Palm oil and the politics of deforestation in Indonesia

Elías Cisnerosy, Krisztina Kis-Katosz and Nunung Nuryartono

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Elías Cisneros[†], Krisztina Kis-Katos[‡] and Nunung Nuryartono[§]

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Abstract

This paper studies the interactions between political and economic incentives to foster forest conversion in Indonesian districts. Using a district–level panel data set from 2001 to 2016, we analyze variation in remotely sensed forest loss and forest fires as well as measures of land use licensing. We link these outcomes to economic incentives to expand oil palm cultivation areas as well as political incentives arising before idiosyncratically–timed local mayoral elections. Empirical results document substantial increases in deforestation and forest fires in the year prior to local elections. Additionally, oil palm plays a crucial role in driving deforestation dynamics. Variations in global market prices of palm oil are closely linked to deforestation in areas which are geo-climatically best suited for growing oil palm and they amplify the importance of the political cycle. We thus find clear evidence for economic and political incentives reinforcing each other as drivers of forest loss and land conversion for oil palm cultivation.

JEL classification codes: O13, Q15, Q56, P16

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[†]University of Göttingen

[‡]University of Göttingen

[§]University of Bogor

1 Introduction

Indonesia is home to one of the largest yet most fragile remaining tropical rain-forests in the world. During the last few decades, forest cover has been rapidly decreasing at an accelerating rate (Hansen et al., 2013) (cf. Figure 1). Migration and agricultural extensification have brought about significant improvements in local livelihoods (Bazzi et al., 2016; Klasen et al., 2016), but these came at the expense of forest and biodiversity losses (Drescher et al., 2016). Deforestation in Indonesia has been linked to both excessive logging (Busch et al., 2015) and the palm oil boom (Austin et al., 2017). Additionally, the process has been accompanied by recent political reforms through democratization and the decentralization of fiscal and environmental responsibilities. Existing empirical evidence highlights the link between local political incentives and deforestation; while decentralization has increased the competition for natural resources (Burgess et al., 2012), it has also decreased ethnic heterogeneity and subsequently potentially improved forest governance (Alesina et al., 2019). Local experts have emphasized the role of corruption of local administrations for the excessive expansion of oil palm plantations (Kartodihardjo, 2018) and resulting increases in deforestation. However, there exists no empirical evidence to date linking political and agricultural incentives to deforestation.

Our study investigates the drivers of the deforestation process by focusing on the interaction between agricultural incentives for growing oil palm and the political incentives of local mayors. We are able to causally identify the effects of political incentives by using the idiosyncratic timing of elections of local mayors (*bupati* in regencies or *walikota* in cities). After the sudden resignation of Suharto in 1998, Indonesia began a staggered process of democratically replacing local mayors, as all mayors appointed by Suharto were allowed to finish their existing terms before leaving office. This introduced a quasi-random timing of mayoral elections across Indonesia which continues today. Using panel data, we link these political dynamics to local incentives for expanding oil palm cultivation areas within districts, approximating economic incentives through a combination of global market price fluctuations of palm oil with time invariant local agro-climatic conditions. Since the expansion of oil palm plantations in Indonesia has been exerting downward pressure on palm oil prices on the world market, the deforestation-inducing effects of price incentives are likely to be underestimated. However, in our setting, their interaction with the exogenously timed local elections is still identified, showing a differential effect of upcoming elections under lower or higher palm oil price exposure.

Our results document that both pre-election political incentives as well as agricultural price incentives fuel deforestation, and in the case of palm oil, they also significantly reinforce each other. The scale of deforestation is substantially larger in the pre-election year in those districts facing concurrent increases in palm oil prices. Pre-election increases in deforestation are mirrored by increases in remotely sensed forest fires around seven to twelve months before local elections. Excess deforestation induced by concurrent political and agricultural incentives is most likely to appear on the agriculturally most productive marginal (lower density and non-primary) forest areas. Results on transitions between different land use types also show that this interaction matters most in the short run and in areas that are directly converted to oil palm.

Our paper is linked to three strands of literature. First, it is related to the growing conceptual and empirical literature on the relationship between institutions and the environment (Ostrom, 1990; Cabrales and Hauk, 2011; Jia, 2014; Fenske, 2013). Specifically, we contribute to the body of research focusing on the impact of local governments on forest conservation efforts, when private or political gains are at stake. (Lemos and Agrawal, 2006; Geist and Lambin, 2001; Ribot et al., 2006; Luttrell et al., 2014; Pailler, 2018; Sills et al., 2015; Cisneros et al., 2015; Oldekop et al., 2019). We contribute to this literature by providing the first causal identification of how political incentives interact with agricultural incentives. Second, this paper also relates to the literature con the environmental externalities of agricultural goods production, which documents that under insufficient enforcement mechanisms, demand shocks and technological advances in agriculture lead to negative impacts on the environment (Angelsen, 2007; Barreto and Silva, 2010; Hargrave and Kis-Katos, 2013; Krishna et al., 2017; Gatto et al., 2017; Busch et al., 2015; Börner et al., 2015). We contribute to this literature by showing that the prospects of future economic benefits drive land use decisions and expand the forest frontier. Finally, our paper also speaks to the broader literature on democratization and decentralization. Decentralization and democratization were seen as tools in bringing decision makers closer to the public, introducing accountability, and improving the provision of public goods (Funk and Gathmann, 2011; Bonfiglioli and Gancia, 2013). Nonetheless, decentralization also opens the possibility for rent seeking and capture of the political process by local elites (Bardhan, 2002; Bardhan and Mookherjee, 2006; Martinez-Bravo et al., 2017). We contribute to the literature on the effects of political decentralization by showing that local elections can have persistent environmental effects by inducing excessive deforestation before local elections.

The remainder of the paper is structured as follows. Section 2 describes the policy environment and the policy framework. Section 3 presents the data and outlines the empirical approach. Section 4 presents the empirical results, while section 5 concludes.

2 Policy environment and conceptual framework

2.1 Decentralizing environmental governance

After the fall of the authoritarian Suharto regime in 1999, Indonesia underwent a rapid decentralization and democratization process. At its cornerstone lay a large-scale shift of administrative and fiscal authority to local (district) administrations in 2001 (World Bank, 2003). A large share of public services was shifted from the national to the district level,[1] and within two years the share of public sector employees responding to regional governments increased from 12% to 67% (World Bank, 2003). The new intergovernmental fiscal relations also redefined three quarters of government transfers as non-earmarked, which resulted in increased fiscal spending (Kis-Katos and Sjahrir, 2017). However, the bulk of revenue generating powers remained centralized, resulting in large intergovernmental fiscal transfers to the regions (Gonschorek et al., 2018). This has also increased the incentives to generate extra funds through the selling of natural resources or outright corruption (Dermawan et al., 2011).

Environmental decision-making was also decentralized, although partial re-centralization was quickly restored afterwards. District administrations gained considerable autonomy over the forestry sector and the profitable timber industry after 1999. This led to the rapid expansion of licencing of timber and logging concessions, which became an important source of further local revenue. After the fiscal reforms, 80% of forestry revenues and 40% of the sizeable "Reforestation Fund" were re-allocated to districts (Barr et al., 2006). The newly allocated licenses often contested previously established land rights and protected areas, motivating efforts by the central government to re-centralize the forestry sector, which were successful by 2002 (Barr et al., 2006). However, some districts continued to issue licences illegally, and new concessions still take into account the official recommendation by district administrations (Ribot et al., 2006). This re-centralization process shifted the attention of local administrations towards large cash crop plantations and the palm oil sector (Barr et al., 2006). In order to open up a new oil palm plantation, districts have to issue a permit for companies to initiate negotiations with rural landholders and the Ministry of Forestry (EIA, 2014). If concessions are targeted at state forests, districts play a crucial role in the release of those forest areas for agricultural production (Barr et al., 2006; Sahide and Giessen, 2015). The overlapping competencies between the different tiers of the government blur the divisions between national and local responsibilities with adverse environmental consequences. For instance, the *de facto* area of Indonesia currently covered by oil palm plantations is substantially larger than the size

[1] Law 22/1999 transferred substantial responsibility related to public works, the provision of health, education and culture, agriculture, communication, industry and trade, capital investment, environment and land to districts (Barr et al., 2006). Matters of defence, security, justice, foreign affairs, fiscal affairs and religion remained fully with the central government.

of all land designated as oil palm growing areas by national authorities (Kartodihardjo, 2018).

In 1999, following the first democratic presidential elections since 1955, new local district parliaments were formed with democratically elected members who then appointed new mayors. A further local electoral reform introduced direct elections in 2005, which elected district mayors by popular vote (Sjahrir et al., 2014). From the start of the democratization process, all old-regime mayors were first allowed to complete their full 5-year term, which resulted in a historically determined, idiosyncratic and asynchronous election cycle for local mayors throughout our period of analysis (Sjahrir et al., 2013). The institutional feature of non-coordinated elections makes it especially easy to identify differences in district-level outcomes that arise just before or directly after mayoral elections. The idiosyncratic introduction of democratic elections has been previously linked not only to increased forest loss (Burgess et al., 2012), but also to excessive administrative expenditures from the district budgets (Sjahrir et al., 2013). Martinez-Bravo et al. (2017) link the staggered democratization process to a consolidation of old political elites and persistently lower governance outcomes.

From the beginning, the decentralization and democratization process introduced incentives to create new administrative units by splitting existing districts. The so-called "*pemekaran*", or district proliferation process, led to the creation of a large number of new administrative units, whereby district splits were triggered by ethnic heterogeneity, expected fiscal or natural resource rents as well as geographic factors (Fitrani et al., 2005). Incentives to split districts differed across mother and child districts: whereas mother districts face a loss of economic and natural resources, the newly formed child districts gain autonomy over resources, but face initial administrative set-up costs. Finally, both units potentially gain from an increase in ethnic and political homogeneity (Alesina et al., 2019; Bazzi and Gudgeon, 2016). District splits were administratively halted twice, from 2004 to 2006 and from 2009 to 2012. Both moratoria arguably introduced a certain exogeneity into the timing of district splits that further allow the identification of socio-economic and environmental effects of the Indonesian decentralization process (Bazzi and Gudgeon, 2016). While administrative spending did not increase following administrative splits (Sjahrir et al., 2014), the likelihood of localized conflict occurrence declined in districts that became ethnically more homogeneous after splitting (Bazzi and Gudgeon, 2016). Focusing on environmental outcomes, Burgess et al. (2012) show that the proliferation of administrative units has lead to excess deforestation, especially in districts with low oil and gas revenues, and forest losses have increased after the introduction of direct elections. Edwards et al. (2020) confirms the effect of district splitting on fires at the village level. On the other hand, Alesina et al. (2019) also show that district splitting has reduced ethnic heterogeneity and lead to declines in deforestation, arguing that forest governance improved due to increasing ethnic homogeneity.

2.2 The palm oil boom

During the 2000s, palm oil production in Indonesia increased by 12% each year. Since 2013, the country has supplied more than 27 megatonnes–half of total world production (FAO, 2018). Palm oil is mainly used as a vegetable oil in the food and cosmetic industry but is also increasingly used for the production of biodiesel (Corley, 2009; Mukherjee and Sovacool, 2014; Pin Koh, 2007). At the national level, it has led to sustained agricultural growth, high export tax revenues and a constant inflow of foreign currency (Falconer et al., 2015).

The palm oil boom has had significant economic effects on the local population. The adoption of oil palm increased land productivity, farm income, and educational attainment (Drescher et al., 2016; Krishna et al., 2017; Edwards et al., 2020). Oil palm is less labor intensive and allows landholders to allocate labor to additional income generating off-farm activities (Krishna et al., 2017). Non-farm households further benefit via labor market mechanisms in regions with higher oil palm adoption rates (Dib et al., 2018). Offering high marginal improvements in income in the poorer regions, industrial companies have been successful at incentivizing villages to shift towards oil palm under contract farming (Palmer and Engel, 2007; Gatto et al., 2017; Naylor et al., 2019).

The positive effects of the transition to large-scale oil palm agriculture remain locally contested, as they have been accompanied by large losses in natural landscapes, negative ecological outcomes, and reductions in biodiversity services (Austin et al., 2019, 2017; Clough et al., 2016; Denmead et al., 2017). Licensing oil palm production has been shown to double deforestation rates (Busch et al., 2015; Chen et al., 2019). In addition to the environmental externalities, the expansion of the palm oil industry has been related to land consolidation, conflict over traditional land rights, and water scarcity (Colchester et al., 2007; Rist et al., 2010; Abram et al., 2017; Merten et al., 2016). At the same time, local populations also suffer from detrimental health effects from forest fires for land clearing (Frankenberg et al., 2005; Koplitz et al., 2016; Marlier et al., 2015; Rangel and Vogl, 2017).

At the national level, there have been some attempts to slow down the extent of deforestation for oil palm. In 2009, Indonesia committed to substantial reductions in greenhouse gas emissions (by 26% in 2020). The Ministry of Forestry implemented a moratorium on new agricultural licenses in 2011, the effects of which on overall deforestation rates have been limited (Busch et al., 2015). In parallel, non-governmental organizations intend to mitigate the negative environmental effects of agricultural production with sustainable certification standards. Voluntary certification has been linked to lower forest losses in Indonesia, and a more stringent monitoring and transparency of these certification schemes bear the potential to significantly reduce deforestation rates nationwide (Carlson et al., 2017; Miteva et al., 2015).

2.3 Elections, palm oil and deforestation

Deforestation arises when the demand for new agricultural land is met by converting previously forested areas into farmland. The demand depends on the expected profits from agricultural production, whereas the supply of new land depends on national land use agendas and local logging licences. Decentralization in Indonesia gave local administrations discretionary power over the supply of agricultural licences, which has led to an excess of logging licences and bribe-taking (Smith et al., 2003). Deforestation rates increased due to the district-splitting process intensifying the competition for natural resources (Burgess et al., 2012). Although aimed at increasing electoral accountability, the newly introduced direct mayoral elections did not yield an increased political accountability and resulted in even more deforestation (Burgess et al., 2012), possibly by changing the structure of political rent extraction, with fewer candidates running for office and larger governing coalitions exerting their influence. On the positive side, districts that ended up with less ethnic fractionalization after splitting have experienced lower deforestation rates and a less strong pre-election cycle in deforestation (Alesina et al., 2019).

Beyond the average effect of democratization on deforestation rates, the political supply of new agricultural land also fluctuates along the election cycle. Electoral campaigns at the district level are highly expensive in Indonesia; issuing additional licences against bribes or campaign contributions in pre-election years offers a possible mechanism through which deforestation in pre-election years can increase. Moreover, corrupt administrations may also be bribed to ignore illegal logging before elections (Smith et al., 2003; Amacher et al., 2012). The effects of the electoral cycle may change depending on how strongly the current administration is involved in financing a re-election campaign, which would result in second-term mayors, after reaching their term limit, handing out fewer licenses before elections than first-term mayors. At the same time, administrations nearing the end of their terms may try to exploit natural resources even more.

Election-cycle related deforestation results not only from corrupt activities but also from local administrations signalling economic competence to the voting public. Forest losses are often interpreted as a deterioration of a public good, but in the context of poor rural economies, the conversion of forest into income generating opportunities is often preferred by local populations. To increase the chances of re-election, candidates or political parties in office can support additional credit and fertilizer subsidies, or the (re-)planting of oil palm trees, thereby accelerating deforestation indirectly. Lastly, deforestation cycles can also be a symptom of a declining administrative capacity before elections. District administrations could divert resources away from environmental enforcement into more tangible public goods such as education or infrastructure, increasing the likelihood of re-election.

Shifts in global agricultural demand have the potential to intensify election-cycle related deforestation. With higher expected profits from agriculture, the demand for new agricultural land can spur the corrupt supply of new agricultural licences in pre-election years, raising the amount of bribes offered. Demand for deforestation will thereby exacerbate the supply side fluctuation stemming from the pre-election incentives. In those pre-election years when economic incentives to convert land are especially strong, we expect an accelerated licensing process, and an increase in deforestation rates, especially in newly licensed areas.

3 Data and empirical approach

3.1 Data and descriptive trends

Since we focus on the political incentives faced by local administrations, our spatial units of analysis are at the level of Indonesian districts, which are the main political decision–making units since decentralization. Our data frame spans from 2000 to 2016. We use the first year to establish initial conditions, then generate a district panel over the remaining 16 years (2001–2016). Out of the 514 total districts in 2016, we restrict our main analysis to those 397 that were substantially forested (had an initial forest cover of at least 40%) in 2000. We deal with the ongoing district proliferation process by fixing our district frame to the end of the observation period, building a balanced panel of geographic entities that became separate districts by 2016. As some of these entities are part of the same parent district in earlier years, we cluster all standard errors at the level of original parent districts as observed in the initial year 2000. Moreover, we use a set of splitting-year fixed effects to capture the time dynamics of our outcome variables in the five years around district splits, allowing for differential pre- and post-split adjustments among mother and child districts.

Our empirical analysis combines several types of data: time-variant remotely-sensed data on forest cover, measures of the local exposure to variation in prices of palm oil (and other agricultural crops), information on the timing of local mayoral elections, and the administrative district splitting process, as well as further information on land use licenses and local conditions (see Appendix A.1 for a more complete description of the data generating procedures). We aggregate all spatial information to the district level and rely primarily on yearly variation across districts.

Our main dependent variable of interest is the yearly size of newly deforested area within each district. It is derived from the database by Hansen et al. (2013) that is based on satellite observations and provides yearly raster files at a 30-meter resolution for the years of 2000 until 2016.[2] Based on these, we sum up all new deforestation pixels detected in the raster to the level of administrative districts by year. In terms of aggregate trends, over the last fifteen years, Indonesia has experienced a steep increase in yearly deforestation, with substantial fluctuation in deforestation rates from year-to-year, which will be exploited in our empirical analysis (see Figure 1).

Moreover, we complement this measure of yearly deforestation dynamics with higher frequency measurements by counting the monthly incidence of fires within each district (based on MODIS data, see Appendix A.1). Combining the fire database with Hansen et al. (2013) data allows us to distinguish between fires on originally forested and non-forested areas (based on forest classification from the year 2000). Observed fires may arise from forest clearing by fire but also precede crop replanting on non-forest areas and pose a major threat to natural habitats, global climate and health (Simorangkir, 2007; van der Werf et al., 2008; Koplitz et al., 2016; Tacconi, 2016).

Figure 2 maps the spatial distribution of total forest loss as well as the total intensity of fires over the full time period per district.[3] The two outcomes are closely spatially (although not perfectly) correlated. They reveal a strong concentration of deforestation as well as of fires within two islands, Sumatra and Kalimantan, which were also the most strongly affected by the expansion of oil palm plantations over the last decades. At the same time, the maps also show substantial within-island variation in deforestation (and fires). Figure A2 in the Appendix plots country-wide trends in fires per month, showing strong seasonality in fire incidence as they occur mainly within the dry season. Hence, when investigating fire dynamics, we will additionally control for this variation by using both month and district-specific season fixed effects.

We measure political incentives by relying on the idiosyncratic timing of mayoral elections within each district, and complementing this with data on the exact timing of district splits. Figure 3 shows substantial variation in the yearly number of elections, which we use to identify the local effects of the idiosyncratic election timing. Figure A3 in the Appendix displays the data by month for the time period of direct mayoral elections.

We measure economic incentives by interacting an index of world market price variation of palm oil with local agricultural suitability for growing oil palm measured at the district level. As the global price trend is not exogenous to the Indonesia-wide trend of aggregate deforestation, we discuss the implications of this in section 3.3 and test for the robustness

[2] We follow Busch et al. (2015) by defining forests as areas with at least a 30% canopy density. In our sensitivity tests, we define initial forest based on a range of other canopy density thresholds.

[3] As a comparison, Figure A1 in the Appendix displays a map based on the pixel-wise raw data used to calculate aggregate measures of deforestation and fires.

of the main results by implementing an IV procedure in section 4.2. Moreover, we contrast variation in palm oil prices with a range of other main agricultural crops, interacting crop prices with crop-specific suitability measures (FAO/IIASA, 2012, see Appendix A.1 for further details). Figure 4 shows the time trends in global palm oil prices in real terms, as well as a weighted average of prices of other main crops used as a comparison. All observed price variables are stationary but show substantial fluctuation over time. Palm oil prices increased in several waves, peaking first in 2004, then in 2008 and in 2011. By the end of our time period, they were more or less back in real value to their starting levels. The prices of other agricultural crops did not always move together with palm oil prices, resulting in distinct time series variation.

In a next step, we calculate location-specific price exposure measures at the district level by combining the indices of crop price variation on the global markets (outlined above) with spatial variation in geo-climatic suitability conditions as weights. Location-specific price exposure, PE^c_{dt}, is hereby defined as:

$$PE^c_{dt} \;=\; S^c_d \times P^c_t \tag{1}$$

where S^c_d denotes the time-invariant average agricultural suitability for growing crop c in a given district d, and P^c_t is based on global crop price variation across time t.[4] We express global price variation in the form of an index that computes deviations of current world market prices from their average over the past five years in order to better capture the new information content of market prices that will affect decisions to expand agricultural land. The underlying hypothesis is one of backward-looking adjustment: market participants observe the profitability of oil palm over recent years and adjust their economic decisions to convert new land in case the current price developments deviate from the prices in the past. Thereby we assume that markets are efficient such that current prices can be taken as best predictors of future price developments. In further results, we contrast the importance of oil palm with other crops by relying on an aggregate measure of ten widely-grown plantation and industrial crops (see Appendix A.1 for further detail).

Among further controls, we allow for differential trends in selected initial conditions—initial suitability for growing oil palm and initial forest area—and control for the district proliferation process. Administrative district splits are motivated by competition over resource use (Burgess et al., 2012), but are also aimed at reducing ethnic heterogeneity within the administrative units, which could have improved governance outcomes (Alesina et al., 2019). We control for this district splitting process descriptively by using a set of yearly indicators to identify parent and newly formed child districts from two years before until two years after the split.

[4] Figure A4 maps the spatial variation in oil palm suitability across districts, showing that lowland areas on Kalimantan, Sumatra and West-Papua are the most suitable for oil palm cultivation.

In order to investigate how changes in deforestation are linked to land use change and bio-physical conditions, we rely on further sources that classify land use types and disaggregate yearly forest losses by the initial (time-invariant) characteristics of the land types in which deforestation occurs. First, we distinguish between forest loss on originally primary and non-primary forest areas (Margono et al., 2014). Forest losses on primary forest areas measure the irreversible loss of tropical rainforests and hence are expected to induce more negative ecological effects. Second, we use bio-physical maps to classify forest losses by original land use typologies, distinguishing between lowland, upland, wetland, montane, and peatland areas (Gumbricht et al., 2017; Margono et al., 2014).

Finally, we investigate whether changes in agricultural land use policies are driving deforestation by collecting policy information on different types of land use concessions. First, we use spatial layers on wood fiber and logging concessions from the year 2014 and oil palm concessions from the year 2017 (Greenpeace, 2018; Global Forest Watch, 2018) and investigate whether economic and political incentives led to more forest losses on future concession areas by their type. Second, for wood fiber extraction and logging, we construct district panels of concession area changes, since information on wood fiber and logging licences (but not on oil palm) is provided with an exact date (Greenpeace, 2018). Figures A5 and A6 in the Appendix display the bio-physical maps and concession boundaries, respectively, whereas Figure A7 shows the trends in newly established concession areas over time. Finally, using long-difference information on the expansion of industrial oil palm (Austin et al., 2017), we are able to distinguish between forest conversion into oil palm versus other land uses (see Figure A8 in the Appendix). Table A1 in the Appendix displays descriptive statistics.

3.2 Empirical models

We investigate the presence of a political deforestation cycle in a panel data setting, regressing the inverse hyperbolic sine[5] of the newly deforested area in district d and year t, D_{dt}, on the idiosyncratic timing of local elections and further controls:

$$D_{dt} = \sum_{\tau} \beta_\tau E_{dt+\tau} + \mathbf{X}'_{dt}\gamma + t \times \mathbf{Z}'_{d0}\delta + \lambda_d + \xi_t + \varepsilon_{dt}. \quad (2)$$

We model the electoral cycle in two ways. First, we test for pre- and post-election dynamics by including up to four indicators equal to one if local elections $E_{dt+\tau}$ take place in the periods $t+2$, $t+1$, t, and $t-1$. In this case, the second lag within the 5-year cycle

[5]The inverse hyperbolic sine function transforms the size of the yearly newly deforested area, Def_{dt}, as $\ln(Def_{dt} + \sqrt{Def_{dit} + 1})$. As compared to a log-transformation, it has the advantage of being defined at zero and yielding near-zero positive values for very small deforestation levels, but allowing for interpreting coefficients in percent similarly to a log transformation.

serves as the omitted category. In a second step, we follow the literature on the political budget cycles (e.g., Sjahrir et al., 2013) by focusing mainly on pre-election changes in deforestation by setting $\tau = 1$.

All regressions include district fixed effects, λ_d, that control for all sources of time invariant district heterogeneity, and year fixed effects, ξ_t, that control for average fluctuations in deforestation due to macroeconomic and common policy shocks. Additionally, our preferred specifications control for the ongoing district splitting process, $\mathbf{X}_{dt}$, by adding a split indicator for parent and child districts separately, together with further two lags and two leads of each. Moreover, we allow for differential time trends by selected initial conditions, $\mathbf{Z}_{d0}$, which include the initial forest size as well as the initial oil palm suitability index. This makes sure that our results are not merely reflecting differential trends in deforestation across structurally different districts. All standard errors are clustered at the level of 251 original parent districts in order to control for correlated outcomes across newly formed districts that used to belong to the same parent district before.

We also investigate the political business cycle at a higher frequency by using monthly data on forest fires, and regress the hyperbolic sine of the number of fires, F_{dqm}, on the exact timing of elections:

$$F_{dqm} = \sum_{q=e-6}^{e+3} \beta_q E_{dq} + \lambda_{ds} + \xi_m + \upsilon_{dqm} \tag{3}$$

Forest fires are measured by the number of detected fires in district d and month m in yearly quarter q. We combine distance to elections by quarter in order to reduce noise due to monthly fluctuations, and hence E_{dq} turns to one if an election took place within the q^{th} quarter before (or after) our month of measurement. We model the political cycle consisting of 10 quarters around elections. We control for seasonal district effects, λ_{ds}, which capture the average propensity to experience fires in each district by season.[6]

Our main specifications extend the political cycle to include a further measure of palm oil price exposure, PE_{dt}, which measures the potential exposure of the local economy to new variation in global market prices of palm oil (and other crops) (cf. section 3.1). Price exposure captures the agricultural incentives to clear land for future oil palm plantations within any district, and varies across districts and across time due to differences in soil suitability for oil palm production and time variation in palm oil prices. To investigate whether the economic and political incentives reinforce each other, we especially focus on the interaction of the electoral cycle with palm oil price exposure. We thus regress deforestation on election timing, the variation in price incentives and the interaction of

[6] In the dry season, which lasts roughly from May until September, there is a generally larger propensity to clear forest with fires.

these two variables, plus further controls as before:

$$D_{dt} = \alpha PE_{dt} + \beta E_{dt+1} + \mu E_{dt+1} \times PE_{dt} + \mathbf{X}_{dt}\gamma + t \times \mathbf{Z}_{d0}\delta + \lambda_d + \xi_t + \varepsilon_{dt} \tag{4}$$

For simplicity, we reduce the full set of indicators for a local election cycle from equation (2) to a pre-election indicator E_{dt+1}. This is a meaningful simplification, because in our data the main shift in deforestation is generally observed one year before elections. Our main coefficient of interest is given by μ, which describes the interaction effect between political and agricultural price incentives. Positive values for α and β would show that both political and economic considerations contribute to deforestation at the district level, whereas a positive μ would imply that the two types of incentives reinforce each other.

3.3 Identification issues

Causal identification of political incentives and price effects requires exogeneity of our localized measures of these incentives. The idiosyncratic process of the timing of local elections enables a convincing identification strategy for pre-election effects, especially since even elections of very close neighbors are not synchronized. The second political process of splitting districts is more endogenous as it is incentive-driven, but the two district-split moratoriums (from 2004 to 2006 and 2009 to 2012) introduce a certain exogeneity in the timing of district splits (see Figure A9). In our analysis, we will primarily investigate the exogenous local election cycle but will also control for the timing of district splits and analyze interactions between district splits and elections.

A bigger threat to causal identification arises from the endogeneity of the variation in the price of palm oil. As Indonesia is a major palm oil producer on the world market (together with Malaysia), we cannot take the fluctuation in the palm oil price as exogenous from a national perspective. The world market supply of palm oil has been increasing continuously through the ongoing extension of oil palm area. Demand shortages during the financial crisis and later the relatively lower pace of demand expansion have started to put downward pressures on the world market price of palm oil. Assuming a less than perfectly elastic demand for palm oil, the agricultural expansion of oil palm area (and hence deforestation) are likely to have contributed to a lowering of the world market price. This induced a negative reverse correlation between aggregate deforestation and palm oil prices. We control for common aggregate fluctuations using year fixed effects and only link differences in across-district variation in the agro-climatic exposure to price variation to changes in deforestation. Nonetheless, the endogenous price reaction (driven by oil palm expansion induced deforestation) will lead us to under-estimate the relative importance of palm oil price variation driving the demand for new land. Hence, our estimates can be interpreted as a lower bound of the possible price incentive effects. Among the sensitivity checks, we also provide an upper bound of the estimate, by using fluctuations in the global business cycle of all trading partners of Indonesia weighted by their relative importance as buyers of Indonesian oil seed exports as instruments for the demand component in the palm oil price variation. Moreover, conditional on year fixed effects, the interaction of the quasi-exogenous political process with a partially exogenous palm oil price variable will still correctly capture the differential effects of political incentives in oil palm growing regions (Nunn and Qian, 2014).

4 Results

4.1 Baseline results

Table 1 shows results on the local mayoral election cycle, based on equation (2). When compared to the middle of the election cycle, none of the yearly cycle indicators reaches significance at conventional levels in column (1), but coefficients are generally negative both during and after elections, and turn positive in the pre-election year. Excluding pre- and post-election years consecutively from the controls (in columns 2 to 4), and hence extending the comparison period to include the middle years in the election cycle, reveals a consistent and statistically significant shift in deforestation rates in the year before local mayoral elections. The positive pre-election coefficient shows an increase in forest losses by about 5% in districts with upcoming mayoral elections in the next year. Upcoming mayoral elections seem to lead to clear shifts in local incentives to engage in deforestation. Before elections, mayors may gather extra revenues by selling licenses for wood extraction or the conversion of areas to oil palm plantations. Additionally, less strict environmental oversight or policies that promote local economic activities in the short run will also contribute to a rise in deforestation. The quasi-experimental variation in local political incentives results in a significant increase in the overuse of natural resources, which is also relevant in economic terms.

The monthly fire data show a more nuanced picture of potential deforestation dynamics around elections, corroborating the presence of a pre-election cycle seen in the yearly deforestation data. Figure 5 reports point estimates and 90% confidence intervals based on equation (3), regressing the inverse hyperbolic sine of monthly number of forest fires on quarterly election indicators and further controls. The observed time patterns confirm our aggregate yearly results. Fires in forested areas, which are most likely triggered by forest clearing activities, increase about four quarters before elections (panel a). At the same time, fires in non-forested areas also increase three to four quarters before elections (panel b). An increased burning of non-forested areas can result from the clearing of shrubland or the replanting of older crop plantations. The effects stay the same when estimating forest fires in moderately forested areas and disappear in very remote regions that started with a forest cover of more than 90% (see Figure A10 in the Appendix). However, election effects are also strong when focusing on forest fires in sparsely forested regions, with a 7% increase in the number of fires four quarters before the election date and a 5% increase in the same quarter when elections take place.

Table 2 contrasts this political pre-election effect with the effect of further economic incentives that drive land conversion to oil palm plantation,[7] showing results based on equation (4). We include a pre-election indicator and measure economic incentives by palm oil price exposure, combining time variation in palm oil prices on the world markets with spatial variation in the agro-climatic suitability for growing oil palm in each district. Column (1) shows a clear positive link between exposure to palm oil price variation and forest loss. A one standard deviation higher local palm oil price exposure results in about 8% more deforestation in a district. The palm oil price exposure coefficient stays precisely the same in column (2), when the pre-election year indicator is also added, underlining the quasi-experimental nature of the election cycle. Results do not change in column (3), when we control for varying deforestation trends by initial oil palm suitability and forest size as well as for the time dynamics of the district splitting process. Column (4) in Table 2 focuses on the interaction between political and economic incentives. The interaction of the pre-election indicator with the palm oil price exposure show a highly significant positive coefficient. This shows that agricultural incentives to convert land to oil palm plantations tend to play a larger role before elections, or, that pre-election incentives result in more deforestation, especially in times and places when and where the agricultural conditions favor land conversion to oil palm. While a one-standard-deviation increase in palm oil price exposure increases deforestation by 7%, the effect doubles in pre-election years, with a combined effect resulting in over 18% more deforestation. Hence, improvements in the incentives to grow oil palm clearly interact with pre-election incentives at times and in places when the incentives to convert land use to oil palm are especially high. We will retain the specification of this column as our preferred baseline specification throughout the following analyses.

Table 3 investigates the same dynamics from an ecological perspective, distinguishing between deforestation on different biomes and on primary and non-primary forests. First, we categorize the initial forest area into five mutually exclusive biomes: lowland, upland, montane, wetland and peatland (following Margono et al., 2014). These five biomes are of different agricultural value, with lowland and wetland areas being especially suited for agricultural production. This is also reflected in the results. In lowland areas, the results are very close in magnitude to the baseline coefficients from Table 2, showing increases in deforestation with increasing palm oil price exposure and also a significant interaction

[7]See Table A2 in the Appendix for full results including controls.

of price exposure with upcoming elections. The other biome showing similar dynamics is wetland, the agricultural conversion of which is somewhat more challenging. Here the interaction of palm oil price exposure with the pre-election indicator turns out significant and larger in magnitude, documenting that agricultural incentives matter mainly before elections. On the agriculturally less-valuable upland and montane areas, point estimates on prices are substantially smaller and insignificant. They are also insignificant on peatland, but also less precisely estimated. These results provide a useful consistency check for our baseline results, since agricultural incentives should be more strongly linked to deforestation in prime agricultural areas. Taken together, these results confirm that in Indonesia the deforestation-inducing effects of oil palm expansion respond to changes in agricultural profitability. The last two columns of Table 3 show that price effects and their interactions with election timing are more significant on non-primary forest areas that lie outside of the tropical rainforest. Nonetheless, the coefficients of deforestation on primary forest are not substantially different, only less precisely estimated.

4.2 Robustness to identification issues

Our main results from Table 2 are robust to how deforestation is measured, and to which districts we include in the analysis. The interaction between price and electoral incentives persists irrespective of what canopy density cut-offs we use to define a forest, or which inclusion criteria we use to define our district sample.[8]

The role of identification issues is potentially more challenging and these have to be addressed more explicitly. First and foremost, the global palm oil price variation that enters the localized price exposure measure cannot be taken as fully exogenous. Indonesia is the worlds' largest palm oil producer and exporter, producing about 54% of total world output in 2015/16 (USDA, 2019). Expansions of oil palm area in the country can be expected to put a downward pressure on the world market price of palm oil. This can lead to an omitted variable bias as the national trend of oil palm expansion not only increases deforestation but will also reduce global palm oil prices, resulting in more conservative (downward biased) price exposure estimates. However, as we do not intend to identify general equilibrium effects of palm oil price changes on total deforested area and control for year fixed effects, the endogeneity of price trends does not cause major concerns. Our estimates will provide lower bounds of the potential price effects. Nonetheless, in what follows, we also show results when using palm oil price variation as predicted by global demand conditions.

[8] Section A.2 and Tables A3 and A4 in the Appendix show that our main results are fully robust to the choice of cut-offs of canopy density as well as to our choice of which districts to include in the sample as long as they had at least 20% of forest cover in 2000. Furthermore, our results stay the same if all administrative cities or all Javanese districts are excluded from the analysis.

We assess the potential biases from endogenous palm oil prices by focusing on price variation triggered by fluctuations in global demand for palm oil, using an instrumental variable (IV) approach. We generate an instrument by adjusting our price exposure measure from equation (1) by interacting local oil palm suitability, S_d^c, with potential shifts in global demand for Indonesian palm oil, rather than simple palm oil prices. We approximate this demand component by using Y_t, a trade-weighted global GDP measure, which includes all trading partners that have been importing oil seeds from Indonesia over an initial period, and weights their real GDP figures by each country's market share in total Indonesian oil seed exports:

$$Y_t = \sum_p \left(\Delta GDP_{pt}^{real} \times \frac{1}{T} \sum_\theta \frac{EX_{p\theta}}{\sum_p EX_{p\theta}} \right),$$

where $EX_{p\theta}$ is the value of total oil seed exports from Indonesia to trading partner p in years $\theta \in [2000, 2005]$ (with $T = 6$), and ΔGDP_{pt}^{real} is the change in annual real GDP per capita of each partner. The interaction of trade-weighted global GDP fluctuations with local oil palm suitability is then used as an instrument to the palm oil price exposure measure.

Table 4 presents the IV results. The instruments are sufficiently strong for predicting variation in palm oil price exposure at the first stage (with an F-statistic of 64.8), but perform worse when predicting the interaction between prices and elections (with an F-statistic of about 6.6, see Table 4). Instrument validity requires the effects of the business-cycle-driven global demand for new land area in Indonesia to be fully moderated through palm oil prices. Since oil palm plantations have been the most quickly expanding land use types in Indonesia, we indeed may expect global demand for palm oil to play a dominant role in agricultural demand. Nonetheless, the IV estimates are likely to provide an upper-bound estimate of the effect of palm oil price incentives, as global GDP fluctuations may also drive demand for other crops (with similar local suitability for oil palm). In Table 4, coefficients on elections and prices decrease and lose significance compared to the baseline results (Table 2), whereas the price coefficients interacted with the pre-election indicator increase substantially. These results show that, in particular, the pre-election effects of palm oil prices, which utilize the quasi-experimental variation from elections, also persist if we use a more exogenous measure of the variation in palm oil prices.

A further concern of omitted variable bias arises because palm oil prices may also proxy for a further range of agricultural incentives to plant other crops. Although oil palm has indeed played a central role in the Indonesian economy, incentives to plant other crops can be expected to also influence deforestation. We check for the robustness of our results by also controlling for the fluctuation in further crop prices. Just like for palm oil, we measure variation in local crop price exposure for ten other main agricultural crops in

Indonesia by interacting deviations in yearly prices from past five-year averages with a local suitability index (as in equation 1). In order to reduce the dimensionality of the comparison, we combine the individual price indices by weighting them by the relative importance of each crop into a single *Other crop price exposure* measure (see Appendix A.1 for further detail). As for the weights, we contrast results using FAO production data with data from the Indonesian System of National Accounts (SNA).

Table 5 contrasts the role of palm oil with a combined measure of other price incentives, which also show a strong correlation with deforestation. A one standard deviation increase in the weighted price exposure measure is linked to about 2 to 8% more deforestation, which is only significant when weighting crops using FAO weights (in column 1). The interaction between the pre-election year and the aggregated crop price incentives turns out insignificant. When accounting for palm oil prices as well as other crop prices together (in columns 2 and 4), the interaction of pre-election incentives is robustly linked to palm oil prices, while staying insignificant for the combined price index of other crops. This corroborates our expectation that palm oil may indeed have a more special role in explaining the political economy of deforestation in Indonesia. Alternatively, Table A5 in the Appendix presents pairwise tests between price exposure of each of the other important agricultural crops and palm oil price exposure, whereby further crops are listed in descending order of their relative national production values. Results on other crop price exposures are only sporadically significant and there is no other crop that would dominate the pre-election effects of oil palm.[9]

The measure of palm oil price exposure crucially relies on the local geoclimatic suitability to grow oil palm. However, this may also simply measure agricultural suitability in general, in which case our price exposure measures again would not be palm-oil specific, preventing us from giving a causal interpretation for the effects. We test for this by generating alternative (false) palm oil price exposure measures that substitute for the oil palm-specific geo-climatic variation using other crop suitability indices, and multiply them with palm oil prices. Table A6 presents the placebo estimates that re-run the baseline estimates (from equation 4) using alternating false measures. The price exposure coefficients remain positive and significant, indicating that for the general price effect, oil palm suitability cannot be clearly distinguished from overall agricultural suitability, as both are highly correlated. However, the interaction coefficient between the pre-election year indicator and the alternative price exposure remains small and insignificant across all placebo regressions. This strengthens our claim that it is the interplay of incentives to plant oil palm with political incentives that drives deforestation rates in Indonesia.

[9] The palm oil price interaction turns insignificant only when also controlling for rubber price exposure. However, since the FAO does not provide rubber suitability maps, for rubber we assume identical suitability with oil palm, which makes us unable to fully disentangle the effects of palm oil and rubber price exposure.

A final concern arises because of the possibility that some of the elections are not fully exogenously timed. Whenever districts split up, child districts have to form newly elected governments, which results in a shortening of the cycle for child districts. 94% of parental districts remain within a five to six year cycle.[10] In selected cases, corruption scandals may have also forced some districts to pre-emptively introduce new elections, whereas few elections have been delayed and take place after more than 6 years. In these cases, election timing cannot be considered exogenous anymore as it is prone to strategic behavior by corrupt administrations. In order to test for the relevance of this concern, we exclude all irregular election cycles in Table A7. Estimates in the more restrictive sample of regular elections increase both in size and significance, ensuring that our results are not driven by irregularities in election timing.

4.3 Political mechanisms and policy instruments

Our main results show that political incentives and the demand for palm oil are jointly driving forest losses in Indonesia. While this finding is fairly robust, it does not pinpoint yet any clear mechanisms for why deforestation increases before elections, and especially in times of rising palm oil prices. When the next elections are drawing nearer, local politicians may target local economic development in general in order to signal their competence towards their voters. Additionally, local administrations may increase the sales of licenses that allow land conversion before elections also in order to collect additional funds that can be used to finance direct hand-outs or other policies that are valued by the local constituencies in the short run. Local politicians may also be more directly connected to the oil palm sector and may especially favour their patronage networks when elections are drawing nearer.

In what follows, we present a series of further results that investigate the potential role of political dynamics as well as local policy actions that can be linked to deforestation. First, we compare whether incentives differ before direct and indirect elections. We also investigate whether pre-election incentives change due to the administrative process of district proliferation. Second, we use time-variant land use maps to link the observed forest conversion to the expansion of oil palm plantations in order to see whether economic and political incentives to deforest are linked to the expansion of oil palm area in the short run or in the longer run. Third, we use information on the yearly amount of newly-allocated licenses to extract timber or wood fiber from the forest in order to see whether policy actions are also directly linked to the economic incentives established above.

Our main results did not distinguish between direct mayoral elections that were introduced in 2005 and the earlier system, where mayors were indirectly appointed by democratically

[10] Six year cycles are predomenantly found for districts that hold elections around new year.

elected local parliaments. Table 6 decomposes the pre-election effects within these two electoral systems, distinguishing between the effects of direct and indirect elections. We expect to find stronger political incentives to pursue populist policies in the regime with direct elections, as they establish a closer link between politicians' actions and their electoral success (Bardhan, 1997). This could increase deforestation pressure directly if the benefits of land conversion are fairly widespread, or indirectly, if revenues from potentially corrupt activities linked to land conversion are then used for financing hand-outs or other voter-pleasing policies before elections. The results in Table 6 are as expected, showing much clearer increases in deforestation before direct elections, as well as in interactions with palm oil prices. However, as indirect elections span over a substantially shorter time period than direct elections (cf. Figure 3), their timing yields less identifying variation and makes it harder to distinguish power issues from a true non-effect.

District mayors face a two-term limit for being in office. As described in section 2.3, second term mayors and first term mayors re-running for office potentially face different incentives to engage in corrupt activities. We collected historical information on Indonesian mayors by scraping Wikipedia pages of Indonesian districts. Due to gaps in the timelines, we can identify if mayors are in their first or second term in 82% of all elections. In years without any information on the mayor incumbency, we assume the mayors is in his first term, which could underestimate the effect of second term mayors in our sample. Results are shown in Table 7. The indicator for second term mayors in column (1) shows a positive sign but remains insignificant, and remains insignificant when interacted with palm oil price exposure in columns (2) and (3). Thus, we find no institutional effects on deforestation resulting from a two-term limit. This may be due to political elites exchanging positions in public office, as we can see descriptively that vice mayors are frequently inaugurated after the second term of their predecessors. In such a setting, local administrations may equally overuse forest resources before elections either to support their own campaigns or to help the electoral bid of the vice mayor.

4.4 Land use dynamics

New land use maps enable us to investigate the dynamics of converting forests into industrial-scale oil palm plantations. Combining remote sensing with visual interpretation, Austin et al. (2017) produce maps of industrial oil palm plantations in five-year intervals from 2000 to 2015 for the islands of Sumatra, Kalimantan, and Papua (see Figure A8). Based on their data, we use raster intersection to account for deforestation that is located on pre-existing oil palm plantations, newly created plantations, or other area. These maps also allow us to analyze when deforested area is being converted into oil palm plantations, distinguishing between short term conversion (within a 1 to 5 year window) and mid-term conversion (within a 6 to 15 year window). We assume that forest losses that are only identified as oil palm plantations at a later point in time must have had an alternative transitory use in the meanwhile. Descriptive statistics on forest loss in Table A8 in the Appendix show that within the reduced sample of 231 districts with data (on three islands), 5% of total forest loss is located on pre-existing oil palm plantations, 24% on new plantations, and 72% is located outside of industrial-scale oil palm plantations.

Column (1) in Table 8 reproduces our main result for the reduced sample located on the three islands (as in Austin et al., 2017). It shows positive though insignificant palm oil price exposure and pre-election coefficients, and a positive significant coefficient on the interaction between electoral and palm oil price incentives. This result is mirrored in the bulk of the sample, representing forest losses located in areas that did not become industrial-scale oil palm plantations until 2015 (see column 2). By contrast, on new plantations that have been converted to oil palm between 2000 and 2015 (in column 3), the interaction between political and economic incentives increases substantially. When agricultural incentives to convert area to oil palm plantations are high in pre-election years, deforestation accelerates. By contrast, column (4) in the same panel can be considered a placebo check. It shows deforestation in areas that have already been converted to oil palm plantations at the beginning of our period, in 2000. Here "deforestation" may reflect replanting or the conversion of an oil palm plantation to some other use. In this specification, the election and price interaction effect vanishes, indicating that neither election nor palm oil price incentives play a role in the agricultural decisions on replanting or conversion for alternative use. Hence, politicians do not simply focus more strongly on promoting agricultural growth before elections, which may also result in more intensive replanting activities, but mainly influence conversion of forests to new agricultural land.

Panel B of the same table extends the results of column (3) of panel A, by distinguishing between deforestation resulting in short-term vs. longer-term conversion and replanting. Immediate conversions account for 70% of cases of forest loss for new oil palm plantations (see Table A8 in the Appendix), and the role of political and economic incentives appears to be extremely large in this case (column 1). By contrast, in areas that first have an alternate land-use type before being converted to oil palm in the longer run (column 2) pre-election and price coefficients turn significantly negative. Upcoming elections and palm oil price increases make it less likely that deforestation will arise in an area that will be later converted to oil palm. This negative effect loses significance when both effects reinforce each other, as the sum of the three coefficients is statistically indistinguishable from zero.

Table 9 provides further evidence on whether legal concessions are linked to the same incentives that also drive deforestation. We classify deforestation according to the latest observed localization of official concession areas (in 2014 to 2017, see Appendix A.1 for details). By that, we investigate how deforestation patterns differ in land types that will end up as a concession area for a specific use around the end of our period of analysis. We are able to distinguish between three types of concessions for agricultural land use: concessions for logging, for wood fiber extraction (which basically results in managed forest use), and for oil palm plantations. The empirical results offer additional evidence on the dynamics of land use change. On areas that later become oil palm concession areas, we even observe statistically significantly less deforestation before elections at the baseline. However, both palm oil prices and our main interaction of interest turn out statistically significantly positive, contributing to more deforestation when political and economic incentives are aligned. By contrast, no similar dynamics can be observed on areas that end up with logging or wood fiber concessions. Column (4) aggregates all concession types and shows relatively similar dynamics to the oil palm concessions. Finally, higher palm oil prices result in more deforestation even on the no-concession areas. These results suggest that land transition dynamics may be more complex and spillover effects across different types of land use may also arise.

A direct link between electoral incentives and policy mechanisms is investigated in Table 10, where we use the legal timing of new concessions for logging and extracting wood fiber to estimate the effect of prices and election cycles on the size of newly licensed concession areas. Although logging and wood fiber licences are officially designated for forest good production, they could still serve as a transition stage before setting up oil palm plantations or as a disguise for oil palm areas, hence we still link them to palm oil price exposure. The baseline palm oil price exposure coefficients are generally insignificant.[11] Unlike in all previous specifications, wood fiber licences are higher not only before but also during and after elections, with a peak in the post-election year (see column 1). The dynamics of logging concessions move in the opposite direction but not significantly so (column 3). The interaction between prices and elections are significantly positive after elections (column 2) for wood fiber, but not for logging licences (column 4). In combination with the effects on deforestation by concession type, this confirms the hypothesis that licensing and deforestation go hand-in-hand but also shows that the actual licenses may follow with a delay. Local politicians may either encourage or ignore deforestation before elections and then legalize the new oil palm areas afterwards. Therefore they seem to make use of wood fiber concessions, which are direct substitutes for the use of the increasingly scarce land resources.

[11] Table A9 in the Appendix shows a somewhat more pronounced relationship between timber price exposure and wood and logging concessions.

5 Conclusion

Our paper investigates how agricultural and political incentives drive deforestation in Indonesian districts. Using a panel over 16 years, we show that deforestation is higher in the year before mayoral elections, and the same dynamics can be observed when focusing on the frequency of monthly fires. Deforestation is also larger in those regions that are more exposed to improving price incentives to grow oil palm, but also other relevant agricultural crops. More substantially, the political and the agricultural incentives interact: deforestation increases by more before elections in those districts that are more exposed to favourable palm oil price shocks whereas other relevant crops do not seem to have similar pre-election effects. The palm oil-induced deforestation is concentrated in the most fertile lowland and wetland areas and in areas with relatively smaller forest density, or mainly secondary forest coverage.

From a political perspective, we find somewhat clearer links between the timing of direct mayoral elections and deforestation than between the early indirect elections. Our results are robust to controlling for the time dynamics of the district-splitting process, although we find no evidence for changes in forest losses in newly formed administrative areas in the year before or after the formation nor on the area of the parent district. Furthermore, the two-term limit for district mayors seems to have no additional effect on forest losses before elections.

When focusing on land use transitions more specifically, the interaction of economic and political incentives fuels deforestation more strongly in the short run and in areas that are then converted to oil palm, providing evidence that direct transition to oil palm is a strong driver of deforestation. Nonetheless, the economic and political incentives to grow oil palm also contribute to deforestation in areas that have not (yet) been converted to oil palm plantations, and especially, that have not been licensed to grow oil palm. Finally, we show that incentives to plant palm oil may contribute to the issuing of new concessions to extract wood fiber after elections, potentially in order to legalize illegal logging that has arisen in the run-up to elections.

These results provide evidence that local politicians expect to receive short-term electoral benefits from either promoting agriculture-driven economic development or raising local revenues by selling licenses to convert forest areas to agricultural production just before elections. The external effects from forest-clearing by fire are increasingly perceived at the local as well as global level. Increasing monitoring, local awareness, and accountability of mayors before elections might slow down accelerating economic and political incentives and mitigate excess deforestation.

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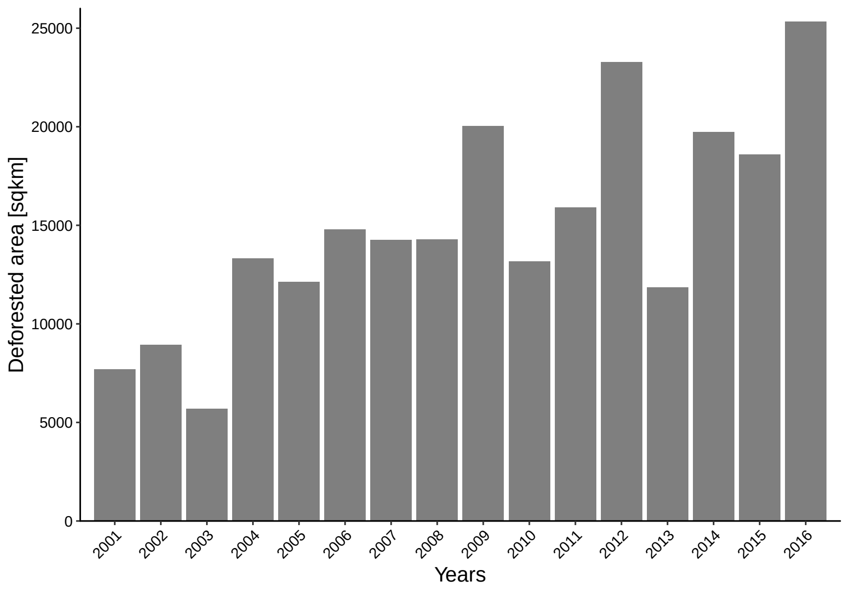
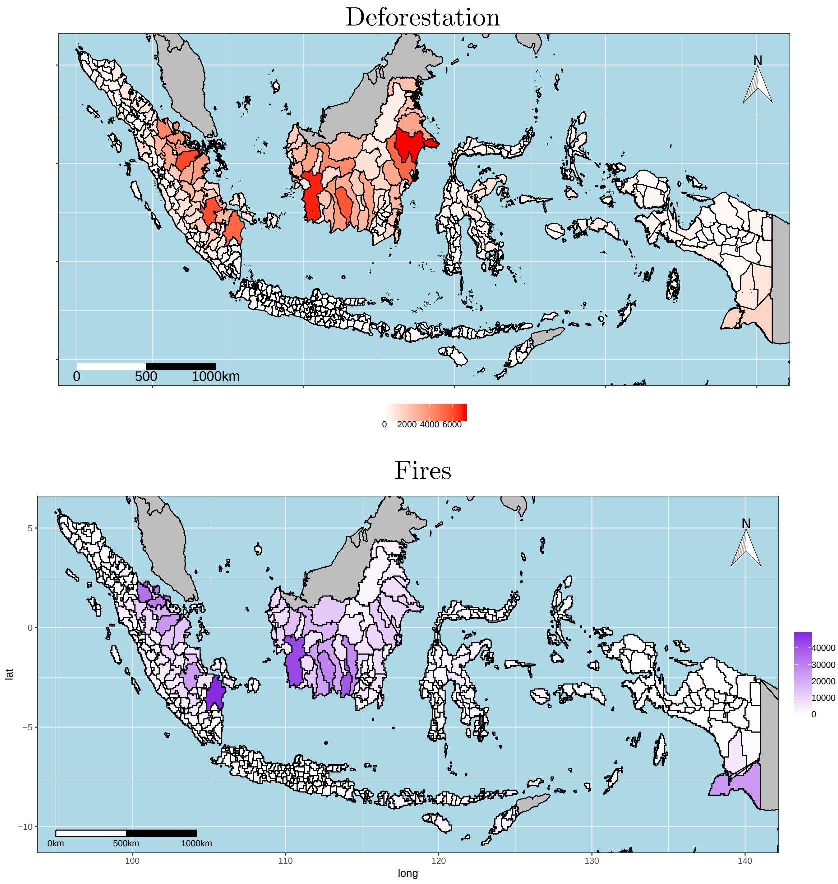
Figures

Figure 1: Total newly deforested area per year



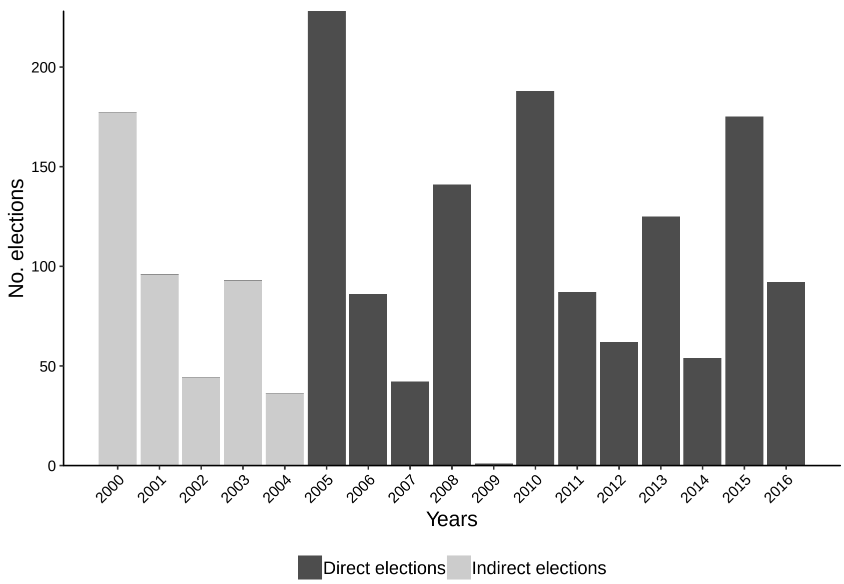
Source: Hansen et al. (2013)

Figure 2: Total deforestation and fire intensity 2000–2016 (per district)



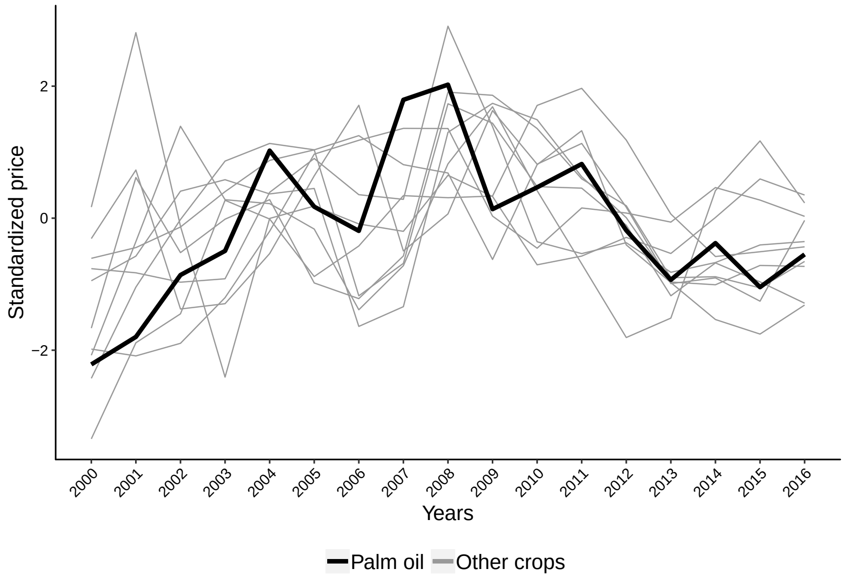
Source: Hansen et al. (2013) and (NASA/GSFC/Earth Science Data and Information System, 2018), combined with a district layer from GISPEDIA.

Figure 3: Number of local mayoral elections per year (indirect and direct)



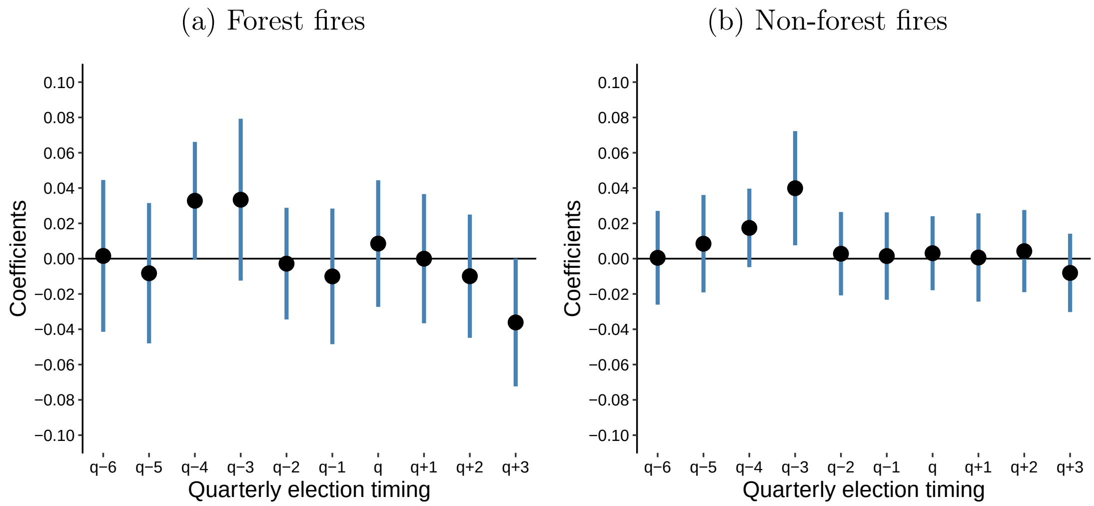
Source: KPU Election registries and Wikipedia

Figure 4: Standardized price trends of palm oil and other major crops



Note: The thin grey lines plot the yearly variation in the normalized real local exposure value of global crop prices of ten major agricultural crops; the thick grey line plots their weighted average (using SNA-based production shares). The thick black line plots variation in real local exposure value of the global palm oil price.

Figure 5: Monthly election timing



Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of monthly fires located on originally forested (a) and non-forested (b) areas. Regressions include island-month and district-season fixed effects. Points represent the point-estimates of the election indicators from 6 quarters before elections to 3 quarters after elections. Bars represent the 90% confidence interval after clustering on the district level.

Tables

Table 1: The political deforestation cycle

Dependent variable	*asinh* Deforestation			
	(1)	(2)	(3)	(4)
Elections				
t-2	−0.025			
	(0.028)			
t-1	0.044	0.054*	0.051*	0.053**
	(0.033)	(0.030)	(0.026)	(0.024)
t	−0.017	−0.006	−0.009	
	(0.035)	(0.032)	(0.029)	
t+1	−0.001	0.010		
	(0.032)	(0.027)		
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352
Adj. R^2	0.887	0.887	0.887	0.887

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 2: Baseline: Local exposure to palm oil prices and elections

Dependent variable	*asinh* Deforestation			
	(1)	(2)	(3)	(4)
Pre-election year		0.053**	0.044*	0.042*
		(0.024)	(0.025)	(0.025)
Palm oil price exposure	0.080***	0.080***	0.082***	0.071**
	(0.031)	(0.031)	(0.031)	(0.032)
Pre-election year				0.075**
× Palm oil price exposure				(0.036)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	No	No	Yes	Yes
Observations	6352	6352	6352	6352
Adj. R^2	0.887	0.887	0.890	0.890

Note: The estimation sample is restricted to 397 districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by initial forest size and the local oil palm suitability index. Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 3: Ecological differences in deforestation

Dependent variable	*asinh* Deforestation						
On biome type	Lowland	Upland	Montane	Wetland	Peatland	Primary forest	Non-prim. forest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre-election year	0.043	0.017	0.055	0.035	0.042	0.074*	0.054**
	(0.028)	(0.046)	(0.069)	(0.065)	(0.062)	(0.044)	(0.026)
Palm oil price exposure (PE)	0.079***	0.029	0.022	0.018	0.072	0.042	0.067**
	(0.029)	(0.053)	(0.046)	(0.051)	(0.055)	(0.046)	(0.033)
Pre-election year	0.078*	−0.042	−0.027	0.140***	0.015	0.052	0.069*
× Palm oil PE	(0.041)	(0.055)	(0.073)	(0.051)	(0.062)	(0.059)	(0.033)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352	6352	6352	6352
Adj. R^2	0.908	0.869	0.872	0.867	0.835	0.930	0.877

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district that occurred on biomes of different types (based on area classification at the beginning of the period). All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial size of forest and biome areas, the local oil palm suitability index. Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 4: Sensitivity: Instrumenting for palm oil price exposure

Stage:	Second	First	First
Dependent variable:	*asinh* Def.	Palm oil PE	Palm oil PE $\times$ Pre-el. year
	(1)	(2)	(3)
Variables of interest:			
Pre-election year	0.034	0.006	0.039**
	(0.026)	(0.012)	(0.019)
Palm oil price exposure (PE)	−0.014		
	(0.048)		
Pre-election year $\times$ Palm oil PE	0.200**		
	(0.092)		
First stage: Instruments:			
Oil palm suitability (OPS) $\times$ Trade-weighted global GDP		0.033***	0.001**
		(0.000)	(0.001)
Pre-election year $\times$ OPS $\times$ Trade-weighted global GDP		0.002*	0.027***
		(0.001)	(0.003)
First-stage F-statistics		64.85	6.63
District fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Further controls	Yes	Yes	Yes
Observations	6352	6352	6352

Note: The estimation sample is restricted to 397 districts with an initial forest cover of at least 40% in 2000. The dependent variable at the second stage measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial forest size, and the local oil palm suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 5: Sensitivity: Palm oil vs. other agricultural crop prices

Dependent variable	asinh Deforestation			
	(1)	(2)	(3)	(4)
Pre-election year	0.045*	0.041	0.047*	0.041
	(0.025)	(0.025)	(0.025)	(0.025)
Palm oil price exposure		0.051*		0.059**
		(0.028)		(0.029)
Pre-election year × Palm oil price exposure		0.083**		0.079*
		(0.039)		(0.042)
Other crop price exposure	0.083*	0.054	0.071	0.026
	(0.045)	(0.040)	(0.044)	(0.041)
Pre-election year × Other crop price exposure	0.019	−0.017	0.045	−0.008
	(0.031)	(0.032)	(0.034)	(0.039)
Source of crop weights	FAO	FAO	SNA	SNA
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352
Adj. R^2	0.890	0.890	0.889	0.890

Note: The estimation sample is restricted to 397 districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. Other agricultural crop suitability is aggregated by weighting individual crops by their relative economic importance within Indonesia in year 1995–2000 using the FAO statistics and in year 2000 using SNA data by BPS. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial forest size, the local oil palm suitability index and the local other crop suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 6: Politics: The role of direct vs. indirect elections

Dependent variable	*asinh* Deforestation		
	(1)	(2)	(3)
Pre-election year (indirect)	−0.039	−0.042	0.043
	(0.083)	(0.084)	(0.033)
Pre-election year (direct)	0.057*	0.056*	0.042
	(0.032)	(0.032)	(0.033)
Palm oil price exposure		0.082***	0.073**
		(0.031)	(0.032)
Pre-election year (indirect) × Palm oil price exposure			−0.006
			(0.118)
Pre-election year (direct) × Palm oil price exposure			0.085**
			(0.041)
District fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Further controls	Yes	Yes	Yes
Observations	6352	6352	6352
Adj. R^2	0.889	0.890	0.890

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size and the local oil palm suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 7: Politics: The role of second term mayors

Dependent variable	*asinh* Deforestation		
	(1)	(2)	(3)
Palm oil price exposure		0.081***	0.079**
		(0.031)	(0.033)
Second term mayor	0.035	0.032	0.031
	(0.032)	(0.032)	(0.032)
Palm oil price exposure × Second term mayor			0.011
			(0.029)
District fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Further controls	Yes	Yes	Yes
Observations	6352	6352	6352
Adj. R^2	0.889	0.890	0.890

Note: The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size and the local oil palm suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 8: Land use dynamics: Oil palm expansion and deforestation

Panel A				
Dependent variable	*asinh* Deforestation			
By land use	All area	Non oil palm in 2015	New oil palm by 2015	Oil palm in 2000
	(1)	(2)	(3)	(4)
Pre-election year	0.029	0.041*	−0.079	−0.001
	(0.025)	(0.024)	(0.058)	(0.048)
Palm oil PE	0.051	0.047	0.030	−0.026
	(0.039)	(0.038)	(0.088)	(0.051)
Pre-election year × Palm oil PE	0.059*	0.057*	0.163***	−0.001
	(0.033)	(0.032)	(0.066)	(0.043)
Adj. R^2	0.905	0.897	0.963	0.976
Observations	3465	3465	3465	3465
Panel B				
Dependent variable		*asinh* Deforestation		
Conversion type		Short-term	Long-term	Replanting
		(1)	(2)	(3)
Pre-election year		−0.155*	−0.164*	−0.134
		(0.086)	(0.090)	(0.092)
Palm oil PE		0.313**	−0.165*	−0.009
		(0.123)	(0.096)	(0.095)
Pre-election year × Palm oil PE		0.359**	0.148	−0.170
		(0.158)	(0.114)	(0.169)
Adj. R^2		0.875	0.957	0.912
Observations		3465	2310	2310
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes

Note: The estimation sample is restricted to 231 districts with an initial forest cover of at least 40% in 2000 on the islands Sumatra, Kalimantan, and Papua. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial forest size, the local oil palm suitability index and the local other crop suitability index). Robust standard errors are clustered on level of 136 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 9: Land use dynamics: Deforestation by final legal concession status

Dependent variable	*asinh* Deforestation				
On final concession area for	Oil palm	Logging	Fibre	Any	None
	(1)	(2)	(3)	(4)	(5)
Pre-election year	−0.082**	−0.008	0.016	−0.062	0.040
	(0.036)	(0.044)	(0.021)	(0.046)	(0.027)
Palm oil price exposure (PE)	0.055**	0.040	0.028	0.075**	0.068**
	(0.026)	(0.036)	(0.031)	(0.035)	(0.032)
Pre-election year × Palm oil PE	0.070**	0.062	0.022	0.079**	0.057
	(0.028)	(0.037)	(0.034)	(0.035)	(0.039)
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes	Yes
Observations (Districts)	6352	6352	6352	6352	6352
Adj. R^2	0.985	0.983	0.984	0.984	0.876

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district that occurred on area which by the end of our observation period was officially granted the denoted concessions (2014 for fiber and logging, 2017 for oil palm). Fiber concessions refer to concessions for wood fiber extraction. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial size of forest and the local oil palm suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table 10: Land use dynamics: New wood fiber and logging concessions

Dependent variable	*asinh* New wood fiber concessions		*asinh* New logging concessions	
	(1)	(2)	(3)	(4)
Pre-election year	0.382*		0.189	
	(0.197)		(0.197)	
Election year	0.359***		−0.088	
	(0.135)		(0.154)	
Post-election year	0.533***	0.355**	−0.136	−0.166
	(0.162)	(0.152)	(0.150)	(0.149)
Palm oil price exposure (PE)	0.184	0.121	−0.082	−0.082
	(0.124)	(0.106)	(0.130)	(0.110)
PE × Pre-election year	−0.064		0.044	
	(0.196)		(0.138)	
PE × Election year	−0.191**		−0.042	
	(0.133)		(0.160)	
PE × Post-election year	0.185	0.242*	−0.086	0.090
	(0.172)	(0.158)	(0.140)	(0.127)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes
Observations	5558	5558	5558	5558
Adj. R^2	0.168	0.167	0.186	0.186

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size, the local oil palm suitability index and initial primary forest size to proxy the potential of high value timber). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

A Online Appendix

A.1 Data generation procedures

Administrative spatial units. The primary administrative subdivision in Indonesia is the province (in Indonesian *provinsi*), followed by the district (either regencies, called *kabupaten* or cities, called *kota*), sub-districts (called *kecamatan*, at times also referred to as districts) and villages or urban precincts (called *desa*). Currently there are 34 provinces, 514 districts, 7201 sub-districts and more than 80 thousand villages and urban precincts. From all these administrative divisions, we focus on the level of districts, as decentralization was primarily targeting this second administrative tier.

Spatial boundaries. We aggregate spatial information to the level of Indonesian districts by using spatial boundaries from GISPEDIA (2018), adjusting the district frame to the end of the year 2016 (to 514 districts). We update the GISPEDIA (2018) district boundaries from 2009 by manually splitting three newly formed districts (Buton, Konawe, Muna in Southeast Sulawesi) and geo-coding official district maps with the help of QUANTUM GIS software.

Deforestation. Our deforestation data is derived from the Global Forest Change database version 1.4 (Hansen et al., 2013), which contains yearly raster files at a 30m resolution for the years of 2001 until 2016. Hansen et al. (2013) emphasize the presence of a structural break in the detection quality after 2011, leading to smaller measurement errors in the later years. We control for the average shift in data quality by using time effects. Our results generally hold also if using a shorter time frame until 2011. We aggregate deforestation pixels to the district level by year. We aggregate the measures of annual forest loss relying on forest canopy density in 2000. We follow Busch et al. (2015) by defining initial forests as areas with at least a 30% canopy density. The area of yearly forest loss per district is calculated by multiplying the number of newly deforested pixels with the mean pixel size within a district. The size of each pixel varies by its location along the North-South axis. We take the center pixel within a given district and calculate its surface area using UTM projections. The according UTM zone is chosen by the location of the pixel.

For instance, the district *Batang Hari* in the province of Jambi has its center pixel at the GPS coordinates (103.4686; -1.852982). The according UTM Zone is 48 South, the projection string is "+PROJ=UTM +ZONE=48 +SOUTH +DATUM=WGS84 +UNITS=M +NO_DEFS"(EPSG:32748), resulting in an average pixel size of 948.63 square meters.

Forest fires. We measure the monthly number of forest fires in each district using the daily fire detection data from MODIS (Collection 6 NRT Active Fire Detection module MCD14DL (M6)). We calculate the number of fires per month both on areas that were still forested in the year 2000 as well as those that were non-forest areas.

MODIS Collection 6 reports fire detection from two satellites, AQUA and TERRA. Our measurements are based only on TERRA, which started to operate in mid-2000s–two years before AQUA. Using a composite of both satellites does not change our results.

Election data. We measure political incentives by relying on the idiosyncratic timing of mayoral elections in each district. Data on the exact timing of elections is only available for direct mayoral elections, starting in 2005 for 497 districts (cf. Bazzi and Gudgeon 2016). The data on the exact timing of direct elections has been provided by the Electoral Committee (*KPU, Komisi Pemilihan Umum*) for the years 2005–2018 and has been complemented by further online sources. More specifically, we use the archives of national newspapers (Kompas and Tempo) as well as online search to find reports on local elections in each district. For the years before 2005, we scrape Wikipedia on the time of mayors' incumbency. Election years are hereby set according to the beginning of the political office.

District splits. Data on the exact timing of district splits has been derived from fiscal accounts and online sources. Starting from 341 districts in 2000, the number of administrative units increased gradually, resulting in 514 districts in 2016.

Crop price exposure: Agricultural prices. Agricultural prices of palm oil (and ten other main crops) are measured as yearly global market averages and taken from FAOSTAT, IMF Primary Commodity Prices and UNCTAD. The US dollar values are converted to constant 2010 Indonesian Rupiah by using exchange rates and a consumer price index from the Federal Reserve Bank of St. Louis (2019).

We express real palm oil (and other crop) prices in the form of price indices, using the deviation of yearly global prices from their medium-term average (calculated over the previous five years) in order to measure current improvements in agricultural profitability. Our underlying assumption is that for market participants, changes in current prices can be considered as a good proxy of expected future price developments.

Crop price exposure: Agricultural suitability. We localize the effects of world market price variation of palm oil and other crops by interacting them with local agricultural suitability for growing oil palm (and other agricultural crop) growth, measured at the district level.

We derive suitability measures from the Global Agro-Ecological Zones database of the FAO, and take a simple average of three crop yield indices modelled for high, medium and low water input use per district (FAO/IIASA, 2012). Data is available for 48 different crops at a spatially dis-aggregated level for the resolution of 5 arc-minutes, or approximately 10km by 10km. We calculate the district-level crop suitability by taking the median suitability over all pixels within a district as it captures the general soil suitability conditions and is less sensitive to outliers.

Crop price exposure: Aggregating other crops. For our price exposure index of other agricultural crops we include the top ten of the most economically relevant crops in Indonesia except for oil palm (which leaves us with the ten major crops). Based on the System of National Accounts (SNA), the top crops for our analyzed time period after oil palm are rice, sugar cane, banana, maize, cassava, groundnut, soy bean, cacao and rubber.

The index for *Other crop price exposure*, PE_d^{other}, is constructed as a weighted average of ten relevant crop exposure indices PE_c^d:

$$PE_d^{other} = \sum_c 1/w_c \times PE_d^c.$$

We contrast results that rely on two different types of crop weights, w_c. We use weights derived from the Indonesian System of National Accounts (SNA) in 2000, and contrast them with the crop prices weighted by crop production data provided by the FAO, generated over the full time period. The aggregated crop price exposure measurements are standardized to take a mean zero and a standard deviation of 1.

Bio-physical maps. Bio-physical maps classify initial forest areas into primary and non-primary forest and distinguish between various land typologies (lowland, upland, wetland, and montane), forest canopy densities as well as peatland (Gumbricht et al., 2017; Margono et al., 2014; Hansen et al., 2013). When overlaid with yearly deforestation maps, they can help to identify on which type of area has deforestation happened within the district.

Concessions. Spatial layers on wood fiber, logging and oil palm concessions in 2015 are provided by the Greenpeace web platform 2018 and by Global Forest Watch 2018, allowing us to distinguish deforestation by final economic use.

In addition, Greenpeace (2018) provide concession dates for wood fiber and logging, which allows us to construct a panel of the size of newly licensed area for wood fiber and logging within each district.

Wood fiber concessions are forest management licences that allow the establishment of sustainable wood plantations. Logging concessions allow for the selective extraction of high value trees. Oil palm concessions allow for the establishment of industrial oil palm plantations.

The expansion of industrial oil palm plantations was mapped at between 2000 and 2015 by Austin et al. (2017) (mapped in Figure A8). An intersection with the deforestation raster allows us to distinguish between forest conversion into oil palm versus other land uses.

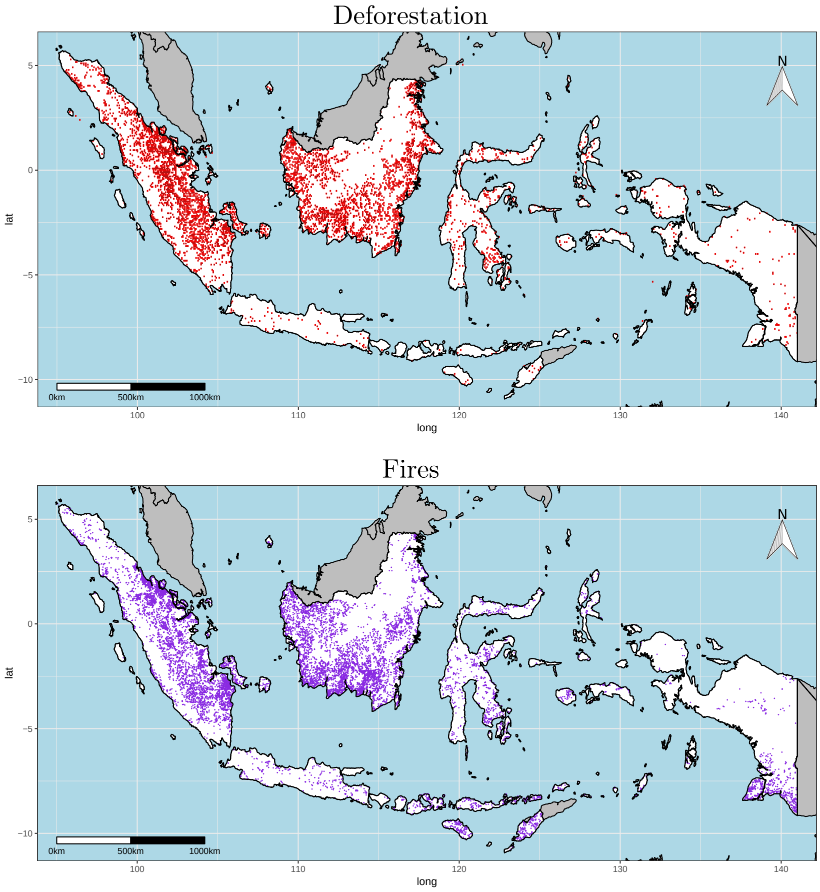
A.2 Further analyses

Canopy density Our deforestation measurement relies on the classification of what has been considered forest area to begin with (in 2000). The main estimates use the official threshold of 30% of canopy density (at the level of 30×30m pixels) to classify areas into forest and only consider deforestation that has occurred on initially forested areas. Table A3 investigates the sensitivity of our results to the use of different ranges of initial canopy densities to define a forest and hence subsequent deforestation by splitting initial densities into groups (30–50, 50–75, 75–100), or using a higher threshold of densities to define a forest (50–100). In general, they show that although point estimates change somewhat, the relevance of economic and political incentives does not hinge on any given cut-off of forest canopy density measurement.

Forest thresholds for sample inclusion Table A4 changes the sample inclusion criteria, expanding the sample to districts with an initial forest cover of less than 40%. In columns (1) and (2), the pre-election year effects as well as the simple palm oil price effects become more pronounced, while the pre-election interaction with palm oil prices turns insignificant. Thus, although elections seem to fuel deforestation also when including marginally forested districts (with a forest cover below 20%), oil palm does not play such a crucial role before elections outside of substantially forested areas. However, starting from an initially somewhat more forested sample of at least 20% (in column 3 and 30% in column 4), results stay very close to our baseline estimates. Column (5) returns to the original sample of districts with a forest cover of at least 40%, but excludes 57 districts from the island of Java. Although these districts are still substantially forested, the island of Java itself is densely populated and substantially more industrialized than other parts of the country, with on average smaller district areas. Our results stay the same when focusing on the islands outside of Java only and hence are mainly driven by dynamics on the main areas suitable to grow oil palm. Alternatively, column (6) excludes all cities from the analysis, keeping only the less densely populated and urbanized regencies. This also does not alter the results substantially.

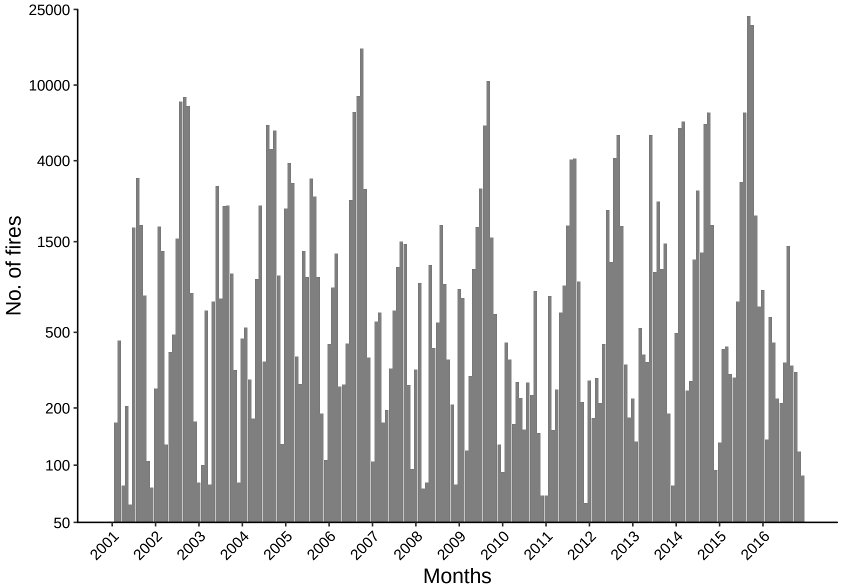
A.3 Online Appendix: Figures

Figure A1: Spatial distribution of total deforestation and fires 2000–2016 (per pixel)



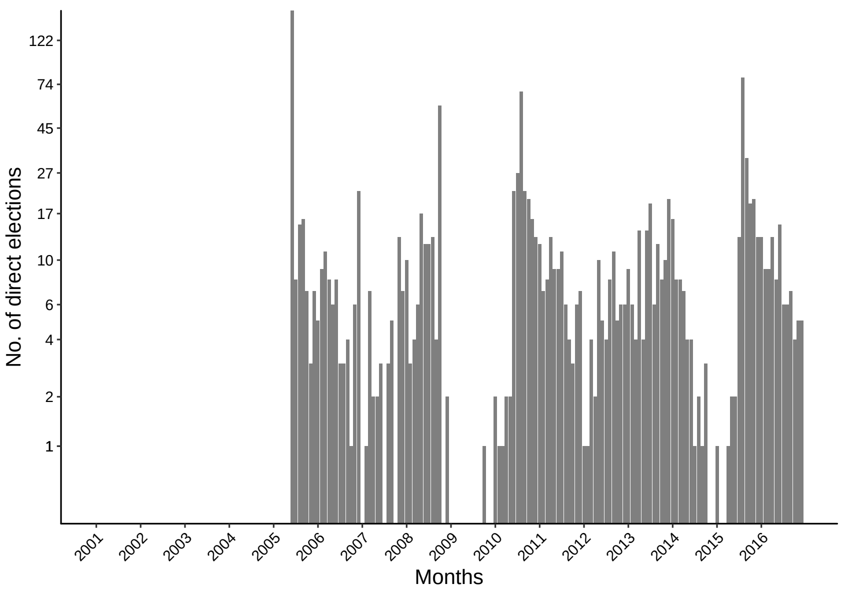
Source: Hansen et al. (2013) and NASA/GSFC/Earth Science Data and Information System (2018).

Figure A2: Monthly forest fires



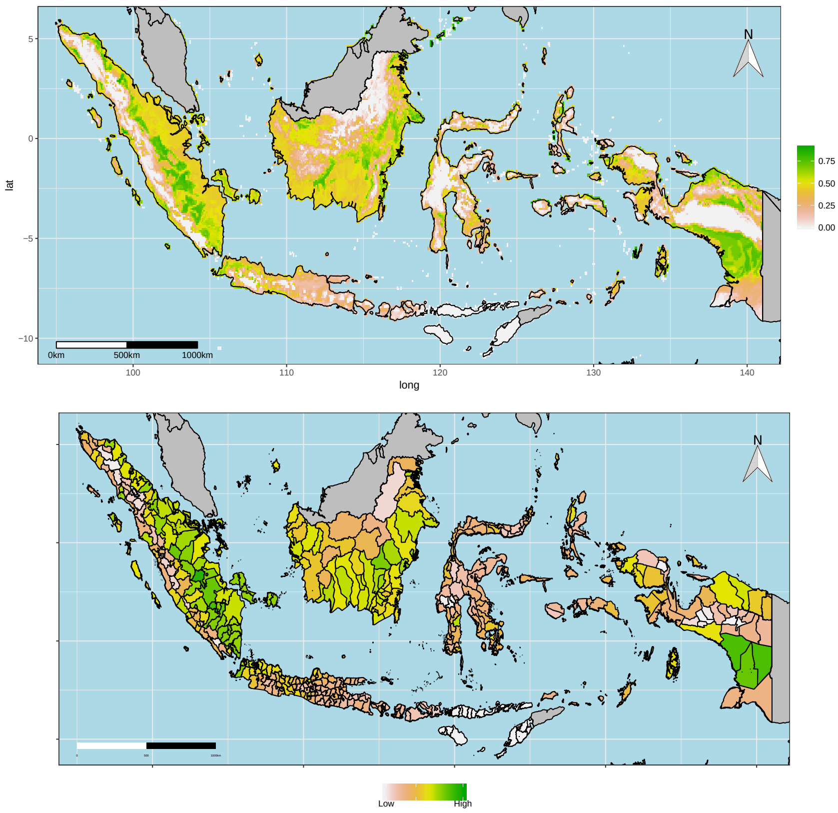
Source: NASA/GSFC/Earth Science Data and Information System (2018). The figure displays the monthly number of distinct fires detected by satellites on a logarithmic scale.

Figure A3: Monthly direct elections



Source: KPU Election registries. The figure displays the monthly number of direct elections on a logarithmic scale.

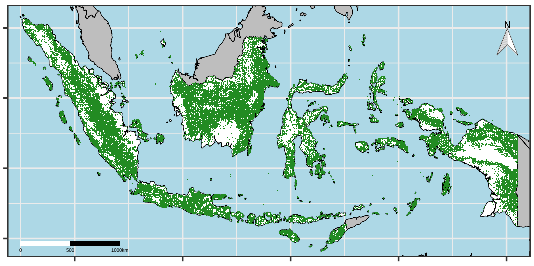
Figure A4: Agro-ecological suitability for growing oil palm (per pixel and per district)



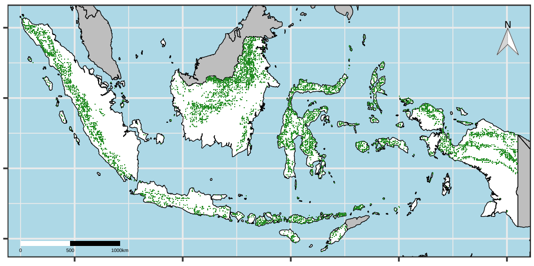
Source: FAO/IIASA (2012) combined with a district layer from GISPEDIA (2018).

Figure A5: Biophysical characteristics

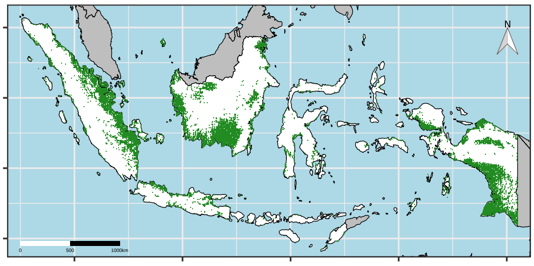
(a) Lowland



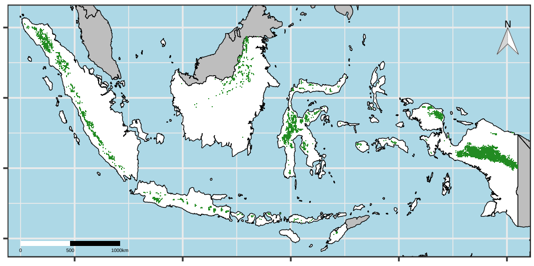
(b) Upland



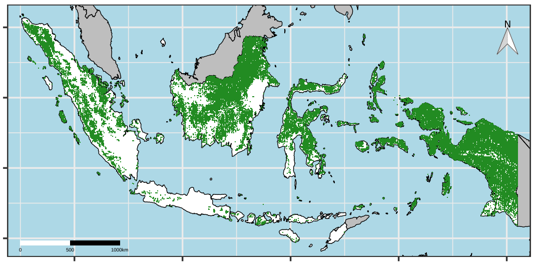
(c) Wetland



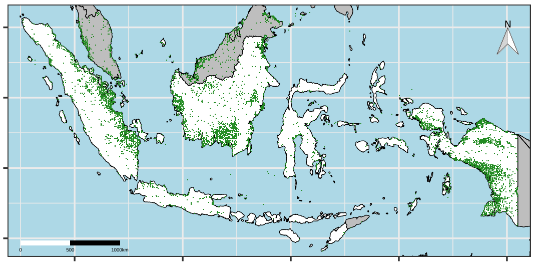
(d) Montane



(e) Primary forest

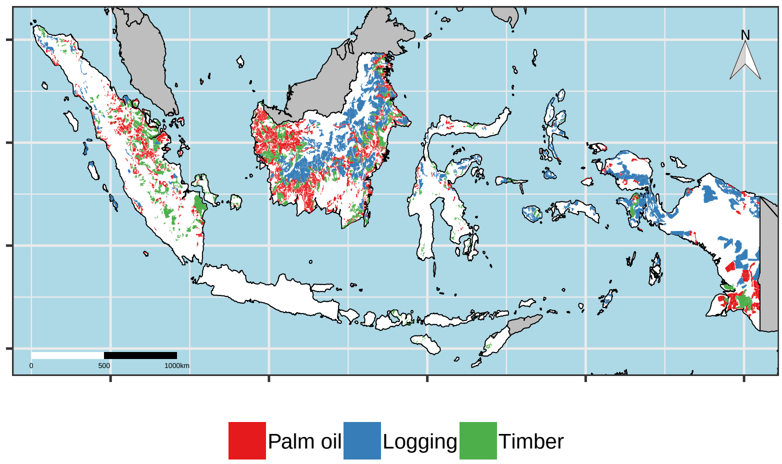


(f) Peatland



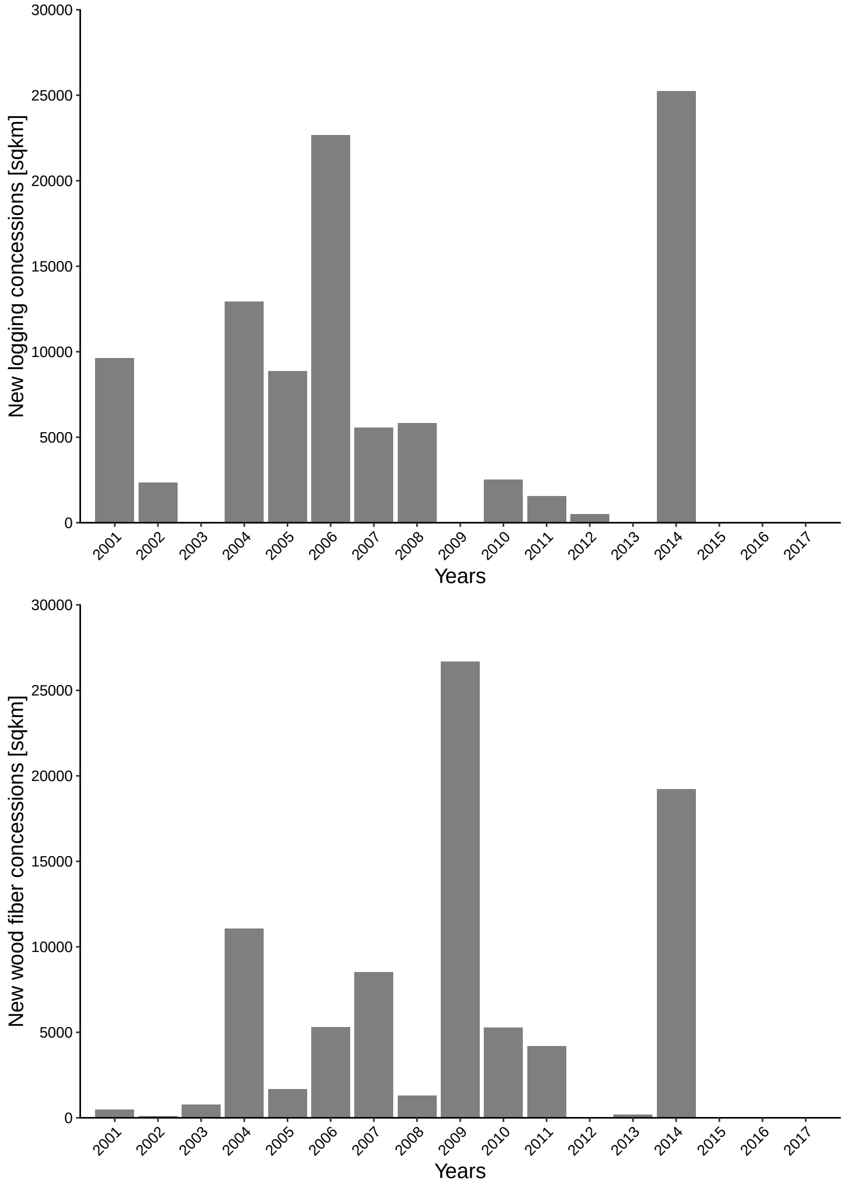
Source: Margono et al. (2014) (panels a,b,c,d,e) and Gumbricht et al. (2017) (panel f)

Figure A6: Agricultural concessions



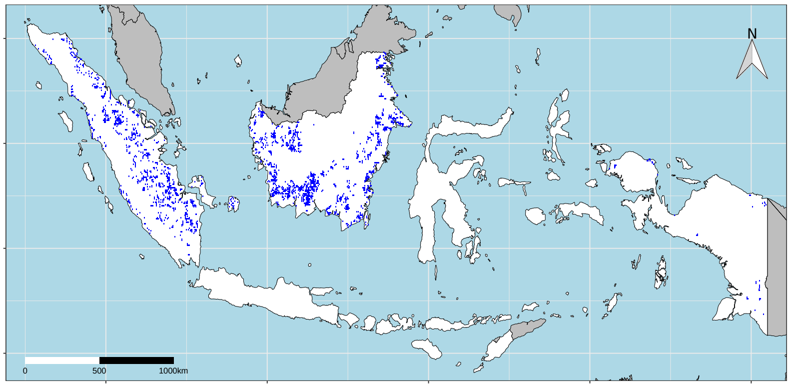
Source: Greenpeace (2018) and Global Forest Watch (2018)

Figure A7: Licensing of agricultural concessions



Source: Greenpeace (2018) and Global Forest Watch (2018). Concession dates continue up to 2014 with no information in years 2015 to 2017.

Figure A8: Oil palm expansion



Source: Austin et al. (2017)

Figure A9: Number of district splits per year

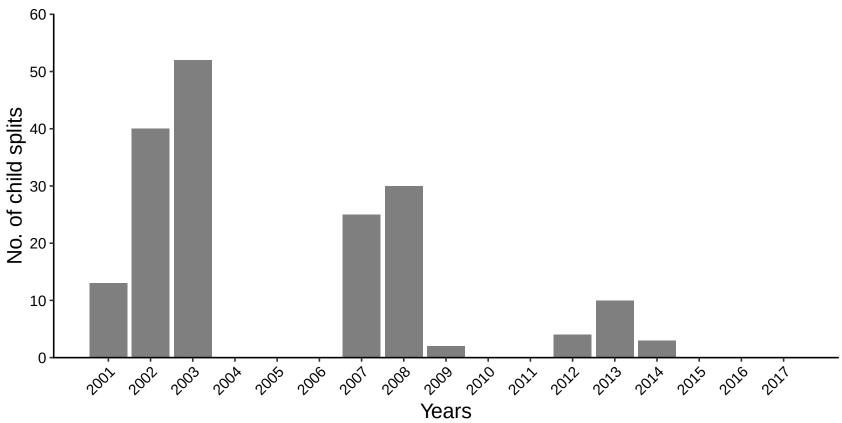
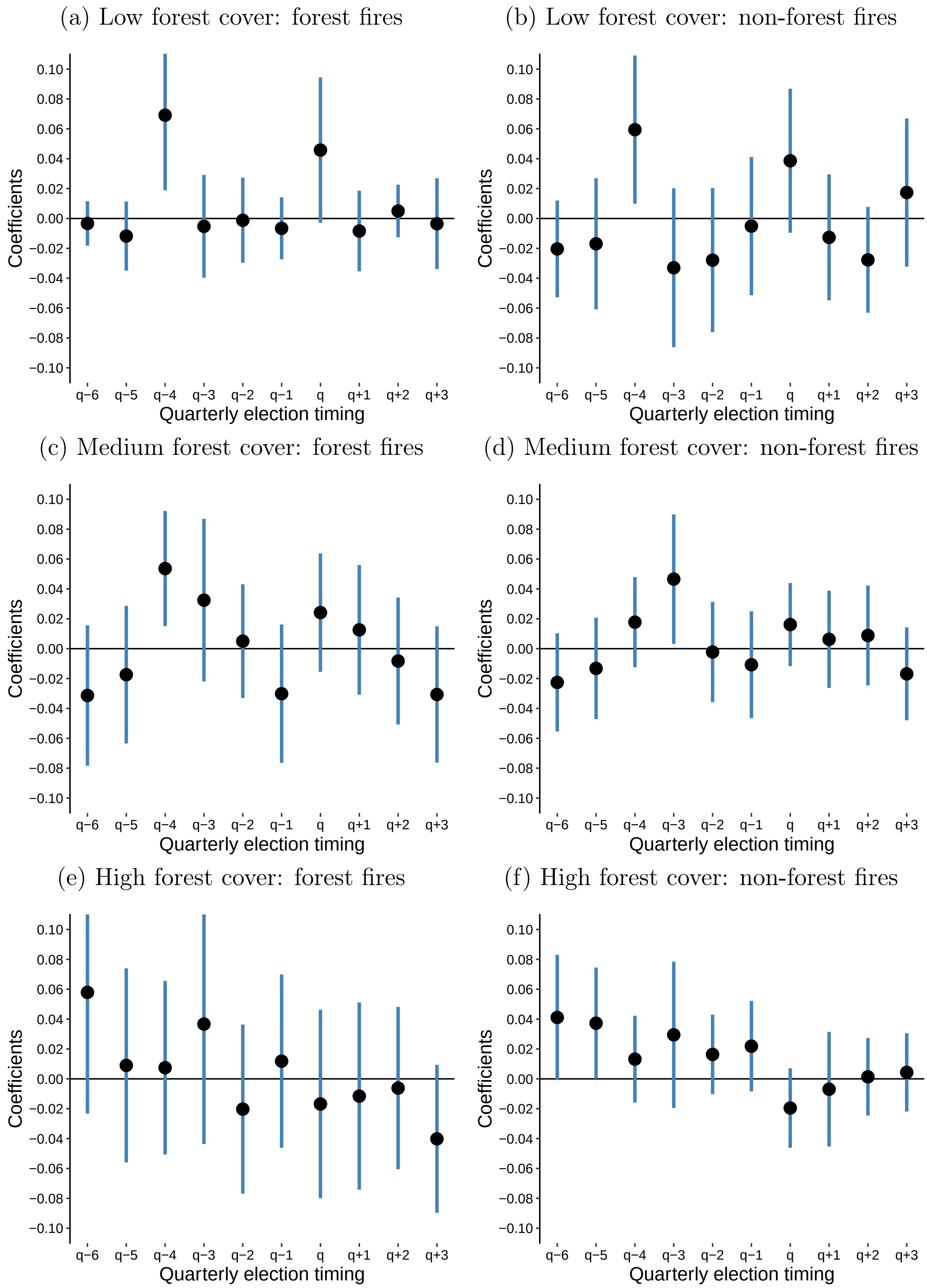


Figure A10: Election timing by quarters (2005–2018)



Note: The estimation samples are restricted to districts with low (00-40%), medium (40-90%), and high (90-100%) initial forest cover in 2000. The dependent variable measures the inverse hyperbolic sine of monthly fires located on originally forested (panels a,c,e) and non-forested (b,d,f) areas. Regressions include island-month and district-season fixed effects.

A.4 Online Appendix: Tables

Table A1: Summary statistics

Variables	Mean	St. Dev.	Min.	Max.
Main outcomes				
Deforestation [km^2]	36.48	82.46	0	1118.65
Monthly forest fire foci	4.24	42.26	0	3968
New wood fiber conc essions [km^2]	194.80	654.47	0	10316.65
New logging concessions [km^2]	476.59	1533.30	0	14223.39
Further dependent variables				
Deforestation on lowland area	22.61	51.69	0	895.85
Deforestation on upland area	1.69	3.94	0	136.41
Deforestation on wetland area	11.65	44.27	0	807.96
Deforestation on montane area	0.4	1.75	0	53.12
Deforestation on peat land area	3.93	16.09	0	381.21
Deforestation on primary forest area	14.66	40.43	0	610.2
Deforestation on non primary forest area	21.81	55.05	0	1064.43
Deforestation on oil palm in 2000	2.65	7.29	0	82.86
Deforestation on new oil palm by 2015 (2000-2015)	12.31	36.63	0	666.59
Deforestation on non-oil palm area	41.73	77.51	0	1055.57
Deforestation on short-term oil palm conversion area expansion	8.54	28.95	0	498.92
Deforestation on long-term oil palm conversion area	4.08	11.43	0	168.19
Deforestation on oil palm replanting area	3.79	12.07	0	201.83
Deforestation on concession land	10.63	35.57	0	680.41
Deforestation on non-concession land	25.85	57.17	0	961.75
Deforestation on final concession area for oil palm	8.2	30.84	0	673.12
Deforestation on logging palm oil concessions in 2014	3.05	12	0	317.75
Deforestation on wood fibre concessions in 2014	5.98	23.71	0	481.24
Explanatory variables				
Pre-election year	0.20	0.40	0	1
Palm oil price exposure	0	1	−4.49	4.03
Other crop price exposure (FAO)	0	1	−2.56	4.57
Other crop price exposure (SNA)	0	1	−2.42	4.99
Forest cover in 2000 [%]	0.79	0.17	0.40	1.00
Oil palm suitability	0	1	−1.7	2.76
District split in t (parent)	0.02	0.14	0	1
District split in t (child)	0.02	0.15	0	1
Suitability $\times$ Trade weighted Δ GDP p.c.	0	14	−24.25	39.5
Pre-election year before direct elections	0.17	0.37	0	1
Pre-election year before indirect elections	0.02	0.14	0	1

Note: The sample is restricted to 397 districts over 16 years with an initial forest cover of at least 40% in 2000.

Table A2: Baseline: Full results including controls

Dependent variable	asinh Deforestation			
	(1)	(2)	(3)	(4)
Pre-election year		0.053**	0.044*	0.042*
		(0.024)	(0.025)	(0.025)
Palm oil price exposure	0.080***	0.080***	0.082***	0.071**
	(0.031)	(0.031)	(0.031)	(0.032)
Pre-election year				0.075**
× Palm oil price exposure				(0.036)
Oil palm suitability × Trend			0.010***	0.011***
			(0.004)	(0.004)
Initial forest cover × Trend			0.128***	0.129***
			(0.023)	(0.023)
Split parent				
t+2			−0.087	−0.084
			(0.066)	(0.066)
t+1			−0.048	−0.044
			(0.063)	(0.063)
t			0.012	0.012
			(0.071)	(0.071)
t-1			−0.060	−0.059
			(0.067)	(0.067)
t-2			−0.098	−0.096
			(0.065)	(0.065)
Split child				
t+2			−0.012	−0.009
			(0.063)	(0.062)
t+1			−0.000	0.001
			(0.070)	(0.069)
t			−0.047	−0.050
			(0.091)	(0.092)
t-1			0.085	0.075
			(0.072)	(0.072)
t-2			0.012	0.011
			(0.075)	(0.075)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	No	No	Yes	Yes
Observations	6352	6352	6352	6352
Adj. R^2	0.887	0.887	0.890	0.890

Note: The estimation sample is restricted to 397 districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A3: Sensitivity: Deforestation by initial forest canopy density

Dependent variable	*asinh* Deforestation			
Initial forest densities	$30-50\%$	$50-75\%$	$75-100\%$	$50-100\%$
	(1)	(2)	(3)	(4)
Pre-election year	0.052	0.045	0.046*	0.041*
	(0.047)	(0.030)	(0.027)	(0.025)
Palm oil price exposure	0.131***	0.096**	0.067*	0.068**
	(0.046)	(0.039)	(0.036)	(0.032)
Pre-election year × Palm oil price exposure	0.091**	0.089**	0.068*	0.075**
	(0.044)	(0.037)	(0.036)	(0.036)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352
Adj. R^2	0.765	0.842	0.888	0.890

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district that occurred in forest of indicated density at the beginning of the period. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial size of forest of each type and the local oil palm suitability index. Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A4: Sensitivity: Varying sample inclusion criteria

Dependent variable	*asinh* Deforestation					
Initial forest cover	0-100%	10-100%	20-100%	30-100%	40-100%	40-100%
District types	All	All	All	All	W/o Java	W/o cities
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-election year	0.077**	0.065**	0.053*	0.048*	0.024	0.035
	(0.033)	(0.027)	(0.027)	(0.027)	(0.019)	(0.025)
Palm oil price exposure	0.136***	0.084***	0.083***	0.069**	0.090***	0.050*
	(0.038)	(0.032)	(0.032)	(0.031)	(0.028)	(0.030)
Pre-election year × Palm oil price exposure	0.020	0.048	0.060*	0.071**	0.077**	0.089***
	(0.042)	(0.033)	(0.034)	(0.035)	(0.030)	(0.033)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7952	7504	7168	6768	5440	6384
Adj. R^2	0.886	0.882	0.888	0.890	0.889	0.890

Note: The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size and the local oil palm suitability index). Robust standard errors are clustered on level of original parent districts in 2000 and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A5: Sensitivity: Oil palm versus single agricultural crops

Dependent variable	*asinh* Deforestation				
Other crop type	Rice	Sugarcane	Banana	Maize	Cassava
Panel A	(1)	(2)	(3)	(4)	(5)
Pre-election year	0.039	0.043*	0.041*	0.040	0.042*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Palm oil price exposure (PE)	0.069**	0.055*	0.077**	0.069**	0.065**
	(0.030)	(0.030)	(0.031)	(0.031)	(0.029)
Pre-election year × Palm oil PE	0.089**	0.074**	0.074**	0.084**	0.079**
	(0.041)	(0.035)	(0.034)	(0.036)	(0.035)
Other crop PE	0.004	0.126***	0.032	0.016	0.029
	(0.037)	(0.039)	(0.025)	(0.034)	(0.035)
Other crop PE × Pre-election year	−0.039	0.007	−0.006	−0.040	−0.018
	(0.038)	(0.027)	(0.042)	(0.026)	(0.026)
Adj. R^2	0.890	0.890	0.890	0.890	0.890
Dependent variable	*asinh* Deforestation				
Other crop type	Coffee	Groundnut	Soybean	Cacao	Rubber
Panel B	(1)	(2)	(3)	(4)	(5)
Pre-election year	0.042*	0.041	0.042*	0.045*	0.050**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Palm oil PE	0.073**	0.064**	0.074**	0.074**	0.051*
	(0.033)	(0.030)	(0.030)	(0.032)	(0.031)
Pre-election year × Palm oil PE	0.081*	0.078**	0.079**	0.054	0.012
	(0.046)	(0.037)	(0.034)	(0.035)	(0.040)
Other crop PE	−0.005	0.036	−0.019	−0.148***	0.032
	(0.034)	(0.036)	(0.032)	(0.039)	(0.036)
Other crop PE × Pre-election year	−0.012	−0.007	−0.016	−0.047**	0.076**
	(0.037)	(0.025)	(0.033)	(0.022)	(0.035)
Adj. R^2	0.890	0.890	0.890	0.891	0.890
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352	6352

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial forest size, the local oil palm suitability index and the local other crop suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A6: Sensitivity: Oil palm suitabiltiy versus other suitability measurements

Dependent variable	*asinh* Deforestation				
Other suitablity	Rice	Sugarcane	Banana	Maize	Cassava
Panel A	(1)	(2)	(3)	(4)	(5)
Pre-election year	0.041	0.041	0.042*	0.042*	0.040
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Other crop suitablity	0.087*	0.133***	0.093**	0.054	0.099**
× palm oil price (OPE)	(0.051)	(0.050)	(0.041)	(0.043)	(0.050)
Pre-election year	0.048	0.044	0.059	0.028	0.050
× OPE	(0.037)	(0.040)	(0.037)	(0.036)	(0.036)
Adj. R^2	0.890	0.890	0.890	0.889	0.890
Correlation of oil palm suitablity wiht other crop suitablity	0.676	0.817	0.897	0.263	0.717

Dependent variable	*asinh* Deforestation			
Other crop type	Coffee	Groundnut	Soybean	Cacao
Panel B	(1)	(2)	(3)	(4)
Pre-election year	0.042*	0.042*	0.043*	0.041*
	(0.025)	(0.025)	(0.025)	(0.025)
Other crop suitability	0.079*	0.022	0.016	0.103**
× palm oil price (OPE)	(0.048)	(0.037)	(0.040)	(0.048)
Pre-election year	0.051	0.049	0.042	0.049
× Open	(0.038)	(0.037)	(0.038)	(0.038)
Adj. R^2	0.890	0.889	0.889	0.890
Correlation of oil palm suitablity wiht other crop suitablity	0.812	0.303	0.289	0.809
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes
Observations	6352	6352	6352	6352

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects as well as further controls (indicators of district splits, separately for mother and child districts, time trends interacted with initial forest size, the local oil palm suitability index and the local other crop suitability index). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A7: Sensitivity: Regular election cycles

Dependent variable	*asinh* Deforestation	
Length of election cycles:	5 years	5-6 years
	(1)	(2)
Pre-election year	0.024	0.042
	(0.042)	(0.031)
Palm oil price exposure	0.048	0.062**
	(0.039)	(0.030)
Pre-election year	0.119**	0.095**
× Palm oil price exposure	(0.055)	(0.040)
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Further controls	Yes	Yes
Observations	2624	3728
Adj. R^2	0.905	0.900

Note: The estimation sample is restricted to 164 and 233 districts resepctivly, with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size and the local oil palm suitability index). Robust standard errors are clustered at the district level and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A8: Land use dynamics: Forest losses on and off oil palm plantations

Time span	All area [km^2]	Oil palm in 2000	2000 –2015	New oil palm 2000 –2005	2005 –2010	2010 –2015	Non oil palm in 2015
2001–2005	40600	0.07	0.21	0.09	0.07	0.04	0.72
2006–2010	68900	0.04	0.29	0.04	0.18	0.07	0.67
2011–2015	78000	0.04	0.20	0.01	0.04	0.15	0.75
2001-2015	187400	0.05	0.24	0.04	0.10	0.10	0.72

Note: Data on oil palm plantations is obtained from Austin et al. (2017) and intersected with the forest loss data from Hansen et al. (2013). Statistics are based on 231 districts on the islands Sumatra, Kalimantan, and Papua with at least 40% forest cover. Total forest losses by time frame are shown in column (1). Values in columns (2–6) show shares of the total deforestation by row.

Table A9: Land use dynamics: Timber prices and wood fiber and logging concessions

Dependent variable	*asinh* New wood fiber concessions		*asinh* New logging concessions	
	(1)	(2)	(3)	(4)
Pre-election year	0.363*		0.192	
	(0.192)		(0.194)	
Election year	0.350***		−0.083	
	(0.133)		(0.144)	
Post-election year	0.519***	0.356**	−0.124	−0.151
	(0.159)	(0.151)	(0.152)	(0.151)
Timber price exposure (PE)	0.121	0.074	0.198	0.194
	(0.078)	(0.072)	(0.152)	(0.133)
Timber PE × Pre-Election year	0.007		−0.191	
	(0.100)		(0.250)	
Timber PE × Election year	−0.171**		0.104	
	(0.084)		(0.159)	
Timber PE × Post-election year	−0.042	−0.003	−0.048	−0.048
	(0.113)	(0.112)	(0.205)	(0.205)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes
Observations	5558	5558	5558	5558
Adj. R^2	0.167	0.166	0.187	0.187

Note: The estimation sample is restricted to the years between 2001 and 2014 with an initial forest cover of at least 40% in 2000. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. Timber price exposure is measured as initial primary forest size times yearly world market prices of high value timber. All regressions include district and year fixed effects. Further controls include indicators of district splits (separately for mother and child districts) as well as time trends varying by selected initial conditions (initial forest size, the local oil palm suitability index and initial primary forest size to proxy the potential of high value fiber). Robust standard errors are clustered on level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).