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 2000 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.

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 World Bank's (2019) INDO-DAPOER data base, cross-walks, 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:

$$PE_{dt}^{other} = \sum_c 1/w_c \times PE_{dt}^c,$$

where

$$PE_{dt}^c = S_d^c \times P_t^c$$

is calculated similarly to equation (1).

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 and logging concessions from the year 2014 and oil palm concessions from the year 2017 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 A10). An intersection with the deforestation raster allows us to distinguish between forest conversion into oil palm versus other land uses.

The IV approach: trade weighted global GDP. We instrument palm oil price exposure $S_d \times P_t$ by interacting local suitability S_d by fluctuation in global agricultural demand. Y_t is a trade-weighted global GDP measure that includes all trading partners that have been importing oil seeds from Indonesia over an initial period (2000 to 2005), 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.

A.2 Further sensitivity 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 A9 investigates the sensitivity of our results to the use of different ranges of initial canopy densities (as measured in 2000) 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 and other sample inclusion criteria Table A10 changes the sample inclusion criteria, first 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.

Correcting for correlated error terms. The estimated significance levels of all three main coefficients presented in column (5) of Table 1 may be too high due to various under-rejection issues. To check for the sensitivity of the significance of our estimates, Table A11 in the Appendix contrasts standard errors corrected for correlations and multiple variable testing. First, standard errors are clustered at the level of parent districts as in Table 1, then at the level of the five main island groups. While this allows for a broad range of within island correlation, it also results in way too few clusters and hence is presented for the sake of comparison only. The Benjamini and Hochberg (1995) standard errors correct for testing three hypotheses within the same model. Finally the last four rows of standard errors are clustered by quantile groups of oil palm suitability. This allows for a correlation across spatially dispersed districts with similar oil palm suitability in the shift-share measure of economic incentives, in the spirit of Adão et al. (2019), but adopted to a case where shares are not multidimensional. Several of these stricter adjustments of standard errors render our estimates less significant, but our main interaction coefficient of interest remains significant at the 90% level in all specifications.

A.3 Corruption scandals in the forestry and oil palm sector

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Indonesia's Corruption Eradication Commission (KPK) detains Suspect in Forest Use Change Case, *kompass.com*, 6/4/2020, https://nasional.kompas.com/read/2020/04/06/06255721/kpk-tahan-tersangka-kasus-alih-fungsi-hutan

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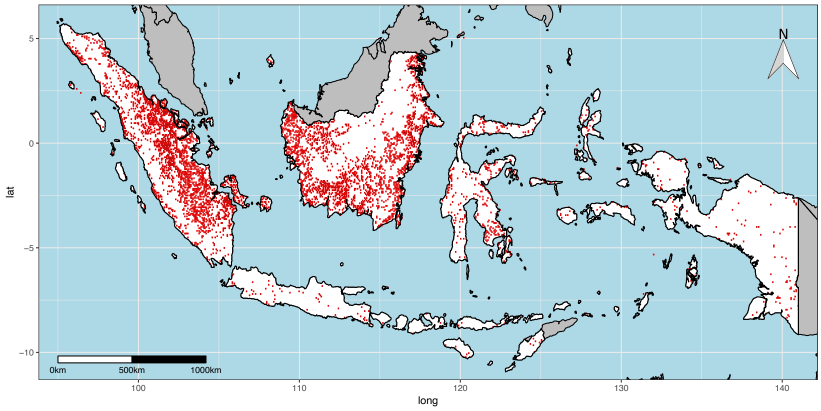
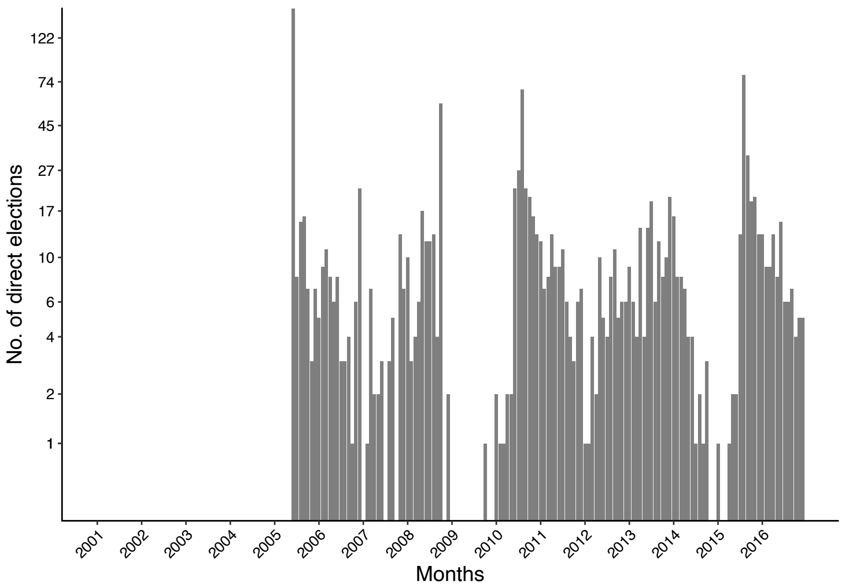
A.4 Additional figures

Figure A1: Spatial distribution of total deforestation 2001–2016 (per pixel)



Note: Map shows forest losses between 2001 and 2016, based on data from Hansen et al. (2013). The original raster pixels of 30x30 m are up-scaled to a higher resolution to highlight deforestation hot spots on the Pixel are down-scaled.

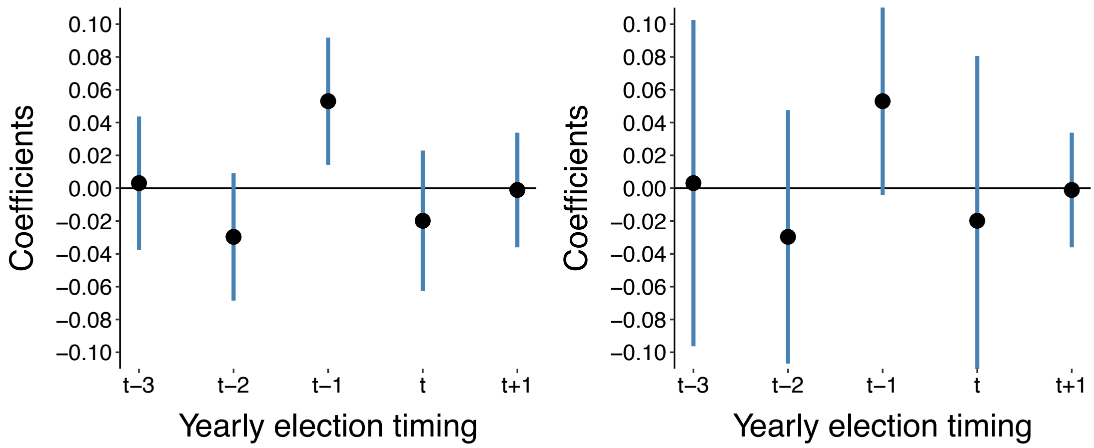
Figure A2: Monthly direct elections



Note: The figure displays the monthly number of direct elections on a logarithmic scale, based on data from KPU election registries.

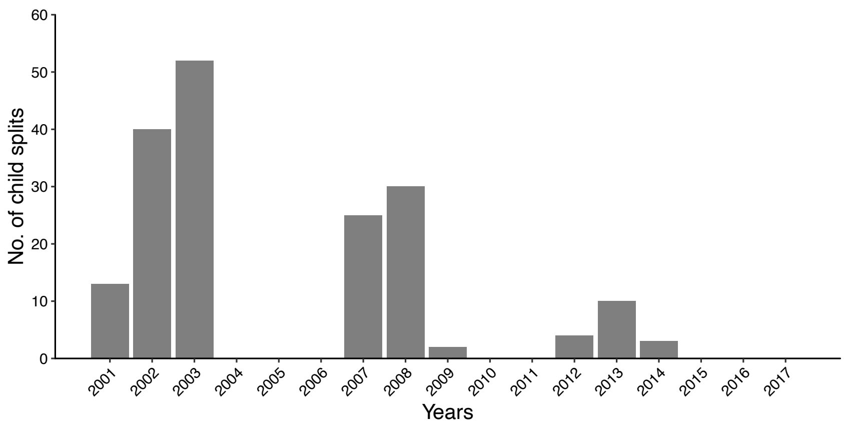
Figure A3: Excess deforestation around the election year

(a) Conf. interv. based on clustered standard errors (b) Confidence intervals corrected for multiple outcomes



Note: Points represent the point-estimates of the election indicators from separate regressions, comparing average deforestation from 3 years before to 1 year after elections. Results are conditional on district and year effects. Comparison group is always all the other years. Bars in panel (a) represent the 90% confidence intervals after clustering on the district level. In panel (b), confidence intervals rely on the Benjamini and Hochberg (1995) correction for multiple variables.

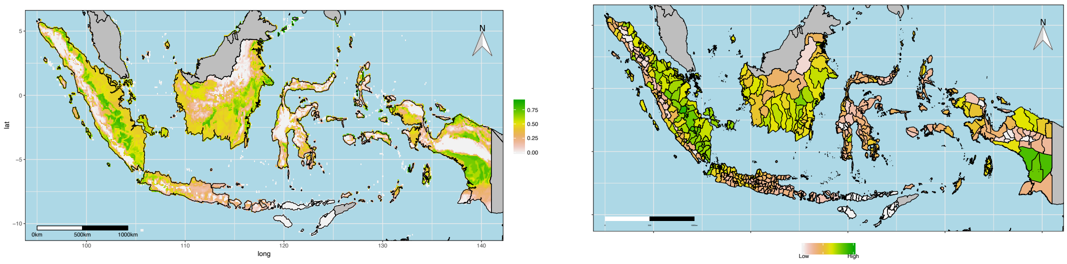
Figure A4: Number of district splits per year



Note: The figure depicts the number of yearly newly formed child districts, based on World Bank's (2019) INDO-DAPER data and complementary online sources.

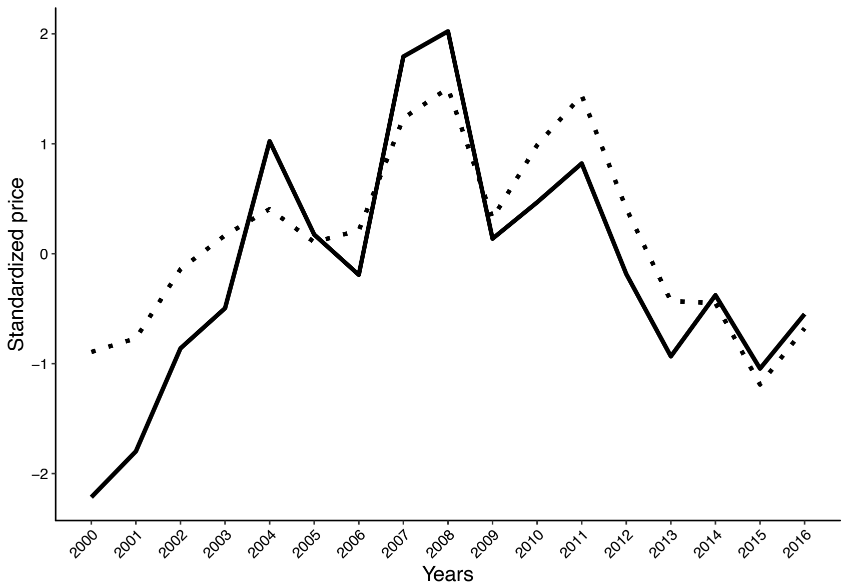
Figure A5: Agro-ecological suitability for growing oil palm

(a) Per pixel (b) Per district



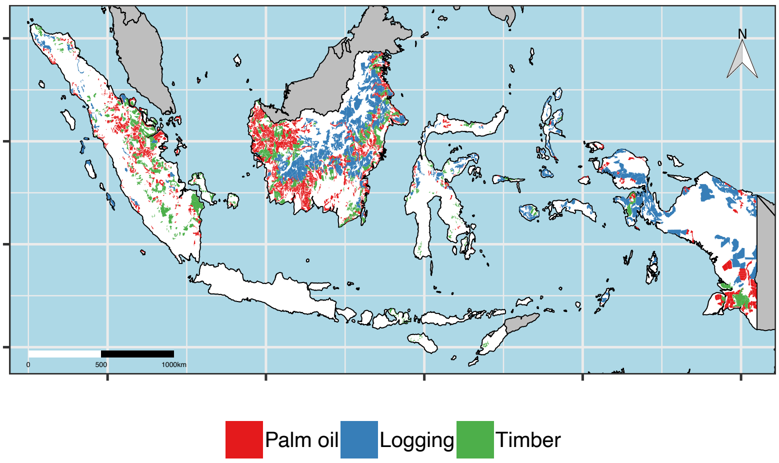
Note: Geo-climatic suitability indices are provided at a 1 by 1 kilometer resolution from FAO/IIASA (2012) (Panel a) and averaged to the district level (Panel b).

Figure A6: Standardized palm oil price exposure—Indonesian Rupiah vs. US dollar



Note: The solid line plots variation in global palm oil prices in real Indonesian Rupiah. The dotted line plots variation in global palm oil prices in US dollar.

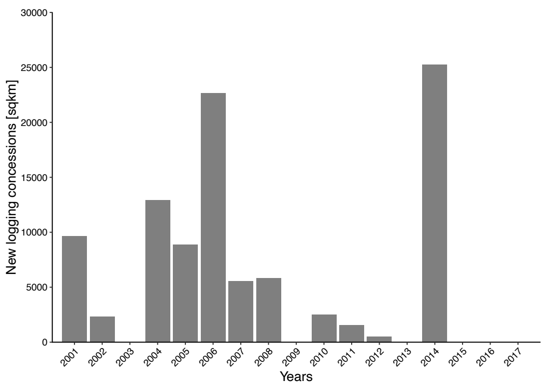
Figure A7: Agricultural concessions



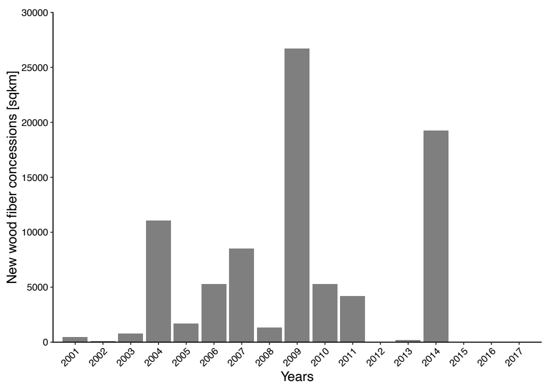
Note: Vectorized data on agricultural concessions for palm oil, logging and timber plantations are obtained from Greenpeace (2018) and Global Forest Watch (2018).

Figure A8: Licensing of agricultural concessions

(a) Logging concessions



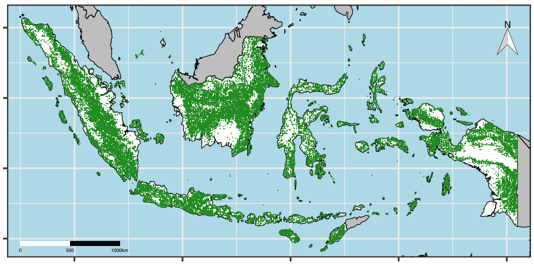
(b) Timber concessions



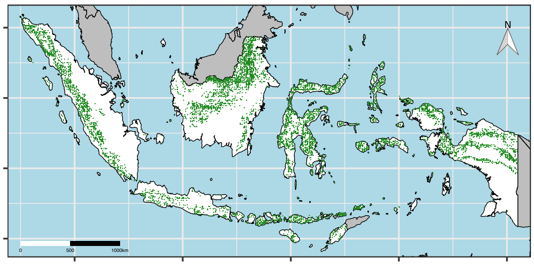
Note: Panel (a) depicts the yearly new area under logging concessions. Panel (b) depicts the yearly new area under timber concessions. Yearly area increases are calculated based on the licensing dates and shapefiles provided by Greenpeace (2018) and Global Forest Watch (2018).

Figure A9: Biophysical characteristics

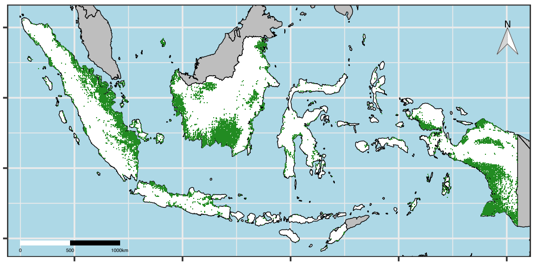
(a) Lowland



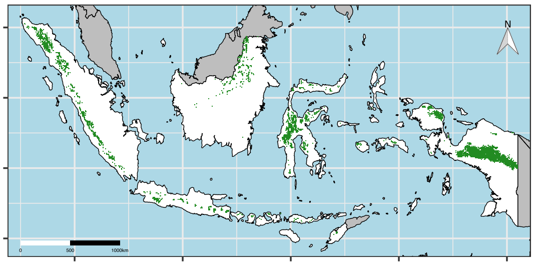
(b) Upland



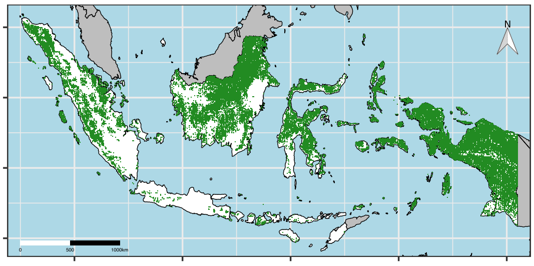
(c) Wetland



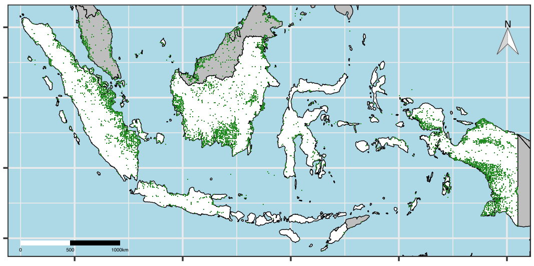
(d) Montane



(e) Primary forest

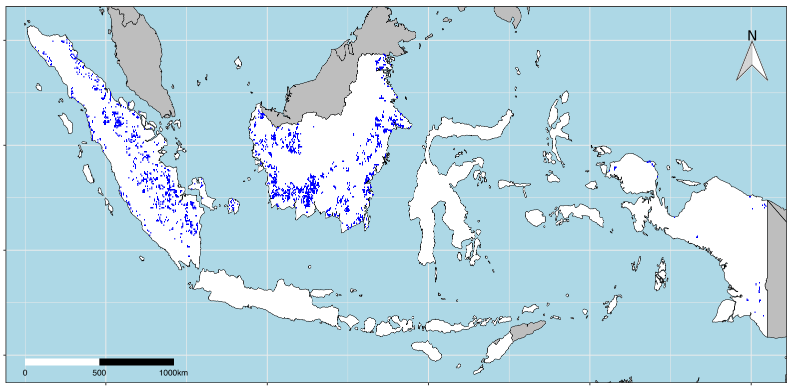


(f) Peatland



Note: Ecological landscape maps are based on Margono et al. (2014) (Panels a,b,c,d,e) and Gumbricht et al. (2017) (Panel f).

Figure A10: Oil palm area expansion from 2000 to 2015



Note: The map shows the new palm oil plantations created between the years 2000 and 2015; Based on data from Austin et al. (2017).

A.5 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

	(1)	(2)	(3)	(4)	(5)
Pre-election year	0.053**		0.053**	0.044*	0.042*
	(0.023)		(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***
				(0.022)	(0.022)
Split parent					
t+2				−0.087	−0.084
				(0.064)	(0.064)
t+1				−0.048	−0.044
				(0.061)	(0.061)
t				0.012	0.012
				(0.069)	(0.069)
t-1				−0.060	−0.059
				(0.064)	(0.064)
t-2				−0.098	−0.096
				(0.063)	(0.063)
Split child					
t+2				−0.012	−0.009
				(0.060)	(0.060)
t+1				−0.000	0.001
				(0.067)	(0.067)
t				−0.047	−0.050
				(0.088)	(0.089)
t-1				0.085	0.075
				(0.069)	(0.070)
t-2				0.012	0.011
				(0.073)	(0.072)
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Further controls	No	No	No	Yes	Yes
Observations	6352	6352	6352	6352	6352
Adj. R^2	0.887	0.887	0.887	0.890	0.890

Note: The table shows the effects of palm oil price incentives and election incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), across 397 districts between 2001 and 2016, with an initially forest cover of at least 40% in 2000. Estimates account for district and year fixed effects. Palm oil price exposure has been normalized by subtracting its mean and dividing by its standard deviation. Robust standard errors are clustered on a 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 trends before the introduction of direct elections

	(1)	(2)	(3)	(4)
year	0.076***	0.076***	0.069***	0.062***
	(0.017)	(0.017)	(0.018)	(0.018)
year × $\mathbf{1}$(Year of first direct election = 2006)	−0.015			
	(0.036)			
year × $\mathbf{1}$(Year of first direct election = 2007)	−0.036			
	(0.049)			
year × $\mathbf{1}$(Year of first direct election = 2008)	0.004			
	(0.025)			
year × $\mathbf{1}$(Year of first direct election = 2010)	−0.093			
	(0.079)			
year × $\mathbf{1}$(Year of first direct election ≥ 2006)		−0.009		
		(0.022)		
year × $\mathbf{1}$(Year of first direct election ≥ 2007)			−0.001	
			(0.024)	
year × $\mathbf{1}$(Year of first direct election ≥ 2008)				0.012
				(0.027)
District fixed effects	Yes	Yes	Yes	Yes
Observations	1985	1985	1985	1985
Adj. R^2	0.889	0.889	0.889	0.889

Note: The estimation sample is restricted to all districts with an initial forest cover of at least 40% in 2000 and to years before the introduction of direct mayor elections. The dependent variable measures the inverse hyperbolic sine of yearly newly deforested area in the district. All regressions include district 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 A4: Sensitivity: Regular election cycles

	5-year election cycles only	Districts with exclusively 5-year election cycles	Districts with exclusively 5-6 year election cycles	Parents and aligned child districts	Parent districts only
	(1)	(2)	(3)	(4)	(5)
Pre-election year	0.056	0.024	0.042	0.033	0.033
	(0.055)	(0.041)	(0.030)	(0.027)	(0.028)
Palm oil price exposure	0.083**	0.048	0.062**	0.064**	0.070**
	(0.038)	(0.038)	(0.029)	(0.028)	(0.028)
Palm oil price exposure × Pre-election year	0.145**	0.119**	0.095**	0.089**	0.088**
	(0.077)	(0.053)	(0.039)	(0.037)	(0.036)
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Further controls	Yes	Yes	Yes	Yes	Yes
Observations	3480	2624	3728	4864	4000
Districts	362	164	233	304	250
Adj. R^2	0.909	0.905	0.900	0.897	0.901

Note: The table shows the effects of palm oil price incentives and election incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), using a restricted set of districts with regular election cycles. Column (1) focuses on the unbalanced panel of district-year observations within regular 5-year election cycles. Columns (2) and (3) rely on districts with strictly regular 5-year or 5-6 year election cycles throughout our time-frame (2001–2016). Column (4) excludes all child districts whose first post-split election did not align with the election cycle of their respective parent district. Column (5) only uses parent districts already existing in 2000, excluding all child districts that split during our period of analysis. All districts have an initially forest cover of at least 40% in 2000. 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. Oil palm price exposure has been normalized by subtracting its mean and dividing by its standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A5: Sensitivity: Oil palm versus single agricultural crops

Other crop type *Panel A*	Rice (1)	Sugarcane (2)	Banana (3)	Maize (4)	Cassava (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	0.069**	0.055*	0.077**	0.069**	0.065**
	(0.030)	(0.030)	(0.031)	(0.031)	(0.029)
Palm oil price exposure	0.089**	0.074**	0.074**	0.084**	0.079**
× Pre-election year	(0.041)	(0.035)	(0.034)	(0.036)	(0.035)
Other crop price exposure	0.004	0.126***	0.032	0.016	0.029
	(0.037)	(0.039)	(0.025)	(0.034)	(0.035)
Other crop price exposure	−0.039	0.007	−0.006	−0.040	−0.018
× Pre-election year	(0.038)	(0.027)	(0.042)	(0.026)	(0.026)
Adj. R^2	0.890	0.890	0.890	0.890	0.890
Other crop type *Panel B*	Coffee (1)	Groundnut (2)	Soybean (3)	Cacao (4)	
Pre-election year	0.042*	0.041	0.042*	0.045*	
	(0.025)	(0.025)	(0.025)	(0.025)	
Palm oil price exposure	0.073**	0.064**	0.074**	0.074**	
	(0.033)	(0.030)	(0.030)	(0.032)	
Palm oil price exposure	0.081*	0.078**	0.079**	0.054	
× Pre-election year	(0.046)	(0.037)	(0.034)	(0.035)	
Other crop price exposure	−0.005	0.036	−0.019	−0.148***	
	(0.034)	(0.036)	(0.032)	(0.039)	
Other crop price exposure	−0.012	−0.007	−0.016	−0.047**	
× Pre-election year	(0.037)	(0.025)	(0.033)	(0.022)	
Adj. R^2	0.890	0.890	0.890	0.891	
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 table show the effects of palm oil price incentives in relation to other crop price incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), across 397 districts between 2001 and 2016, with an initially forest cover of at least 40% in 2000. Other crop price exposure measures are constructed intersecting each crop price suitability map with the respective price trend (cf. equation 1). Crops are listed in descending order of their relative national production values from 1995–2000. Estimates account for 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, the local oil palm suitability index, and the local other crop suitability index. Price exposure measurements have been normalized by subtracting their mean and dividing by their standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A6: Placebo test: Oil palm suitability versus other suitability measurements

Other crop suitability *Panel A*	Rice (1)	Sugarcane (2)	Banana (3)	Maize (4)	Cassava (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 suitability	0.087*	0.133***	0.093**	0.054	0.099**
× palm oil price	(0.051)	(0.050)	(0.041)	(0.043)	(0.050)
Pre-election year	0.048	0.044	0.059	0.028	0.050
× other crop suitability	(0.037)	(0.040)	(0.037)	(0.036)	(0.036)
× palm oil price					
Adj. R^2	0.890	0.890	0.890	0.889	0.890
Correlation between oil palm suitability	0.676	0.817	0.897	0.263	0.717
and other crop suitability					
Other crop type *Panel B*	Coffee (1)	Groundnut (2)	Soybean (3)	Cacao (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	(0.048)	(0.037)	(0.040)	(0.048)	
Pre-election year	0.051	0.049	0.042	0.049	
× other crop suitability	(0.038)	(0.037)	(0.038)	(0.038)	
× palm oil price					
Adj. R^2	0.890	0.889	0.889	0.890	
Correlation between oil palm suitability	0.812	0.303	0.289	0.809	
and other crop suitability					
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 table shows the placebo effects of palm oil price incentives and election incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), across 397 districts between 2001 and 2016, with an initially forest cover of at least 40% in 2000. Placebo price incentives are constructed as the interaction between palm oil prices and suitability maps of other non-palm oil crops. Estimates account for 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, the local oil palm suitability index, and the local other crop suitability index. Price exposure measurements have been normalized by subtracting their mean and dividing by their standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A7: Politics and policies: 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	0.121	0.074	0.198	0.194
	(0.078)	(0.072)	(0.152)	(0.133)
Timber price exposure × Pre-Election year	0.007		−0.191	
	(0.100)		(0.250)	
Timber price exposure × Election year	−0.171**		0.104	
	(0.084)		(0.159)	
Timber price exposure × 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 table shows the effects of timber price incentives and election incentives on new agricultural concessions (measured as the inverse hyperbolic sine of new concession area), across 397 districts between 2001 and 2014, with an initially forest cover of at least 40% in 2000. Timber price exposure is measured as initial primary forest size times yearly world market prices of high value timber. Estimates account for 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, the local oil palm suitability index, and initial primary forest size to proxy the potential of high value fiber. Timber price exposure has been normalized by subtracting its mean and dividing by its standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A8: Ecology and land use: Forest losses on and off oil palm plantations

Time span	All area	Oil palm in 2000	New oil palm 2000–2015	2000-2005	2005–2010	2010–2015	Non-oil palm in 2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2001–2005	40600 km^2	0.07	0.21	0.09	0.07	0.04	0.72
2006–2010	68900 km^2	0.04	0.29	0.04	0.18	0.07	0.67
2011–2015	78000 km^2	0.04	0.20	0.01	0.04	0.15	0.75
2001-2015	187400 km^2	0.05	0.24	0.04	0.10	0.10	0.72

Note: The table shows the distribution of forest losses for oil palm and non-oil palm agriculture across time. Maps on oil palm plantations are 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% initial 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: Sensitivity: Deforestation by initial forest canopy density

Initial forest densities	30 − 50% (1)	50 − 75% (2)	75 − 100% (3)	50 − 100% (4)
Pre-election year	0.052	0.045	0.046	0.041
	(0.047)	(0.030)	(0.027)*	(0.025)*
	[0.047]	[0.031]	[0.029]	[0.026]
Palm oil price exposure	0.131	0.096	0.067	0.068
	(0.046)***	(0.039)**	(0.036)*	(0.032)**
	[0.069]*	[0.053]*	[0.040]*	[0.039]*
Pre-election year	0.091	0.089	0.068	0.075
× Palm oil price exposure	(0.044)**	(0.037)**	(0.036)*	(0.036)**
	[0.052]*	[0.049]*	[0.041]*	[0.042]*
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 table shows the effects of palm oil price incentives and election incentives on deforestation of initial forest cover densities (measured as the inverse hyperbolic sine of yearly forest losses). Forest canopy density in 2000 is measured in percent at a 30-by-30 meter resolution (Hansen et al., 2013). The sample is based on a panel of 397 districts between 2001 and 2016, with an initially forest cover of at least 40% in 2000. Estimates account for 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. Palm oil price exposure has been normalized by subtracting its mean and dividing by its standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A10: Sensitivity: Varying sample inclusion criteria

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)
	[0.038]**	[0.032]**	[0.031]*	[0.029]	[0.020]	[0.027]
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)*
	[0.050]***	[0.039]**	[0.038]**	[0.035]**	[0.035]**	[0.032]
Pre-election year	0.020	0.048	0.060	0.071	0.077	0.089
× Palm oil price exposure	(0.042)	(0.033)	(0.034)*	(0.035)**	(0.030)**	(0.033)***
	[0.042]	[0.036]	[0.037]	[0.039]*	[0.036]**	[0.041]**
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 table shows the effects of palm oil price incentives and election incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), across 397 districts between 2001 and 2016, with varying initially forest cover. Column (1) includes all Indonesian districts with 0-100% of initial forest cover. Column (2)-(6) increasingly restrict the sample to districts higher levels of initial forest cover, while column (5) further restricts excludes the island of Java and column (6) excludes all cites (*kotas*). Estimates account for 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. Palm oil price exposure has been normalized by subtracting its mean and dividing by its standard deviation. Robust standard errors are clustered on a level of 251 original parent districts and reported in parentheses. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).

Table A11: Sensitivity: Correcting standard errors

Covariates:	Pre-election year	Palm oil price exposure	Pre-election year × Palm oil price exposure
	(1)	(2)	(3)
$\hat{\beta}$	0.042	0.071	0.075
Adjusted standard errors:			
Clustering standard errors geographically:			
At parent district level in 2000†	0.025*	0.032**	0.036**
At island level	0.020**	0.029**	0.017***
Correcting for multiple hypothesis testing:			
Benjamini and Hochberg (1995)	0.025*	0.037*	0.039*
Clustering standard errors within groups of similar oil palm soil suitability:			
40 quantile groups	0.029	0.032**	0.045*
60 quantile groups	0.028	0.033**	0.041*
80 quantile groups	0.028	0.032**	0.037**
100 quantile groups	0.027	0.032**	0.038**

Note: The first row repeats the point estimates of column 5 in Table 1. The estimates β report the effects o palm oil price incentives and election incentives on deforestation (measured as the inverse hyperbolic sine of yearly forest losses), across 397 districts between 2001 and 2016, with an initially forest cover of at least 40% in 2000. † The clustered standard error estimates in row 2 are equal to the estimates reported in column 5 of Table 1. The quantile groups in rows 5 to 8 are based on initial oil palm suitability shares. Significance at or below 1 percent (***), 5 percent (**) and 10 percent (*).