Causes of Indonesia's forest fires

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Abstract

The economic costs of Indonesia's 2015 forest fires are estimated to exceed US $16 billion, with more than 100,000 premature deaths. On several days the fires emitted more carbon dioxide than the entire United States economy. Here, we combine detailed geospatial data on fire and local climatic conditions with rich administrative data to assess the underlying anthropogenic causes of Indonesia's forest fires at district and village scales. We find that El Nino explains most of the year-on-year variation in fire. The creation of new districts increases fire and exacerbates the impacts El Nino on fire. We also find that regional economic growth has gone hand-in-hand with the use of fire in rural districts. We proceed with a 30,000-village case study of the catastrophic 2015 fire season on Sumatra and Kalimantan and ask which villages, for a given level of spatial fire risk, are more likely to have fire. Villages more likely to burn tend to be more remote, considerably less developed, and have a history of using fire for agriculture. Although central and district level policies have contributed to voracious environmental degradation, the close link between poverty and fire at the village level suggests that the current policy push for village development—and the strengthening of the village as an administrative unit—could offer opportunities to reverse this trend.

Keywords: forest fire, El Nino, decentralization, economic growth, rural development, poverty

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1 Introduction

Deforestation accounts for over ten percent of global carbon emissions: more than the entire European Union (IPCC, 2018). Reducing tropical deforestation is one of the most cost effective ways to address climate change. Halting deforestation while allowing damaged forests to recover could reduce global net emissions by as much as 30 percent (Busch and Seymour, 2017). An increasingly prominent yet understudied mechanism to clear tropical forests is fire. Whether spontaneous or deliberately lit by humans, drying landscapes, rising temperatures, and intensifying El Ninos are seeing wildfires become increasingly common, intense, and costly. The world's largest contributor to deforestation and land related emissions is Indonesia, where fire is commonly used to clear forest, manage semi-forested landscapes, and prepare land for agriculture. The third largest and most populous developing economy in the world and the largest in the equatorial tropics, Indonesia provides the ideal setting to study the anthropogenic drivers of tropical forest fires and potentially offers important insights for other countries at risk of deforestation where fires are increasing in prevalence and intensity (Ordway et al 2017).

Indonesia's 2015 fire season burned more than 2.6 million hectares, an area larger than the entire U.S. state of Vermont. Much of this land of land was rich in biodiversity and endangered species like the orangutan, tiger, rhino, and elephant (World Bank, 2016). Though the 2015 fire season was extreme, it was not particularly unique. 163,000 hectares burned in 2013 and 2–5 million in 1997–98 (Dennis, 1999; Gaveau et al., 2014). Impacts span environmental, economic, and social dimensions. Fires release extreme amounts of carbon into the atmosphere and are a major contributor to air pollution and climate change (Page et al., 2002; Bowman et al., 2009; Pribadi and Kurata, 2017). The 1997 fire season released the carbon equivalent to 15% of global fossil fuel emissions that year. On more than one occasion, a single day of burning in the 2015 fire season emitted more carbon than the entire United States economy (World Bank, 2016).

Fire can destroy homes, crops, and forest resources, cause work and school closures, and create significant firefighting and rebuilding expenses. The economic costs of Indonesia's fires are estimated to exceed US $4.5 billion in 1997–98 and $16 billion in 2015 (Dennis, 1999; World Bank 2016). Pollution from the 1997 fires is estimated to have caused 15,600 child, fetal, and infant deaths, with early mortality costs of over $15 billion (Frankenburg et al., 2005; Jayachandran, 2009). The 2015 fire season caused more than half a million respiratory infections, in both Indonesia and Singapore, and is estimated to have caused more than 100,000 premature deaths (Koplitz et al., 2016; Sheldon and Sankaran, 2016). A Pollution Standard Index reading of 350 is considered hazardous, yet regularly exceeds 2,000 during fires. Although greater in number and ferocity during El Nino induced dry seasons, Indonesia's fires are for the most part a human phenomenon. Spontaneous ignitions are rare. Despite their political, economic, social, and environmental importance and their growing prominence as a low cost way to clear land, relatively little is known about what causes the deliberate ignition of fires, how much of their variation and intensity is explained by human versus natural activity, or what constitutes effective fire prevention and management policy.

This study's objective is to systematically analyze the anthropogenic causes of forest fires in Indonesian jurisdictions at district and village scales and over different time horizons. We first assess the short-run impacts of El Nino, government decentralization, and regional economic growth. Combining a new geospatial panel dataset on district forest fires and climatic conditions with administrative data on government decentralization and regional economic growth, we use panel data techniques to disentangle time-varying common factors (e.g., national policies, commodity prices, and seasonal factors) and fixed spatial determinants (e.g., regional climate, culture, and geography) from political and economic changes of interest. Identification exploits exogenous variation in El Nino, the timing of administrative reforms, and the longitudinal features of the data (i.e., fixed effects and unit-specific trends).

The first key finding is that El Nino explains most of the annual variation in fires within districts. A one-degree increase in sea surface temperature (SST) in the Pacific corresponds to over a 50 percent increase in average annual hotspot detections per rural district. The mean number of hotspots from 2001—2015 is 286 and the sea surface temperature anomaly was over 2 degrees in the 2015 and 1998 fires seasons. Negative local rainfall anomalies are particularly important in explaining year-on-year variation, while local temperature shocks appear less important.

Indonesian fires have a strong human element. The second key finding is that political decentralization has caused more fire. The proliferation of local government units—which enjoy considerably more funding, autonomy, and power in relative terms—is associated with increased fires in split jurisdictions, with an almost 60 percent increase relative to pre-split years. Local government proliferation has also exacerbated the impacts of El Nino on fires, a key climate-politics interaction receiving little attention to date. More recent village-level decentralization, which similarly has led to increased autonomy and resources, may thus present an imminent fire threat.

The third key finding is that regional economic development has gone hand-in-hand with the use of fire in rural districts. There tends to be more fires in periods of stronger than average economic growth. A year with an economic growth rate one percent higher than average has around 50 percent more fire. Economic-environmental trade-offs have long characterized large-scale agricultural expansion in the Indonesian countryside, and rural economic development and environmental degradation does not yet appear to have decoupled (see, also, e.g., Edwards, 2018). Districts appear to use fires to create economic opportunity, which in turn may increase residents and firms' capacity to move, acquire land, and burn more.

District variation masks considerable heterogeneity within districts. We then shift our focus to longer-term determinants and the village level with a case study of the Indonesia's 2015 fire season—the largest fire catastrophe since satellite-based fire records started being collected at the start of this century. We create a new cross-sectional dataset linking geospatial and administrative information for over 30,000 villages on the large, fire-prone islands of Sumatra and Kalimantan and ask the following simple question: what types of villages were more likely to set fire? To this end, we use a spatial fixed effects approach to compare villages against their neighbors facing similar climate variability, geography, history, institutions, and other spatially-correlated unobservables. Our focus on the village is also important. Like district-level decentralization before it, the Village Law of 2014 (and earlier decrees) devolved significant fiscal, administrative, and policy responsibilities to rural villages and placed them at the heart of Indonesia's development policy agenda (Antlov et al., 2016; Naylor et al., 2018). Emergent fire prevention and response efforts are largely centered around the village as an autonomous administrative unit as well.

We find that villages more likely to burn tend to be more remote, be involved in secondary or plantation crops, have a history of burning for agriculture, and be less developed according to a wide variety of multi-dimensional poverty indicators. A one-percentage point increase in the village poverty rate corresponds to a staggering 20 percent increase in the probability of having a fire detected, after accounting for district-level spatial fire risk. Based on our estimated impacts of district-level decentralization funding windfalls, further village-level fiscal decentralization seems to present an imminent fire threat. On the other hand, the village proliferation rate is lower than districts' and the close links between poverty, underdevelopment, and fire at the village level suggests that the current policy push for village development—if successful—could potentially reduce fire. While central and district level policies in the post-decentralization era have contributed to voracious resource extraction and environmental degradation, the strengthening of the village as an administrative and developmental unit could offer opportunities to reverse this trend.

Our central contribution here is providing, to the best of our knowledge, the first systematic quantitative evidence on the human drivers of tropical forest fires. A large body of scientific work documents the incidence, extent, and costs of fire, including in Indonesia (see, e.g., Page et al., 2002; Bowman et al., 2009; Cattau et al 2016; Pribadi and Kurata, 2017; Dennis, 1999; Dennis et al 2005; Gaveau et al., 2014; Koplitz et al., 2016; Sheldon and Sankaran, 2016). This antecedent work, mostly in the natural and remote-sensing sciences, tends to focus on a single time period, event, or area, and is often descriptive in nature. Studies at the nexus of social and environmental science also tend to be geographically and temporally focused, usually relying on secondary and interview data. Remotely-sensed (i.e., satellite) information on fire is rarely linked to quantitative socioeconomic data for more integrated analysis, as has occasionally been done for deforestation (see, e.g., Burgess et al 2012; Wheeler et al 2012). We build on prior work by linking thermal hotspot detections with subnational administrative, socioeconomic, and climate data. Guided by four of the most salient issues at the nexus of environment and development (El Nino, decentralization, economic growth, and village development) and the two most important subnational policy-making units (districts and villages), we use modern social science statistical techniques to identify the key human drivers of ignitions.

Our multi-scalar analysis effectively responds to the growing academic and public interest in jurisdiction-based approaches to complex sustainability challenges and provides important new evidence to assist different actors, at different scales, to better target and design effective fire prevention and response activities. Our spatial and temporal extent is the whole archipelago since 2000 for our district analysis, and the entire islands of Sumatra and Kalimantan in 2015 for our village-level analysis. By using the world's largest tropical developing country and largest contributor to land-related emissions as a case study, the findings are likely to be of global significance and informative for other countries facing similar challenges.

The remainder paper is structured as follows. The next section introduces the satellite-based fire data and explains how we create our two main jurisdisctional datasets. Section 3 presents our district-level analysis, estimating the short-run impacts of El Nino, government decentralization, and local economic growth on forest fires. Section 4 presents our village-level case study of the 2015-16 fire season, and Section 5 concludes with a brief discussion with respect to policy.

2 Data

2.1 Jurisdiction-based fire data

Thermal hotspot detections are taken from the National Aeronautics and Space Administrations (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Product (MCD14ML). For each fire detected by the Terra or Aqua MODIS sensor, the MODIS Active Fire Product includes fire location (at a 1 km spatial resolution), date, and time of detection. MODIS hotspots are the most accurate and complete method for detecting fires and highly correlated with the area burned on the ground (R2=0.75), including on peat soil (Langner and Siegert, 2009; Cattau et al, 2016; Tansey et al., 2008). MODIS is generally believed to underestimate fire on Kalimantan and Sumatra (even in light of any confidence-related false alarms) because it can miss fast-burning fires, those in dense canopy that do not produce enough heat, and those under dense cloud cover or smoke (Ballhorn et al., 2009; Tansey et al., 2008; Miettinen et al., 2007; Langner et al 2009). Hence, measurement error is likely to attenuate rather than overstate our estimates in this paper.

All hotspots detected over the lifetime of MODIS's hotspot acquisition period (2001–present) are combined with Indonesia's 2010 Population Census administrative boundaries to calculate the total number of hotspots detected in each jurisdiction-year. Although fires are a seasonal phenomenon, Indonesia's fire season is typically from

July–November, even in El Nino years, so suitable for year-on-year or single calendar year analysis. Other studies utilize raw MODIS data but approaches vary. Ardiansyah et al. (2017) assume any grid cell with a hotspot was 75% burned to avoid using burned area pixel data. Cattau et al. (2016) use hotspot "spreading" to estimate the expansion of individual fires, with adjacent pixels that burn simultaneously or sequentially assumed to be one fire. Our jurisdiction-year hotspot count complements these approaches and captures fire duration, scale, and intensity well by increasing (a) in the times a given fire is observed in the same space, and (b) in any multiple detections of single or related fires across pixels.

Figure 1 illustrates the spatial distribution of fire across Indonesian districts. Specifically, the the total number of hotspots detected in each 2000-definition district is mapped, with fractured districts overlaid in with finer black lines. Fire is concentrated on the forested islands of Kalimantan (particularly central Kalimantan province), Sumatra (particularly Riau province), and southern Papua. Several districts with the most fire have also fractured into smaller, new districts since 2000.

[Figure 1 approximately here]

2.2 Linking fire to climate and socioeconomic data

We link jurisdictional fire data to two new datasets: a district-by-year longitudinal panel, and a 2015 village cross-section. For the district panel, a redistricting variable is constructed by coding district-year observations with a dichotomous district split treatment indicator for when the new district becomes operational—i.e., when it begins receiving its general purpose grant from central government. This is usually one year, sometimes two, after the law creating it is promulgated. Separate treatment variables are created for the year of the split and post-split years, the former capturing the "shock" and the latter the permanent "regime shift". Sea surface temperature anomalies are taken from NOAA, average district precipitation is calculated from Funk et al. (2015), and average district temperature

is calculated from Legates and Willmott (1990). Regional gross domestic product (RGDP) data are official subnational accounts from Badan Pusat Statistik, Indonesia's central statistics agency. Indonesian districts proliferated from 292 in 1998 to over 500 today. 2000 district boundaries are applied to obtain an uninterrupted, nationally-exhaustive panel of 286 constant-area geographic units from 2000–2013. Urban districts (i.e., cities in 2000) are excluded from the sample throughout.

The cross-sectional dataset covers over 30,000 rural villages on the two large, forested, and fire-prone islands of Sumatra and Kalimantan. 2015 MODIS hotspots per village are linked using geographic information systems (GIS) to palm oil processor locations from the World Resource Institute's Global Forest Watch database, village poverty estimates from the SMERU Research Institute (combining census and survey data in standard poverty mapping techniques), and a host of other administrative, geographic, and other characteristics from the 2014 census of village heads (Potensi Desa, or PODES), conducted by BPS. All spatial joins and calculations rely on 2010 village definitions and administrative boundaries as defined in the 2010 Population Census.

3 Regional analysis

3.1 Empirical framework

Our district-level empirical approach compares the number of fires in a district when a variable of interest shifts relative to its average level. The counterfactual "control" for a "treated" district is the same district in a non- or less-"treated" state. Annual hotspot detections are related to time-varying district characteristics with the general panel data model:

$$y_{d,t} = \alpha + \beta T_{d,t} + \delta_d + \tau_{i,t}\gamma_t + yd * Td + \epsilon_{d,t} \tag{1}$$

where $y_{d,t}$ is the natural log of the total number of hotspot detections in district d in year t. Hotspots detections are approximated to a continuous variable because almost all districts have hotspots. The average is around 300 per year. Results are similar not logging fires and using alternative models for over-dispersed count data. $T_{d,t}$ is an dichotomous indicator for redistricting, district annual economic growth rates, or an ENSO variable—specifically, sea surface temperature, precipitation, or temperature. District fixed effects (δ_d) absorb fixed spatial confounders (e.g., geography, culture, history, and, long-run climatic and fire risk conditions) and allow for level differences across districts. Island-by-year fixed ($\tau_{i,t}$) effects ensure that the estimated relationships are identified from local idiosyncrasies by absorbing common trends to each region and removing the influence of any time-varying common confounders across regions (e.g., global and regional economic and climatic conditions, world commodity prices, and national policy changes and political shocks). District-specific trends (yd * Td) capture secular trends specific to every spatial unit, exploiting only deviations around these trends. $\epsilon_{d,t}$ is a robust error term, clustered by district to allow arbitrary serial correlation within districts.

β is the semi-elasticity of hotspot detections (the percentage change) in response to a one unit change in the explanatory variable of interest (an elasticity for logged variables). β offers a causal interpretation if there are no problematic omitted variables (a) correlated with $y_{d,t}$ and $T_{d,t}$ that vary over time within districts, and (b) that are influential enough to systematically affect district fire incidence. An example of such a time and district varying confounder might be district-level environmental and fire policies, but if and only if districts enact these selectively in dry ENSO years, when redistricting, or in periods of differential economic growth. Local fire policies tend to be concerned with fire response and management, rather than prevention, and most general laws and regulations about

land use and burning tend to be national and thus captured by time fixed effects. Active prevention efforts are more recent (i.e., following the 2015 fire season) and in just a few regions, so unlikely to be a major concern for identification. Ultimately, the credibility of the identification assumption depends on the explanatory variable used.

The main advantage of panel data is neutralizing confounding across the data]s spatial and temporal dimensions. Since the model includes unit and period fixed effects, we rely on variation across time within each spatial unit as the source of identifying variation (rather than variation across spatial units). The underlying identification thus relates time series (i.e., year-on-year) deviations from location-specific means in explanatory variables to deviations in hotspot detection, providing short-run effects. ENSO (Hsiang and Meng, 2015), weather shocks (Dell and Olken, 2012; Dell et al 2014; Hsiang, 2016), and the arbitrary timing of district splits (due to administrative lags and a moratorium, see, e.g., Burgess et al., 2012; Bazzi and Gudgeon, 2018) all offer plausibly exogenous variation well-suited to identify causal effects. Local economic growth, by contrast, is deeply endogenous. Time and district varying factors affecting economic growth may also affect fire, and fire response efforts could temporarily increase economic output. Thus, when analyzing the empirical relationship between fire and regional economic growth, our estimates do not have a strictly causal interpretation.

3.2 Results—climate and decentralization

The first key finding is that El Nino cycles explains much of the annual variation in fire within Indonesian districts. Figure 2 illustrates this visually with the raw aggregate time series data, plotting monthly hotspot detections and ENSO anomalies. Fire is extremely seasonal and persistent, and peaks strongly coincide with the largest ENSO anomalies.

[Figure 2 approximately here]

Since ENSO varies across years but not districts, we follow Hsiang and Meng (2015) and include district-specific linear trends and fixed effects to identify the annual ENSO effect beyond district fixed characteristics and local secular trends. Column 1 of Table 1 quantifies the impact of El Nino anomalies on hotspot detections within districts: important aggregate seasonality we sweep away in subsequent estimates with year fixed effects. A one-degree increase in sea surface temperature (SST) in the Pacific corresponds to over a 50 percent increase in annual district hotspot detections (mean=286).

[Table 1 approximately here]

To put these magnitudes in perspective, consider that the sea surface temperature anomaly was over 2 degrees in the 2015 and 1998 fires seasons, around 1.5 in 2002–3 and 2009–10, and under 1 degree in other anomaly years. The greater magnitudes of this common seasonal variation (relative to local idiosyncrasies is important context for the multiplicative ENSO-governance effects we proceed to document. Column 2 of Table 1 replaces SST, which is the same across districts, with log district annual average precipitation and temperature, to proxy regional ENSO exposure. Island-year fixed effects capture regional climatic differences and ensure we only exploit weather fluctuations among districts within islands. Negative local rainfall anomalies leads to more fire. Temperature, with limited variation in the tropics, is statistically insignificant. The average year-on-year impacts of ENSO cycles on fire appear to be coming mostly through negative rainfall shocks and intensified dry seasons. Although our results contrast with Ferndandes et al's (2017) finding that temperature change is increasing fire even in non-dry years, our two sets of results are not necessarily incompatible. Our results merely suggest that dryness may just be more important on a year-on-year basis within districts.

The second key finding from our district-level analysis is that political decentralization caused more fire. Specifically, the proliferation of local government units—which enjoy considerably more funding, autonomy, and power in relative terms—is associated with more

fire in split jurisdictions. Column 3 of Table 1 finds that hotspot detections increase by 40 percent as new districts become operational. Column 4 finds that in the following years following a split, there is an almost 60 percent increase relative to pre-split years. Results are similar with less demanding panel specifications, for example dropping the linear trends or relaxing the island-year FEs to only year FEs (omitted for brevity). Since the timing of district splits is likely to be exogenous (Burgess et al, 2012; Bazzi and Gudgeon, 2018), these estimates can be interpreted as causal. We thus offer quantitative backbone to the qualitative arguments in Purnomo et al (2017) and complement Burgess et al.'s (2012) finding that redistricting has reduced tree cover (exploiting the same identifying variation). Specifically, our results suggest that fire is likely to be an important mechanism underpinning any observed tree cover change and a crucial part of Indonesia's modern resource governance story. More recent village-level decentralization efforts— which also coincide with more administrative units, greater autonomy, and more fiscal resources—may present an continuing fire threat.

Column 5 of Table 1 unifies our decentralization and El Nino findings by switching our time (island-year) fixed effects back out for ENSO (SST) and including an additional interaction term for post-split district-years and ENSO anomalies. The ENSO coefficient is almost identical to Column 1. The post-split treatment effect is considerably larger than those in Columns 6 and 7, unsurprising since island-year fixed effects constitute a much richer set of controls than year dummies. The interaction coefficient in the final row reveals a multiplicative impact of administrative decentralization on fire in El Nino years. Indonesia's seismic shift in governance from Jakarta down to the regions appears to have intensified the impacts of El Nino on fire, a key climate-governance interaction that—to the best of our knowledge—has not received any attention to date.

3.3 Results—regional economic growth

We now turn out attention to regional economic development dynamics, finding that district economic growth has generally gone hand-in-hand with the use of fire in the Indonesian countryside this century. Table 2 reports estimates regressing fire on the natural log of district per capita regional gross domestic product or, for a growth interpretation, its first-difference. Districts set more fires in years with higher economic growth. A year where the local economy is growing one percent higher than the district decadal mean has over 50 percent more fire (Column 2). Magnitudes are qualitatively similar with only district and island-by-year fixed effects (Column 1), with these plus district-by-district trends (Column 2), and excluding oil and gas GDP (Column 3). Disaggregating economic growth by sector, this effect is principally driven by manufacturing growth (omitted for brevity). In the rural districts with persistent fire, manufacturing growth is mostly agricultural processing, including for palm oil. We find no evidence that differential rates of economic growth exacerbate the effect of El Nino on fires, nor any robust relationship between district-level poverty or household consumption (omitted for brevity), which often move with economic growth over the medium term in palm expansion regions (Edwards, 2018).

[Table 2 approximately here]

4 Village analysis—the 2015 fire season

4.1 Empirical framework

The objective of our 2015 case study is to identify what types of villages are more likely to set fires. Village characteristics are observed in administrative data at most every three years with little variation across years. An interest in variation across villages and longer-term drivers motivates a classic "between" design. Specifically, by exploiting

the equilibrium differences between villages, we obtain a natural long-run interpretation, retain cross-village variation of interest, and make no ad-hoc timing assumptions about the relationship between fire and village characteristics (Baltagi and Griffin, 1984; Burke and Nishitateno, 2015; Stern, 2010). We estimate the following equation:

$$y_v = \alpha + \gamma R_v + \beta X_v + \delta_d + \epsilon_v \tag{2}$$

where y_v is a dummy variable set to one if village v in district d had any fire in 2015. R_v is a village characteristic of interest. Equation 2 is estimated with a linear probability model, althought probit, logit, and negative binomial models with the original count data give similar results (omitted for brevity). Spatial fixed effects (δ_d) capture district-specific confounding, for example related to overall fire risk, geography, history, culture, and district government environmental and land use policies. District fixed effects also fix comparisons against neighboring villages in the same district. X_i is a vector of potential control variables. Village area and a complete polynomial in latitude and longitude (i.e., the latitude and longitude of each village's centroid and the squared terms) are included as controls throughout, to scale the probability of fire by district size and help purge other geographically-distributed unobservable confounding. ϵ_v a heteroskedasticity-adjusted error term.

If R_v increases by one unit, the probability of fire increases by γ percentage points relative to observably similar villages in the same district. γ has a causal interpretation if there are no problematic omitted variables (a) varying across villages within districts, and (b) systematically correlated with the village characteristics of interest and 2015 fire events. Even though most candidate confounders are captured by the spatial fixed effects, this possibility cannot be ruled out.

To provide the reader with some additional confidence in our estimates and interpretations, we also present results (a) including a host of geographic controls in the linear model and (b) dramatically increasing the number of fixed effect groups by exactly matching villages according to district, terrain, coast, river access, forest proximity, accessibility, and administrative remoteness (c.f., only district fixed effects as groups).

4.2 Results—geography

District-level analysis masks considerable heterogeneity within districts. Figure 3 presents village hotspot detections in 2015 on Sumatra, and Figure 4 on Kalimantan. The black lines represent district boundaries. Notice that some villages had no hotspots detected in 2015, while neighbors within the same district have hundreds. We explore these within-district differences, where villages otherwise face similar geographic, political, and macroeconomic fire risk. Results are presented in coefficient plots thematically, by (a) geographic and factors, (b) village agricultural activities and opportunities, and (c) by socioeconomic development indicators, including man-made infrastructure variables and multi-dimensional poverty indicators.

[Figures 3 and 4 approximately here]

Figure 5 reveals a nuanced picture of the underlying geography of fire. Dots represent point estimates. Lines are 95% confidence intervals. All estimates include district fixed effects, village area, and a complete polynomial in latitude and longitude as controls. Panel A estimates Equation 2 separately for each explanatory variable of interest, since there is some collinearity (villages sometimes exhibit multiple characteristics). The sample size is generous, at over 30,000 villages, and most coefficients are precisely estimated. Since explanatory variables are binary, they can be effectively interpreted as conditional differences in mean (conditional on being in a given district and holding district size and other locational factors constant with latitude and longitude controls). Villages in and near forests are around

10 percent more likely to set fire. The terrain in burning villages tends to be less flat. Coastal villages are slightly less likely to set fire than their neighbors, but fire is much more likely along villages with river access. Rivers are crucial transport corridors in remote, forested parts of Kalimantan and Sumatra with limited physical infrastructure. Specifically, villages on rivers are 6 percent more likely to set fire than their neighbors in the same district. Relatedly, villages that are accessible all year by vehicle are 5 percent less likely to set fire. The magnitude is similar but in the opposite direction for those above the median distance to the district capital city. The final row of Panel A in Figure 5 looks at whether villages that have agreed their boundary maps with district governments in regulation—a proxy for environmental governance—have more fire. We find that villages mapped to the district governments are less likely to have fires, but the magnitude is small. This result suggests that recent initiatives to synchronize overlapping maps across Indonesia's different levels of government may help reduce fire but alone are unlikely to be a panacea.

[Figure 5 approximately here]

Panel B of Figure presents results from including all the geographic variables from Panel A in the one regression model, rather than one-by-one as the explanatory variable of interest—"knocking out" those which are less important in relative terms. Here, the magnitudes on being in or near a forest, in less rugged terrain, on a river, and able to access the village by road all year are relatively unchanged. Forest proximity and river access are quantitatively the most important geographic variables.

4.3 Results—agriculture and development

Figure 6 turns to human factors, grouped by agricultural and development-related variables. For each set, we also exploit the additional geographic variables used in Figure 5 as exogenous controls and as exact matching criteria to impose more demanding counterfactuals. Panels A, B, and C of consider agriculture. The first six rows look at the

primary source of income in the village, across six key agricultural sub-sectors. Villages involved in forestry, secondary crops, and plantation agriculture are much more likely to set fire. Rice farming villages less likely to burn. The probability of fire varies considerably across crops, with forestry villages around 12 percent more likely to set fire and plantation villages 2 percent more likely. Several plantation crops (e.g., oil palm) are perennials which only require land clearing (and thus burning) at planting. Trees usually then stay planted for around 25 years. Thus, farmers using fire to clear land in plantation villages are likely to be in the establishment stage, and villages transition to plantation crops will report their primary income as being in another subsector (e.g., forestry or secondary crops). These agriculture-fire patterns are robust to including additional geographic controls, but point estimates are significantly attenuated when exactly matched. This may reflect the fact that agricultural practices are a function of the underlying geography, with exact matching removing much of the within-group variation of interest and statistical power.

[Figure 6 approximately here]

Given the centrality of palm oil in Indonesian fire-prone landscapes, the bottom half of Panel A in Figure 6 looks more directly at exposure to palm oil supply chains. Using a dichotomous treatment indicator for whether a villages is within 5, 10, 25, and 50 kilometers of a palm oil mill, we find that villages near palm oil mills are not much more likely to have set fire than other villages in the same district. Coefficients are small, and move around based on estimation technique. Specifically, we find that palm-exposed villages are less likely to burn in our baseline model, but slightly more likely using a more demanding geographic matching estimator. Two points bear mentioning here. First, the distance across a district is often smaller than a supply shed. Second, although the palm oil mill data used here is the best currently publicly available, it is are highly incomplete. It may be the case that mills we can observe select into the public sample because they do not mind being observed, and that that villages in the supply sheds of missing mills are burning. The final two rows of

Panels A, B, and C look the probability of fire in villages that rely on firewood for cooking, and in villages with a tradition of burning for agriculture. Villages that rely on firewood for cooking are around 7 percent more likely to have hotspots detected, and those with a history of burning are more than 12 percent more likely. These magnitudes are similar under alternative specifications, suggesting that underlying traditional practices involving fire remain an important risk. Cultural and behavioral change around these practices is likely to form an important part of any sustainable fire reduction strategy.

Panels D, E, and F explore socioeconomic determinants. Here, magnitudes are robust across models, although matching estimates the least precise. We focus our in-text discussion on Panel D, which uses the parsimonious specification with only district fixed effects, village area, and a polynomial in latitude and longitude as controls. Consistent with the earlier results in Figure 5 highlighting the importance of remoteness and forest proximity, villages with above-median population density are 25 percent less likely to have hotspots detected. Villages with improved roads are also less likely to burn, as are those with street lighting and cell phone reception (omitted for brevity). Similarly, villages agricultural kiosks (input dealers) and cooperatives—which we take as a crude proxy for more effective agricultural organization— were around 3 percent less likely to have fire. However, villages with physical marketplaces are slightly more likely to burn than their neighbors without markets.

The most striking result in Figure 6 relates to poverty and underdevelopment. After accounting for district-level spatial fire risk, a one percentage point higher village poverty rate corresponds to a staggering 20 percent increase in the probability of burning. A similar pattern is observed using a poverty line of twice the domestic line and including additional geographic controls. Non-monetary poverty indicators paint a similar picture. Villages (a) with fewer households with access to electricity, (b) without clean cooking fuel, and (c) with poor sanitation, are considerably more likely to have fires detected. Thus, across a wide range of welfare indicators, villages more likely to have hotspots detected are systematically less

developed. These results are consistent with those in the final rows of Panels A, B, and C, as poorer villages tend to cook with firewood and are less likely to have modernized agricultural practices. Finally, in the bottom rows of Figure 6 we show that there is little correlation between fire and village conflict within districts, at least as reported by the district head in the triennial village census.

5 Discussion and concluding remarks

In this article, we took a multi-scalar approach to shine light on the underlying anthropogenic causes of forest fires in Indonesia. At the district level, we identified important changes over time which coincide with heightened fire activity. Although El Nino explains a great deal of the year-on-year variation in fire, there is systematically more fire in periods of stronger local economic growth. We also find that administrative decentralization—specifically the creation of new jurisdictions—has increased fire in splitting jurisdictions, and exacerbated impacts of El Nino on fire in those jurisdictions. At the village level, we found that remoteness, river access, underdevelopment, and traditional fire practices are important in predicting fire across villages within a given locality. Poverty is particularly important. Villages engaged in certain types of agriculture are also much more likely to have fires, namely those plantation crops, secondary food crops, and forestry.

Our results offer several insights for policy makers, international organizations, and non-government organizations interested in reducing forest fire. First, the importance of El Nino and intensified dry seasons means that preparing for and mitigating the impacts for extreme seasons is and will remain a crucial ingredient for overall policy settings. Second, there is likely scope to better integrate economic, social, and overall governance policies to temper the rising environmental and human costs of fire. Our district level results highlight how certain institutional reforms have the potential to compound the already

significant environmental and human costs of climate change. Decentralization reforms have played an important role in shaping fire patterns over space. More fire in response to decentralization funding windfalls—as new districts experience a dramatic increase in per capita funding—raises concerns as Indonesia implements its next wave of decentralization reform (through the 2014 Village Law) while still recovering from the catastrophic 2015 fires. The important flip-side here is that if increased opportunities for resource and rent extraction with redistricting can increase fire, strengthening governance to reduce such opportunities and better align local economic and political incentives could potentially reduce it.

Our district results also highlight the close link between environmental degradation and economic growth in the Indonesian countryside. In other words, the economic-environmental trade-offs that have long characterized large scale agricultural and forestry expansion in the Indonesian countryside remain today, with scant evidence of decoupling (Edwards, 2018). There are two plausible and related explanations for this finding: (a) districts use fire to create economic opportunity and grow the local economy, and (b) economic growth increases residents' and local firms capacity to move, acquire land, and burn further. A third explanation, that fire prevention is costly and thus may be temporarily propping up the local economy, appears unlikely since fire prevention activities have only ramped up in recent years. These environmental-economic findings also relate to a broader literature on the environmental Kuznets curve, which posits that environmental degradation is strongest at earlier stages of development, tapering off and declining as incomes rise (Burke 2010; Stern 2004; Stern 2017; Burke et al 2015). Firmly placed as a lower-middle income country, Indonesia's economic growth still appears to be coming at the cost of the environment. Future policy might help to encourage faster decoupling.

Our most policy-relevant results are likely those from our village case study. Rural development policy in Indonesia is today characterized by the 2014 Village Law: the dramatic scale-up of nationwide community-driven development programs initiatives in the early 2000s, increasing and sustaining large and unconditional cash grants to Indonesia's rural villages while providing greater policy and administrative autonomy. Our case study of the 2015 fire season identifies precisely what types of villages were more likely to have fire, assisting decision makers to target prevention and response policies in the future. Our results collectively suggest that poverty reduction need not go hand in hand with local environmental degradation, at least at the village level. That within-district disparities in remoteness, underdevelopment, and poverty still characterize the local geography of fire also suggests that the current policy push for village development—if successful—could reduce the demand for fire among rural villagers in Indonesia, in addition to potentially increasing the willingness to pay for environmental preservation. More generally, rural development and poverty reduction is likely to be an important part of affecting sustainable behavioral change in economically and environmentally-fragile tropical landscapes where the drivers of environmental degradation appear mostly opportunistic.

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Tables

Table 1: District-level Results—Fires, Climate and Decentralization

Dependent variable	Log hotspot detections				
Column	1	2	3	4	5
Sea surface temperature (SST)	0.575***				0.563***
	(0.032)				(0.033)
Log rain		-1.282***			
		(0.188)			
Log temperature		1.823			
		(1.531)			
District split (=1)			0.394***		
			(0.071)		
Post district split (=1)				0.583***	1.174***
				(0.112)	(0.134)
Post district split * SST					0.138**
					(0.070)
District fixed effects	Y	Y	Y	Y	Y
District-by-district trends	Y	Y	Y	Y	Y
Year-island fixed effects	N	Y	Y	Y	N
Districts	266	266	266	266	266
Observations	3728	3458	3728	3728	3728

Notes: Sample is a balanced panel of all rural districts at 2000 district boundaries. Any changes in samples size due to data availability. Robust standard errors are in parentheses, clustered at the district level. Stars represent statistical significance at the one, five, and ten percent levels. Island groups are defined as Java, Kalimantan, Sumatra, and Sulawesi, with remaining islands grouped together as eastern Indonesia.

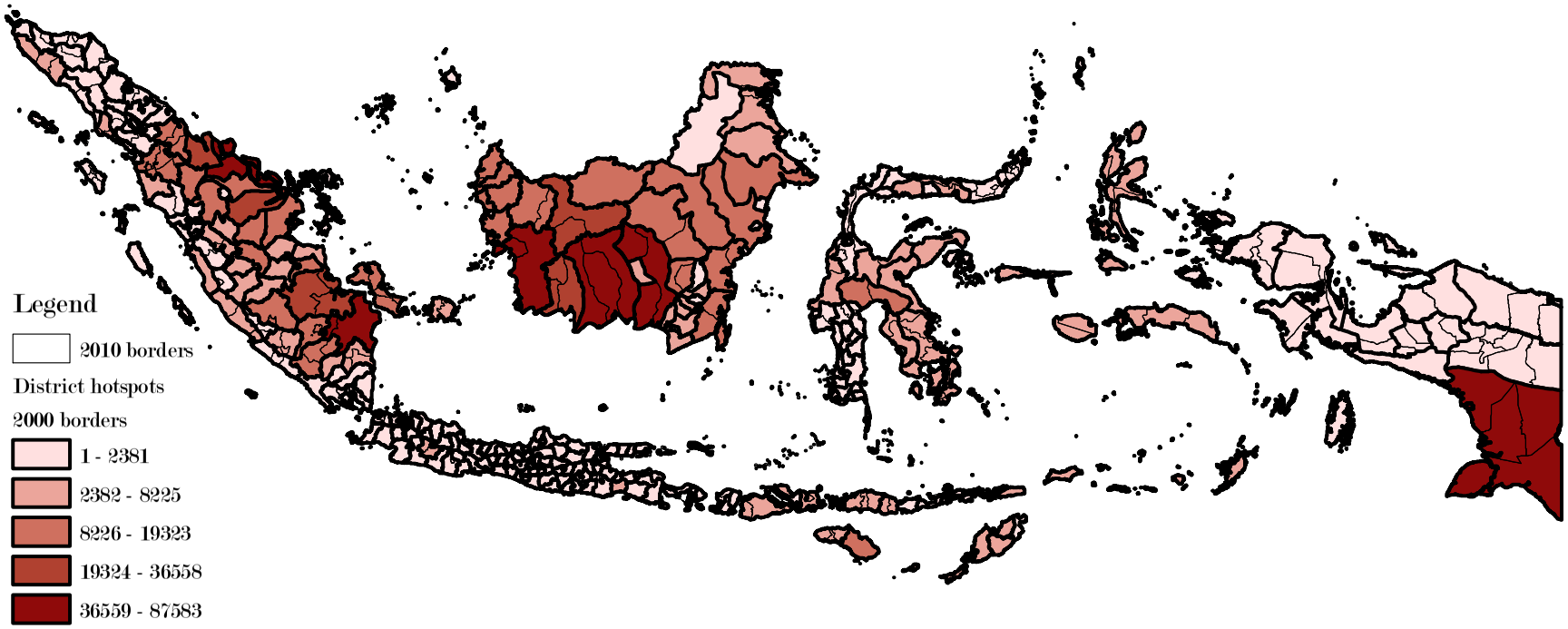
Table 2: District-level Results—Fire and Economic Growth

Dependent variable	Log annual district hotspot detections					
Estimation approach	Levels			First differences		
Column	(1)	(2)	(3)	(4)	(5)	(6)
Levels						
Log GDPPC	0.43***	0.56***		0.29***	0.40***	
	(0.15)	(0.12)		(0.10)	(010)	
Log GDPPC excl. oil & gas			0.63***			0.40***
			(0.13)			(0.108)
District fixed effects	Y	Y	Y	Y	Y	Y
Island-year fixed effects	Y	Y	Y	Y	Y	Y
District-by-district trends		Y	Y		Y	Y
Districts	266	266	266	266	266	266
Observations	2967	2967	2719	2742	2742	2240

Notes: Sample is a balanced panel of all rural districts at 2000 district boundaries. Any changes in samples size due to data availability. Robust standard errors are in parentheses, clustered at the district level. Stars represent statistical significance at the one, five, and ten percent levels. Island groups are defined as Java, Kalimantan, Sumatra, and Sulawesi, with remaining islands grouped together as eastern Indonesia.

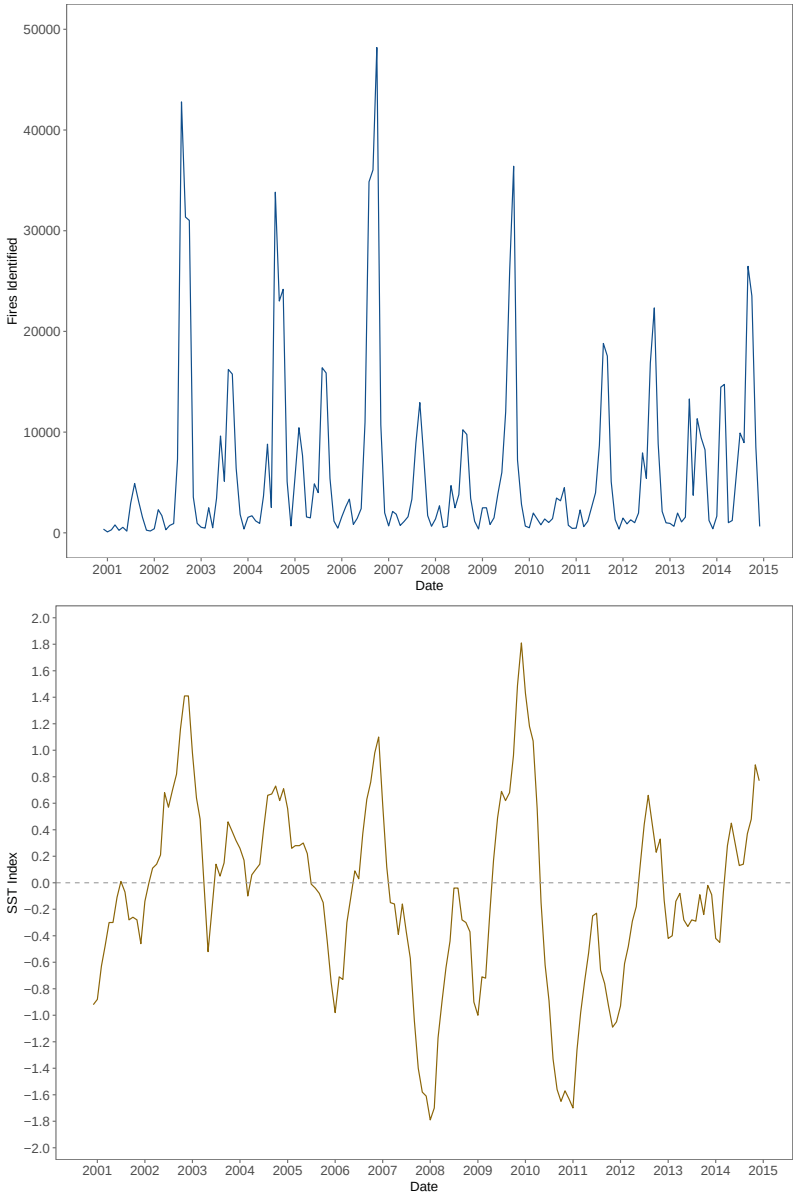
Figures

Figure 1: District Hotspot Detections, 2000–15



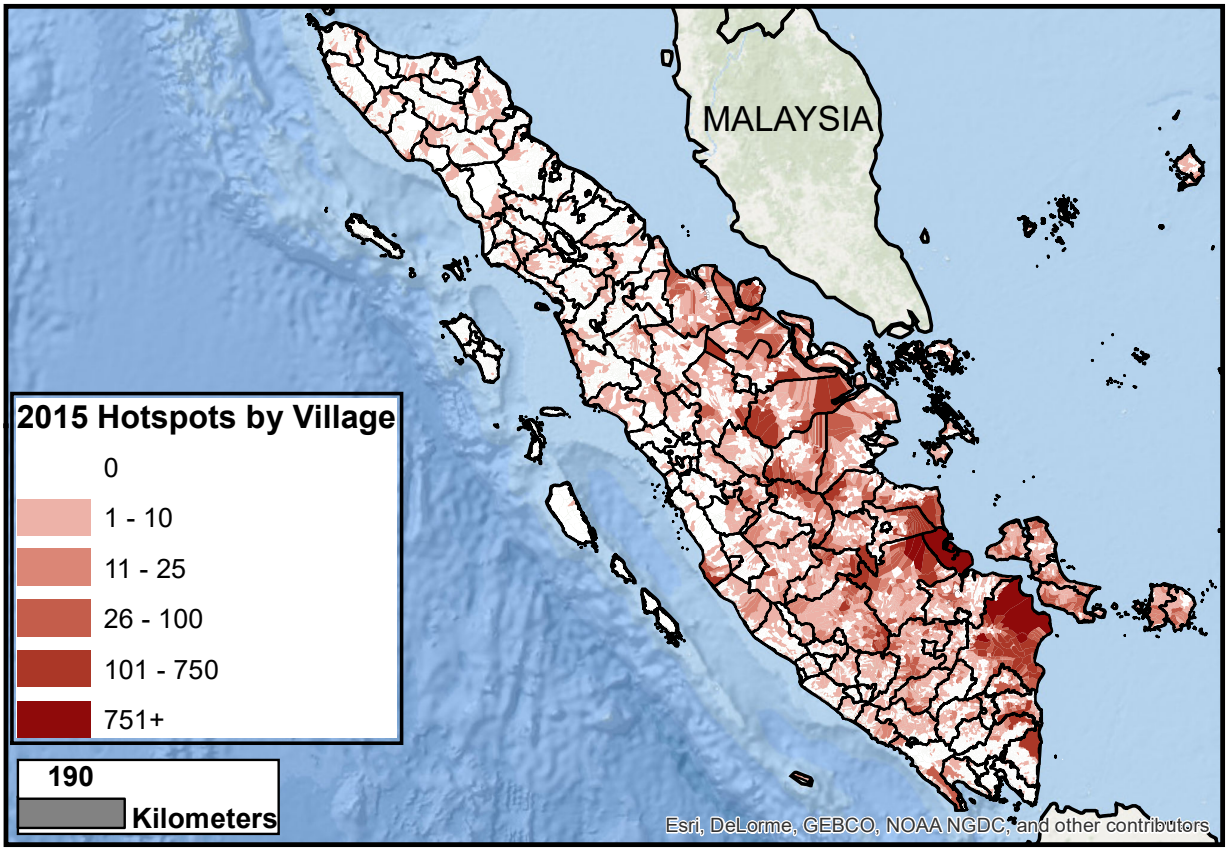
Notes: The figure illustrates the spatial distribution of fire across districts, mapping hotspots detected in each district since 2000. Fire data are raw MODIS detections. District boundaries from the 2000 and 2010 censuses, with the original 2000 boundaries thicker. Thin boundaries represent proliferated districts, and district fire counts are calculated based on the original district definitions.

Figure 2: Fire and El Nino



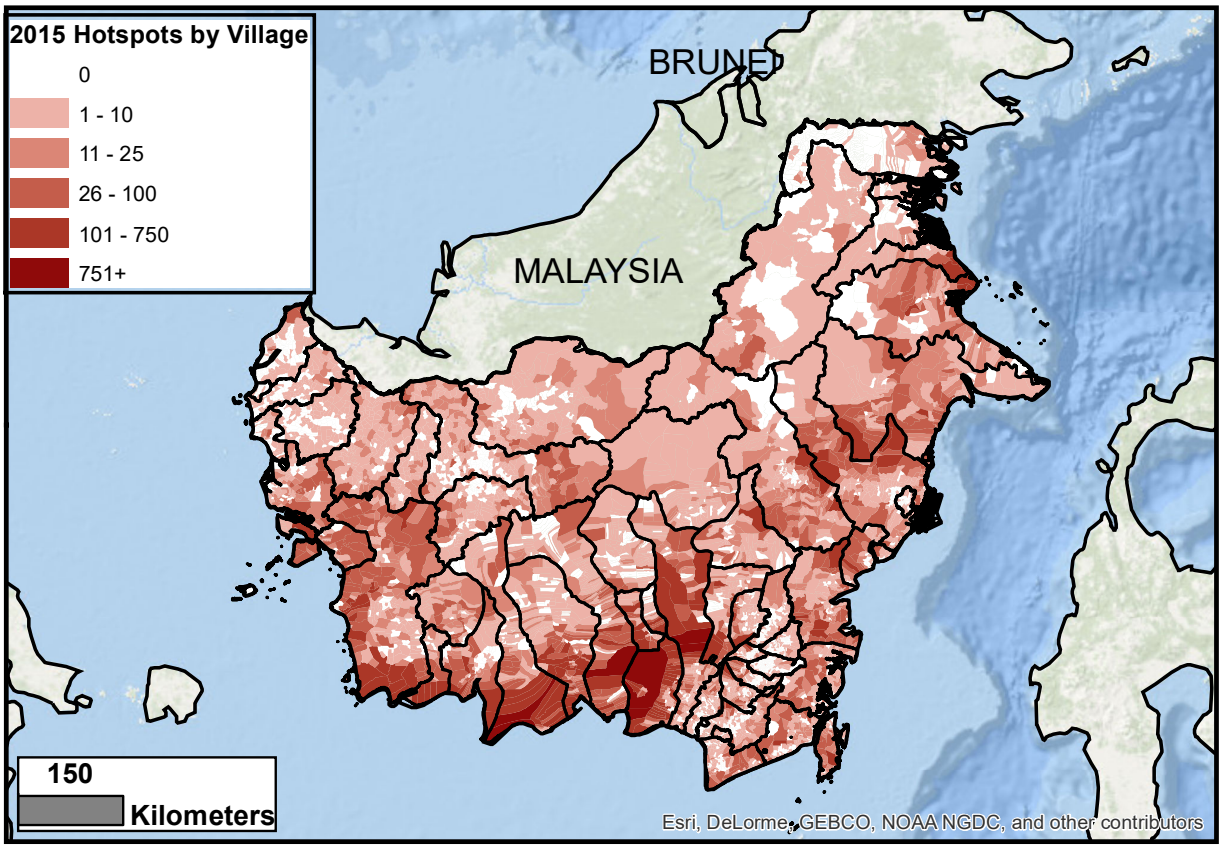
Notes: El Nino data are taken from NOAA (ENSO SST index) and fires identified are raw MODIS hotspot detections by month.

Figure 3: Village Hotspot Detections on Sumatra, 2015



Notes: The figure maps village hotspots on Sumatra in 2015. Fire data are taken from MODIS. Village and district boundaries follow 2010 definitions. District boundaries are black.

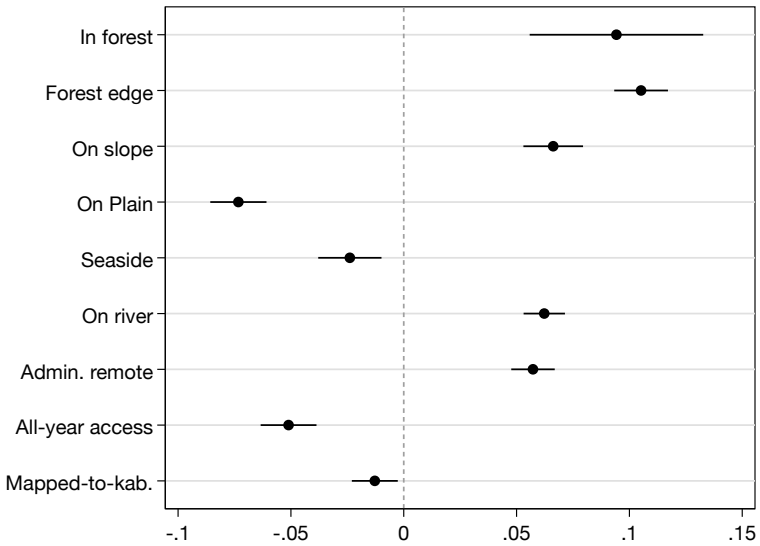
Figure 4: Village Hotspot Detections on Kalimantan, 2015



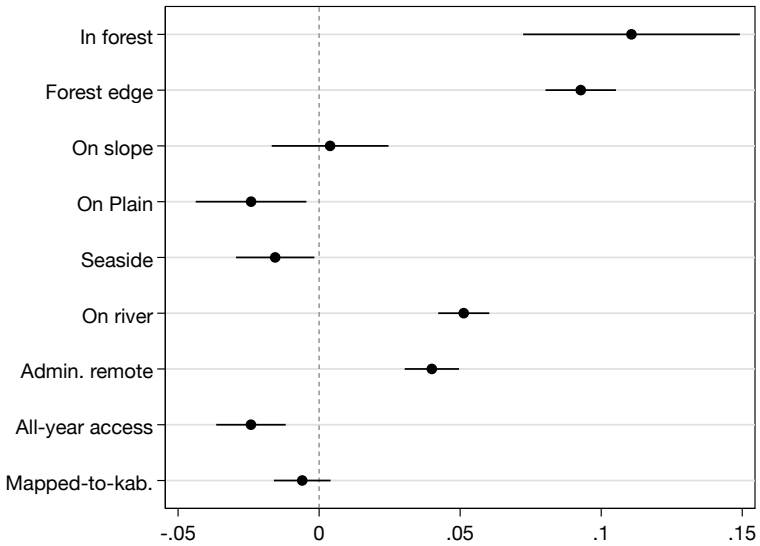
Notes: The figure maps village hotspots on Kalimantan in 2015. Fire data are taken from MODIS. Village and district boundaries follow 2010 definitions. District boundaries are black.

Figure 5: Village-level Results—Fire and Geography

(a) One-by-one

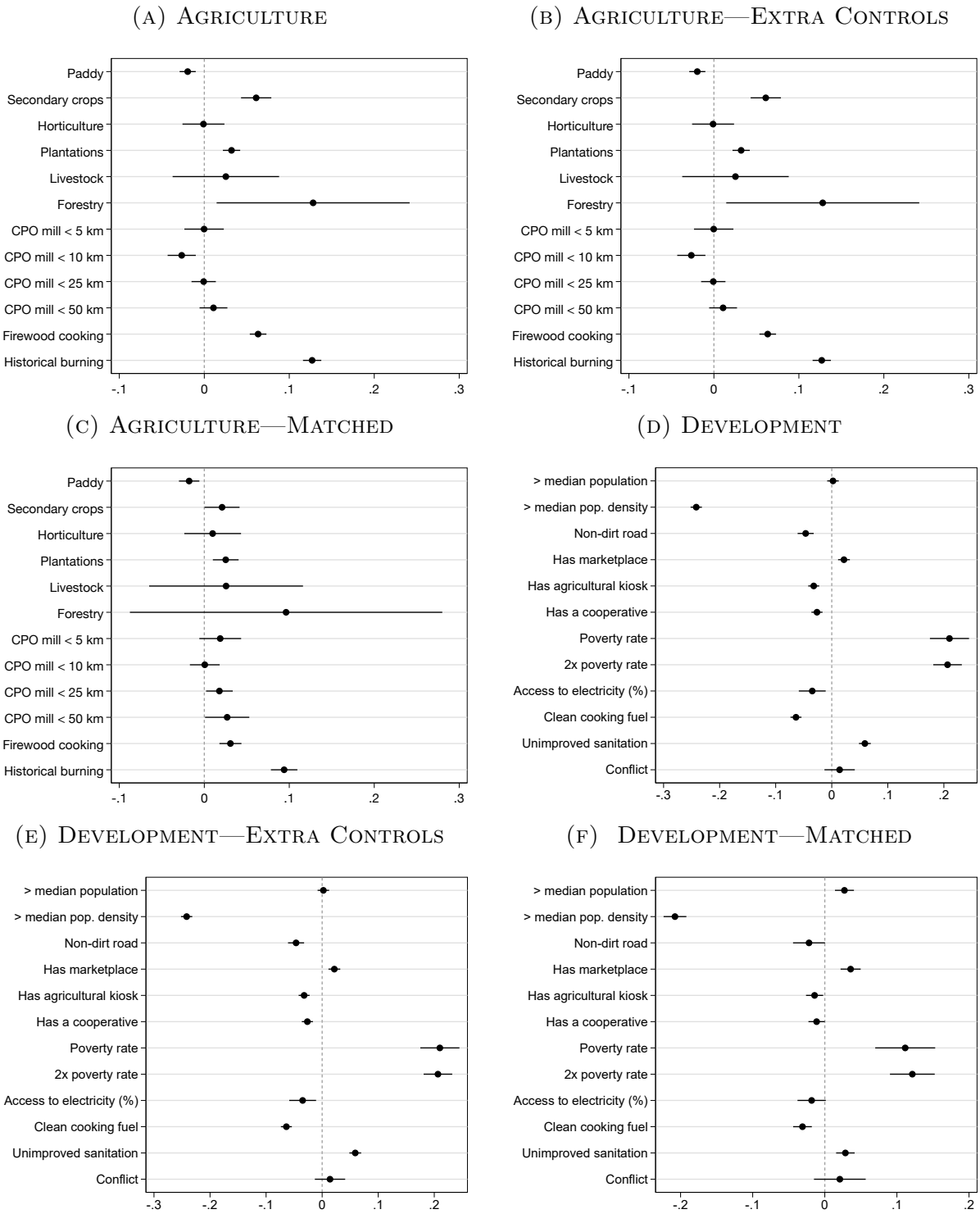


(b) Together



Notes: This figure plots the coefficients from estimating Equation 2. All estimates include district fixed effects, village area, and a polynomial in latitude and longitude. Lines represent 95% confidence intervals. Panel A iteratively estimates the coefficients of interest one by one in separate models, while Panel B estimates the one model including all the explanatory variables together.

Figure 6: Village-level Results—Fire, Agriculture, and Development



Notes: This figure plots the coefficients from estimating Equation 2. All estimates include district fixed effects, village area, and a polynomial in latitude and longitude. Lines represent 95 percent confidence intervals. Extra controls includes plain, coast, forest, river, accessibility, and administrative remoteness as covariates matched exactly matches on these variables.