	(0.142)	(0.190)	(0.175)	(0.287)	(0.247)
Last year	0.015	0.046	-0.050	0.064	0.326
	(0.101)	(0.129)	(0.113)	(0.225)	(0.285)
Observations	1289568	335968	478077	52550	57268
Mean of DV	0.012	0.017	0.016	0.013	0.008
Spatial FE	Pixel	Pixel	Pixel	Pixel	Pixel
Temporal FE	Year	Year	Year	Year	Year
Joint p-value	<0.01	<0.01	0.100	0.026	0.132
This vs. last:					
Difference	0.373	0.527	0.225	0.415	0.240
p-value	<0.01	<0.01	0.129	0.039	0.301

Note: Poisson regressions. Outcome is number of fires in t after deforestation in t-1, omitted category is two years after election. Robust standard errors clustered at district level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Impact of Wind Speed on Fire Spread

Dependent variable = Average fire spread area (burned area minus ignition area)	Pixel FE	Pixel Month & Year FE
Wind speed in standard deviation units	0.9645***	1.3521***
	(0.1813)	(0.2196)
Observations	5,444	5,444
Mean of Dep. Var.	4.753	4.753

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 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 4: Ignition Results by Surrounding Land Ownership

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
Wind speed in standard deviation units	1.9651***	2.2243***	2.1240***	1.4309***	1.8695***	2.4978***
	(0.1777)	(0.1718)	(0.1725)	(0.2148)	(0.1658)	(0.2449)
Wind speed * Num pixels in 6km buffer in same concession as central pixel	-0.007766***	-0.005212***	-0.003611**	-0.007140***	-0.003347**	-0.002124*
	(0.001665)	(0.001716)	(0.001515)	(0.001593)	(0.001468)	(0.001267)
Observations	4,729,680	4,729,680	4,729,680	4,721,940	4,729,680	4,721,940
Control: Wind speed × Island	NO	YES	NO	NO	NO	YES
Control: Wind speed × Concession Type	NO	NO	YES	NO	NO	YES
Control: Wind speed × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Wind speed × Concession Area	NO	NO	NO	NO	YES	YES
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: Interaction of wind speed and "Num pixels in 6km buffer outside same concession as central pixel".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Spread Results by Surrounding Land Ownership

Dependent variable = Spread extent (total fire area minus ignition area)	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs
Wind speed in standard deviation units	1.1314	2.0927**	1.2942*	0.08411	1.1607	1.7668*
	(0.7607)	(1.0586)	(0.7633)	(0.6507)	(0.7520)	(0.9782)
Wind speed * Num pixels in 6km buffer in same concession as central pixel	-0.0001894	-0.0004962	0.002779	0.001601	-0.002400	-0.001433
	(0.007647)	(0.008013)	(0.007612)	(0.007386)	(0.007189)	(0.007270)
Observations	20,099	20,099	20,099	20,068	20,099	20,068
Control: Wind speed × Island	NO	YES	NO	NO	NO	YES
Control: Wind speed × Concession Type	NO	NO	YES	NO	NO	YES
Control: Wind speed × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Wind speed × Concession Area	NO	NO	NO	NO	YES	YES
Mean of Dep. Var.	1.335	1.335	1.335	1.335	1.335	1.335

OLS regressions. Robust standard errors clustered at level of 50km2 grid cells. Pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands containing at least one fire spreading beyond its ignition area. Omitted category: Interaction of wind speed and "Num pixels in 6km buffer outside same concession as central pixel".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Ignition Results by Surrounding Land Type

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
Wind speed in standard deviation units	2.1466***	2.8208***	2.1390***	1.6878***	2.1028***	2.9294***
	(0.3509)	(0.2620)	(0.3268)	(0.3952)	(0.3323)	(0.3165)
Wind speed * Num pixels in 6km buffer in same concession as central pixel	-0.008974***	-0.009351***	-0.004257	-0.008609***	-0.004862**	-0.005633***
	(0.002555)	(0.002418)	(0.002591)	(0.002453)	(0.002310)	(0.001991)
Wind speed * Num pixels in 6km buffer in different concession from central pixel	0.003277	-0.002204	0.003914	0.002680	0.003174	-0.001034
	(0.003443)	(0.002648)	(0.003039)	(0.003197)	(0.003348)	(0.002467)
Wind speed * Num pixels in 6km buffer outside forest estate	-0.01752***	-0.01942***	-0.01203***	-0.01769***	-0.01681***	-0.01562***
	(0.004005)	(0.003228)	(0.003878)	(0.003906)	(0.003866)	(0.003225)
Wind speed * Num pixels in 6km buffer in protected forest	-0.01363***	-0.01192***	-0.009082**	-0.01264***	-0.01297***	-0.008950***
	(0.004108)	(0.003206)	(0.003721)	(0.003956)	(0.003951)	(0.002913)
Wind speed * Average population density in 6km buffer	0.002547	0.001097	0.002002	0.002503	0.001211	0.0007037
	(0.002293)	(0.001986)	(0.001797)	(0.002368)	(0.002046)	(0.001625)
Observations	4,729,680	4,729,680	4,729,680	4,721,940	4,729,680	4,721,940
Control: Wind speed × Island	NO	YES	NO	NO	NO	YES
Control: Wind speed × Concession Type	NO	NO	YES	NO	NO	YES
Control: Wind speed × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Wind speed × Concession Area	NO	NO	NO	NO	YES	YES
Mean of Dep. Var.	0.008226	0.008226	0.008226	0.008226	0.008226	0.008226

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: Interaction of wind speed and "Num pixels in 6km buffer in productive forest outside concession". Suppressed categories: Interactions of wind speed and "Num pixels in 6km buffer in protected forest in concession", "Num pixels in 6km buffer outside forest estate in concession", "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: Spread Results by Surrounding Land Type

Dependent variable = Spread extent (total fire area minus ignition area)	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs	Pixel M & Y FEs
Wind speed in standard deviation units	2.2172	3.3458*	2.2866	1.2479	2.2295	2.8069
	(1.7858)	(2.0024)	(1.7810)	(1.5817)	(1.7809)	(1.8166)
Wind speed * Num pixels in 6km buffer in same concession as central pixel	-0.007606	-0.009116	-0.005003	-0.006942	-0.009501	-0.01018
	(0.01412)	(0.01396)	(0.01408)	(0.01395)	(0.01321)	(0.01275)
Wind speed * Num pixels in 6km buffer in different concession from central pixel	-0.006128	-0.008068	-0.005948	-0.008158	-0.006305	-0.008422
	(0.01195)	(0.01162)	(0.01177)	(0.01203)	(0.01188)	(0.01114)
Wind speed * Num pixels in 6km buffer outside forest estate	-0.02631	-0.02555	-0.02367	-0.02862*	-0.02665	-0.02413
	(0.01672)	(0.01644)	(0.01667)	(0.01698)	(0.01657)	(0.01596)
Wind speed * Num pixels in 6km buffer in protected forest	-0.02453	-0.02418	-0.02174	-0.02264	-0.02513	-0.02037
	(0.01939)	(0.01927)	(0.01884)	(0.01888)	(0.01934)	(0.01847)
Wind speed * Average population density in 6km buffer	-0.003537	-0.004520	-0.003954	-0.004830	-0.002867	-0.003778
	(0.003077)	(0.003194)	(0.003000)	(0.003285)	(0.003048)	(0.003410)
Observations	20,099	20,099	20,099	20,068	20,099	20,068
Control: Wind speed × Island	NO	YES	NO	NO	NO	YES
Control: Wind speed × Concession Type	NO	NO	YES	NO	NO	YES
Control: Wind speed × Forest Cover 2000	NO	NO	NO	YES	NO	YES
Control: Wind speed × Concession Area	NO	NO	NO	NO	YES	YES
Mean of Dep. Var.	1.580	1.580	1.580	1.580	1.580	1.580

OLS 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: Interaction of wind speed and “Num pixels in 6km buffer in productive forest outside concession”. Suppressed categories: Interactions of wind speed and “Num pixels in 6km buffer in protected forest in concession”, “Num pixels in 6km buffer in concession outside forest estate”, “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 8: Government Punishment Results

Dummy = 1 if firm investigated	No FEs	Island FEs	Province FEs
Pixels outside forest estate burned by fire	0.02596	0.03508	0.02096
	(0.06401)	(0.03746)	(0.05168)
Pixels in unleased productive forest burned by fire	-0.05160***	-0.02640	-0.02523
	(0.01248)	(0.02019)	(0.01960)
Pixels in protected forest burned by fire	0.04320	0.08288*	0.08836**
	(0.04512)	(0.04367)	(0.04310)
Total area of fires burned Sep 2014-Aug 2015	0.01790***	0.01304**	0.01313***
	(0.002862)	(0.006506)	(0.004864)
Concession area (km2)	0.001115	0.001577*	0.001688*
	(0.0007603)	(0.0008940)	(0.001019)
Population in fire extent	0.0006187***	0.0004503**	0.0004517**
	(0.0001654)	(0.0002127)	(0.0001907)
Observations	597	597	567
Mean of Dep. Var.	0.157	0.157	0.160

Logit regressions. Robust standard errors clustered at level of firm groups. All pixels inside wood fiber and palm oil concessions inside forest estate excl Java and Lesser Sunda Islands. Omitted category "Pixels in productive forest in concession burned by fire". Suppressed categories "Pixels in Malaysia / PNG burned by fire", "Pixels in concession outside forest estate burned by fire", and "Pixels in concession in protected forest burned by fire".
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Counterfactual simulation results

Counterfactual % reduction from:	Ignitions	Area burned
Assign all concessions to single owner	6%	
Agents treat all buffer pixels as concession land with same owner	14%	
Zone all unleased productive forest as protected forest	26%	
Agents treat all buffer pixels as land outside forest estate	80%	
Agents treat all buffer pixels as protected forest	67%	
Prevent fires from spreading beyond concession in which they started		23%
Prevent fires from extending into protected forest and populated areas		2%
No fires started inside palm oil concessions owned by RSPO members		3%

Note: In first four counterfactuals, concessions and associated ignitions are wood fiber and palm oil concessions within the forest estate only.