Losing territory: The effect of administrative splits on land use in the tropics*

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Abstract

State decentralization is often promoted as a way to improve public service delivery. However, its effects on forest are ambiguous. Decentralization might not only improve local forest governance, but also change the incentives to promote agricultural expansion into forests. This study focuses on the power devolution stemming from the proliferation of new administrative units in Indonesia during the last two decades. The discontinuous changes in government responsibilities at new administrative borders provide exogenous spatial variation to study forest outcomes. Using a spatial boundary discontinuity design with 14,000 Indonesian villages, we analyze the effects of 115 district splits between 2002 and 2014. Results show a 35% deforestation decline within new (child) districts relative to the existing (mother) districts both immediately before and after the splitting. In pre-split years, these changes can be explained by agricultural divestment by the mother districts on territories that are soon to be lost. In post-split years, the short-term forest conservation benefits are neither rooted in an increased social cohesion nor stronger development. Instead, newly formed districts seem to be temporarily suffering from administrative incapacity to attract large-scale agricultural investments. In the long run, no lasting local forest conservation benefits persist as deforestation equalizes between child and mother districts few years later.

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1 Introduction

Tropical forests are under strong pressure from the demand for land conversion for alternative use. Their existence is essential for both climate and biodiversity protection, making conservation efforts a key policy goal worldwide. To be successful, interventions crucially rely on local governance and institutions (Burgess et al., 2012; Wehkamp et al., 2018). In recent decades, sub-national administrations have gained substantial influence on conservation outcomes due to broad decentralization reforms that sought to improve public service delivery (Besley and Coate, 2003; Faguet, 2004). While the empirical evidence on the effects of decentralization is extensive, its results are at times mixed (Gadenne and Singhal, 2014). Conceptually, decentralization policies often combine both a transfer of administrative responsibilities and an increase in the number of sub-national jurisdictions, also referred to as government fragmentation (Grossman and Lewis, 2014; Pierskalla, 2016). In a decentralized state, these (new) administrative entities become influential actors, yet understanding how their proliferation affects developmental outcomes remains understudied (Pierskalla, 2016; Grossman et al., 2017).

We focus on Indonesia, which provides the ideal environment to study the relationship between sub-national government fragmentation and deforestation: After the fall of the Suharto-regime in 1998, the country embarked on far-reaching decentralization reforms labelled as a "big bang" (Fitrani et al., 2005). The new legislation paved the way for jurisdictional adjustments, allowing for the formation of new districts, which received considerable power as part of the reforms (Ostwald et al., 2016). Consequently more than 150 new administrative units across the entire Indonesian archipelago came into existence within 14 years, which were carved out of existing ones and had to establish new capitals and corresponding institutions from scratch. At the same time, Indonesia—home to one of the world's most pristine tropical rainforests—has experienced rampant deforestation and land-use change (Austin et al., 2019).

Our analysis exploits the fact that administrative boundaries between the newly split entities were idiosyncratic to local conditions in both topographic and socioeconomic terms. In the framework of a spatial regression discontinuity design, the new administrative boundaries represent sharp cutoffs between otherwise comparable villages.[1] Existing literature in the Indonesian context has focused on the impact of splits at the district- and provincial-level, highlighting the role of inter-administrative competition and ethnic homogeneity. In contrast, our analysis (i) is conducted at the highly local-

[1]Note that we use the terms districts and jurisdictions as well as new district boundary and split boundary interchangeably.

ized village-level and by that deals with a series of important heterogeneities (Grossman and Lewis, 2014); and (ii) studies a new mechanism through which the creation of new jurisdictions affects deforestation: Anticipatory strategic land-use decisions with regard to oil palm expansion by local administrations.

From a theoretical perspective, ex-ante it is ambiguous how villages' land-use trajectories in a close neighborhood of the new boundary might develop once a split is expected and implemented. In our cross-sectional analysis of 115 district splits realized between 2002–2014, we show that deforestation in villages located in the newly formed child districts decreases compared to the ones located in the existing mother districts. This effect materializes from up to two years before to three years after the split came into effect. At around 35%, the reduction in deforestation is considerable and is supported by a host of robustness and placebo tests.[2]

Guided by existing research in the context of decentralization and land-use decisions, we identify mechanisms related to altered cost-benefit considerations that both existing and new governments face with regards to promoting or preventing land-use change. Taking into account both anticipatory short-run and strategic medium-run effects before and after the splits, we discuss and empirically verify five potential mechanisms: The role of (i) immediate land-use rents from deforestation; (ii) medium-term land-use rents by strategic investments into oil palm plantations; (iii) changing constituency preferences through decreasing ethnic fractionalization; (iv) temporarily diminished administrative capacity in new districts; and (v) the creation of new political centers and the subsequent expansion of human settlements in the neighborhood of new capitals. From these proposed mechanisms, we find empirical evidence for strategic divestment from land-use conversion by the existing district government. Because medium-term rents from investments into oil palm expansion on contested land will go towards the new government, deforestation pressures are temporarily reduced already before the district split takes place. While this mechanism has not been documented before, it reconciles well with the fact that in Indonesia, deforestation responds strongly to political-economic incentives (Burgess et al., 2012), fostering especially land-use change towards oil palm cultivation (Angelsen, 2007; Austin et al., 2019; Cisneros et al., 2021). A few years after the split, both oil palm expansion and deforestation in the child districts accelerate once again, yielding no sustained protection of natural resources at the boundaries of newly formed districts in the longer run.

Our paper is related to several strands of literature. First, by focusing on the role of district splits for deforestation, it contributes to the literature on the determinants of deforestation in the tropics, and especially on the political economy of deforesta-

[2] Annual deforestation in our sample is around 1.5% of 2000 forest cover. Our results thus imply that annual deforestation rates are temporarily reduced to 1.0% in villages at the boundaries of a child district.

tion (Burgess et al., 2012; Austin et al., 2019; Cisneros et al., 2021). Second, by showing temporary localized effects of government fragmentation, our paper also relates to the ongoing debate on decentralized natural resource management (Blackman and Bluffstone, 2021). Third, the paper adds to the growing literature on the unintended outcomes of decentralization (Pierskalla, 2016), by showing that decentralization reshapes land-use incentives: While most studies find negative side-effects (Grossman et al., 2017), our result implies a positive temporary impact in terms of forest protection. Lastly, we add to the growing literature that uses administrative borders as spatial discontinuities in economics more broadly (Michalopoulos and Papaioannou, 2013; Pinkovskiy, 2017) and in environmental economics in particular (Bonilla-Mejía and Higuera-Mendieta, 2019; Burgess et al., 2019; Cuaresma and Heger, 2019).

The remainder of the paper is organized as follows: Section 2 outlines our study's context, followed by a discussion of the theoretical framework in section 3. Section 4 presents an overview of data and the empirical methodology. Section 5 discusses the results and section 6 concludes.

2 Background

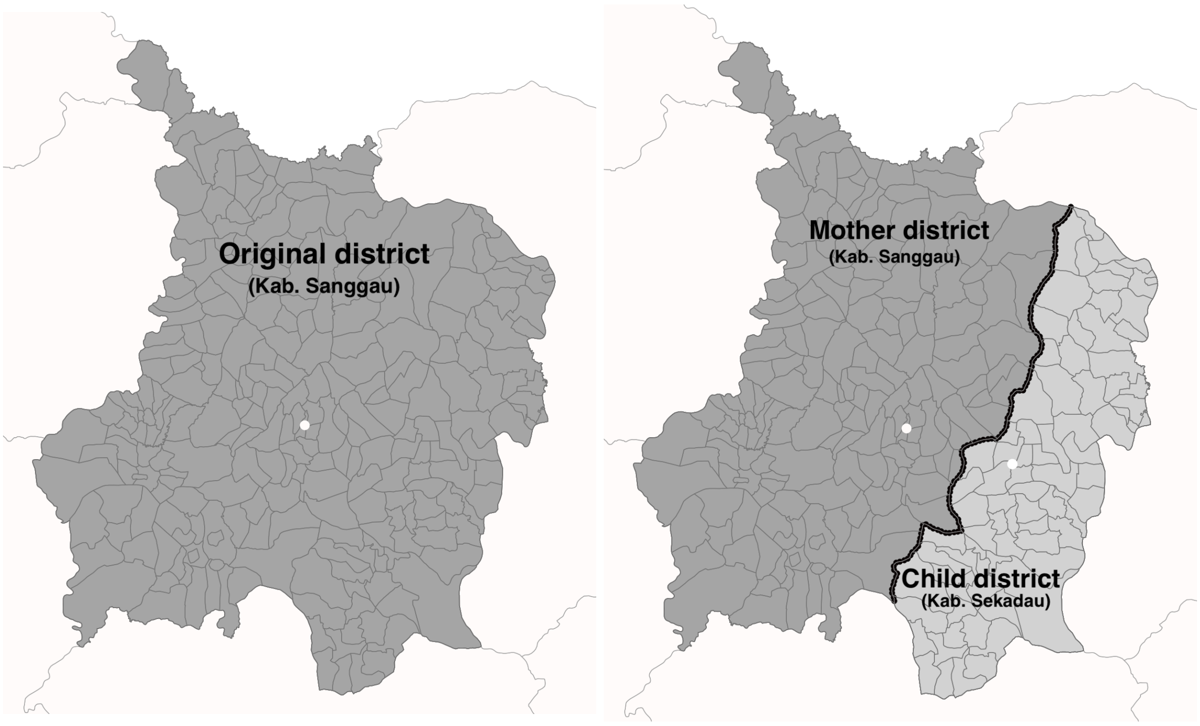
2.1 Indonesia's decentralization reforms

After the fall of the Suharto-regime in 1998, a period of rapid reforms triggered massive decentralization (Fitrani et al., 2005). It involved two related, however conceptually notably different components: On the one hand, classical decentralization resulted in vertical power devolution to lower tiers of government in administrative, fiscal, and political terms. While the administrative hierarchy remained unchanged, the second tier administrative districts (*Kabupaten*, or so-called regencies and *Kota*, or cities) received substantial new administrative and fiscal powers.[3] Increased fiscal transfers along some competencies to levy taxes were accompanied by the responsibility to deliver a large part of local public services (Ostwald et al., 2016). On the other hand, these reforms paved the way for the creation of new districts, additionally leading to horizontal power devolution by increasing the number of administrative units. Known as *pemekaran* (or the "blossoming" of districts), from 2001 onward, more than 150 new districts were created in a process of government fragmentation. This sequence of vertical, followed by horizontal power devolution is typical for developing countries' decentralization reforms worldwide (Grossman and Lewis, 2014), yet it is considered

[3]Indonesia's administration is organized along provinces (*Propinsi*), districts (*Kabupaten/Kota*), subdistricts (*Kecamatan*) and villages or urban precincts (*Desa/Kelurahan*).

particularly pronounced in Indonesia.[4]

Figure 1: Administrative reorganization in an exemplary district split



Note: The original mother district *Kabupaten Sanggau (left)* split into two units in 2003 *(right)*, establishing the new administrative child district, *Kabupaten Sekadau*. The dotted line depicts the new boundary between the mother and child district and the grey lines correspond to village boundaries. The white dots show the locations of the respective two capitals.

New districts were formed through administrative splits of existing ones, where the original district—referred to as the *mother*—retained its administrative capital and institutions, while the new district—referred to as the child—had to establish these institutions from scratch in a newly designated capital. Figure 1 illustrates this process for the district of *Sanggau*, from which the new district of *Sekadau* seceded in 2003. Between them, a new jurisdictional border was formed, which due to the preceding decentralization reforms, now divides the sphere of control between two local and influential decision-making units. Legislation foresaw that splits may only be facilitated within provincial boundaries, hence new boundaries do not overlap with existing provincial boundaries.[5] Given that mountain ranges and large rivers mostly coincide with upper-tier provincial boundaries, the newly established district boundaries are also largely independent of important geographical features (Burgess et al., 2012).

[4]For a discussion of the different dimensions of Indonesia's decentralization reform see for example Sjahrir et al. (2014), Ostwald et al. (2016), and Kis-Katos and Sjahrir (2017). The determinants of district splits are discussed in Fitrani et al. (2005) and Pierskalla (2016).

[5]Splits usually followed sub-district lines, which do not play a relevant role as polities within Indonesia and were themselves also subject to splits in the same period (Pierskalla, 2016).

The legislation guiding the district splitting process was complex and required the fulfilment of numerous criteria (Alesina et al., 2019). This resulted in an average gap of one to three years between the first proposal and an official decree legislating the split (Burgess et al., 2012). Because early lobbying for splits was commonplace even before the proposal (Pierskalla, 2016), the actual waiting time from first plans to the final realization of the administrative split was at times even longer. In practice, more than 150 splits fulfilled the criteria, leading to an increase in the number of districts from 341 in year 2000 to 511 districts in year 2014. In terms of regional coverage, splits were dispersed across the entire Indonesian archipelago, covering all major islands as shown in Figure 2.[6]

2.2 Forestry and natural resource management

Districts also became in charge of forestry management, which underwent the most drastic decentralization reforms (Barr et al., 2006). Instead of reporting to the Ministry of Forestry, the newly created district forest departments became responsible for monitoring and levying taxes (Thung, 2019). In the early stages of decentralization, they were also granted the right to issue logging licenses, but continued to do so even in later years (Alesina et al., 2019). At the same time, legislation foresaw that districts receive 80% of forestry sector revenues and royalties from other natural resource extraction, e.g., from oil and mining, that originated on their own land.[7] While these revenues—generated from, e.g., concessionaire dues—are collected by the central government, the original fiscal distribution scheme remained in place despite later recentralization tendencies (Ostwald et al., 2016). As a result, resource rents have quickly become an essential source of funding for district governments and local elites (Thung, 2019).

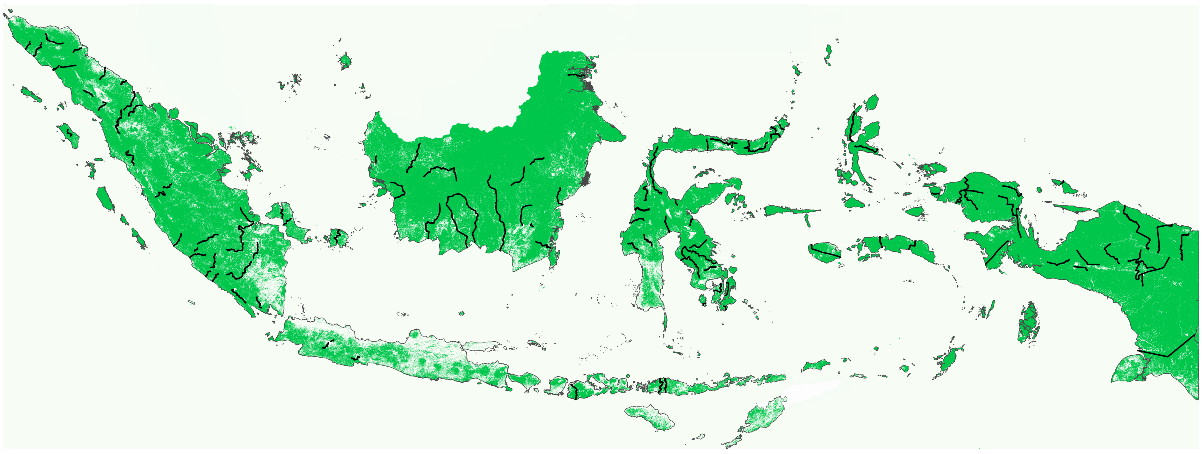
In contrast to forestry revenues, fiscal decentralization did not mandate direct revenue sharing between central and local governments with respect to rents from oil palm, which became the dominant agricultural crop in Indonesia since the reforms. As the world's largest producer, the Indonesian oil palm sector employs more than 20 million people directly or indirectly (Nurfatriani et al., 2022) and is a crucial revenue source. Instead, the central government collects revenues related to palm oil as a commodity via, e.g., export levies, while district governments receive legal revenues from taxing land and income (Nurfatriani et al., 2022). However they have also been illegally selling land concessions (Smith et al., 2003; Barr et al., 2006), ignoring illegal deforestation

[6] Figure 2 displays only those splits that we use in our analysis (cf. section 4).

[7] Decentralization law UU 25/1999 Article 6.2 stipulates that such revenues go towards the originating district government. See Thung (2019) for a detailed discussion of Indonesian forestry sector decentralization.

(Amacher et al., 2012), and accepting electoral campaign contributions from the oil palm sector (Mongaby, 2018; Cisneros et al., 2021). District governments thus have an incentive to attract oil palm plantations, often by facilitating forest conversion (Irawan et al., 2013; UNEP, 2016), and consequently became important players in terms of their leverage to issue licenses (Sahide and Giessen, 2015).

Figure 2: District splits and forest cover across Indonesia



Note: Black lines denote the new boundaries between mother and child district of the 115 splits included in our sample, described in section 4. Green shading indicates the extent of forest cover in 2000 from Global Forest Change (GFC) data based on 30×30m grid cells (Hansen et al., 2013), grey lines outline the extent of Indonesian land territory.

Alongside the Amazon and Congo basins, Indonesia is home to the largest tropical forests worldwide. With its abundant wildlife and as a natural carbon sink, its protection plays a key role for reaching international climate-change and biodiversity targets. Over the past decades, this rich natural habitat has been under heavy deforestation pressures due to both human settlement and agricultural land expansion. In the first decade of the 21st century alone, Indonesian forests have been cut at an average rate of 47,600 hectares per year, reducing the extent of primary forest by 6% over 12 years (Margono et al., 2014). These trends have also persisted in the following decade. Recent estimates show that deforestation is primarily driven by large-scale oil palm and timber plantations (40%), followed by grassland conversion and small-scale agricultural activities (20%) (Austin et al., 2019). As a consequence of the decentralization reforms, district governments have become key actors for forest protection not only directly (Burgess et al., 2012), but also indirectly by controlling one of the major drivers of deforestation in Indonesia, oil palm expansion (Austin et al., 2019; Cisneros et al., 2021).

3 Theoretical framework

Land-use change creates large economic benefits for local administrations via revenues from land rents or illegal collusion (cf. e.g., Alesina et al., 2019; Thung, 2019). 80% of revenues from the forestry sector are transferred to the originating district (cf. section 2). Beyond taxes and payments from the central government, such revenues have become an important income source for district governments and local elites (Thung, 2019). In the aftermath of the decentralization reforms, district governments had considerable influence on land-use change decisions. This included the expansion of agribusinesses, most notably oil palm, which became an important resource base for district governments and local elites, creating incentives for rent-seeking (Cisneros et al., 2021). In fact, opportunities to generate greater income from natural resources are seen as a key motivation behind district splits (Fitrani et al., 2005; Pierskalla, 2016). As a consequence, together with rising global demand for palm oil, the oil palm plantation area has significantly expanded since the early 2000s. At the same time, land-use change also bears political costs when associated for example with land grabbing, labor market marginalization, the loss of environmental services, or environmental damages (Krishna et al., 2017; Brito et al., 2019; Xu et al., 2022). Local administrations therefore face a benefit-cost calculation when deciding to support the conversion of natural forests into agricultural use. District splits change this benefit-cost calculation of both the existing (mother) districts and the newly formed (child) districts.

Immediate land-use rents District splits fundamentally alter the local governments' prospects to access land rents in the future, starting from the moment that a split becomes foreseeable and likely. Mother governments will have an increased incentive to extract immediate rents that are to be generated through legal (or illegal) deforestation before the split is legislated, and the jurisprudence of the territory is passed to the new child district. Once a split is formalized, the relevant district area is transferred to the sphere of influence of the new child government. Immediate rents from forest conversion now yield income opportunities for the new government. Together with the fact that new districts need to build their own institutions and resource base (Grossman and Lewis, 2014), this might exert an upward pressure on deforestation after districts splits.

Medium-term land-use rents A mother district aims to maximise the economic benefits from land use and will therefore reassess its investment strategy in anticipation of future district splits. Once a district split is expected to take place, mother governments will face a much lower incentive to foster the establishment of new oil palm plantations on the area of the prospective child district as their future revenues will not go towards the mother government. This is especially true as there is a time-lag of about three years between the seeding of trees and the first harvest (Ismail and Mamat, 2002). In the short-run, the anticipation of a split thus potentially de-incentivizes land conversion and hence deforestation. Once the split is effective, future rents associated with investments in oil palm in the new area will go towards the child government. Because palm oil is a key industry in rural areas—where most of the split (boundaries) are located—and payments contribute towards district governments' revenues, child districts will also face an incentive to expand oil palm plantations. In the medium run after the splits, deforestation thus potentially increases due to land-conversion pressures.

Constituencies' preferences Splits might also substantially reduce deforestation rates by moving government policies closer to the preferences of district constituencies. New districts have tended to become ethnically more homogeneous (Pierskalla, 2016; Alesina et al., 2019; Bazzi and Gudgeon, 2021),[8] which is associated with improved public service delivery—both in general (Alesina et al., 1999) and in Indonesia in particular (Bandiera and Levy, 2011).[9] This has been shown to improve forest protection, where homogeneous populations can control elected leaders more closely (Alesina et al., 2019). Local administrations therefore consider the political costs of land-use change and contrast them to the potential rents they generate. If a district split results in greater ethnic homogeneity in the new child district and forest conservation and the protection of small farmers are valued by the local population, we should observe a sustained longer-term slowdown of deforestation rates, but only in the aftermath and not before of district splits.

Administrative incapacity As long as the new district governments are in the process of formation, their capacity to monitor illegal deforestation might not yet be fully-fledged, which could increase deforestation rates immediately after the split. Moreover, as new district governments still need to set-up licensing processes and attract industries to exploit land-use associated rents, larger investments into new oil palm (or other) plantations may only materialize in the medium-run after the split. This could cause a decline in deforestation rates in the short-run but at the same time increase deforestation and oil palm expansion in the medium-run.

The creation of new political centers Existing literature suggests that when cities become administrative capitals, this induces significant economic growth and an expansion of urban settlements (Bluhm et al., 2021). While the mother district's capital retains its role in the process of jurisdictional splits, a new capital with all its relevant

[8] This has also been documented for other countries, where underrepresented areas tend to split off more frequently (Grossman and Lewis, 2014).

[9] Greater homogeneity in new districts has also been shown to reduce conflicts (Bandiera and Levy, 2011; Bazzi and Gudgeon, 2021). Government fragmentation improves the fiscal resource base of new administrative entities by triggering yardstick competition between them (Grossman et al., 2017), which potentially improves service delivery for residents.

institutions has to be formed in the child district. This way, previously administrative-subordinate cities suddenly become central hubs for the new jurisdiction, inducing local construction booms and thereby stimulating the economy (Fitrani et al., 2005; Grossman and Lewis, 2014; Thung, 2019). At the same time, urbanization is known to be a small, yet significant driver of deforestation in Indonesia (Austin et al., 2019). Spillovers from urban expansion in new centers thus potentially increase deforestation rates once a split has taken place, but not before. The distance to the new capital however potentially has heterogeneous effects as land rents decrease with the distance to cities (Angelsen, 2007). Once a district splits, the spatial relationship between child villages in close proximity to the new boundary and their expanding new capital changes profoundly. While on average most villages move closer to the capital, some are located in new peripheries and thus have less access to resources accumulated in the center (Grossman et al., 2017). In short, the literature suggests that in the aftermath of district splits, child villages that come closer to the newly formed capitals will face larger deforestation pressures.

In summary, we expect decentralization and the creation of new districts to affect deforestation patterns both before and after the district splits take place. The interplay of opposing incentives makes ex-ante predictions about the direction of the effect ambiguous: In anticipation of a split, the mother governments' land-use decisions depend on a trade-off between short-term gains from deforestation and the expected revenue losses in the medium-run if oil palm plantations locate in the soon-to-be-lost areas. If short-term incentives dominate, deforestation might increase before the split. By contrast, if anticipatory considerations—particularly with regard to oil palm plantations—play a dominant role, deforestation might decrease before the split.

After a split has taken place, deforestation trends in neighboring villages will depend on differences in the decisions by the mother and the newly formed child government. Children continue to face the incentive to extract short-term rents from forestry, and deforestation might also be exacerbated due to a temporarily more limited monitoring capacity. At the same time, increases in the ethnic homogeneity of the population might alleviate deforestation pressures. Changes in the spatial relationships with respect to the new capital will have heterogeneous effects: Spillovers from the development of new capitals could increase deforestation in more central locations, but decrease it in new district peripheries. Finally, in the medium run, the incentives to raise revenues from oil palm plantations are likely to foster land-use change and increase deforestation, whereas in the immediate aftermath of the split these dynamics might be still mitigated by limited administrative capacity.

4 Data and methodology

4.1 Data

We identify 115 newly created relevant boundaries between mother and child districts by relying on official district boundaries from 2014 from Statistics Indonesia (BPS), tracing back administrative entities to their historical boundaries for each year between 2000 and 2014.[10] These district splits reshape the administrative environment of 33,787 villages within the boundaries of mother and child districts, which we track from 2000 to 2018 using administrative and remotely sensed land-use data. Villages can appear multiple times in our analytical sample if they are located close to several new boundaries: For instance, because a child district was subject to a further split in a later year, or because they are located close to several newly formed child districts. Our sample therefore consists of repeated cross-sections of villages recorded at different periods in time, re-centered relative to the year of the district split. The empirical strategy will account for potential issues raised by duplicate villages as treated or controls.

Our main variables of interest are based on remotely sensed high-resolution data measuring different land-use dynamics: a) Forest losses between 2001 and 2018 (Global Forest Change data, Hansen et al., 2013); b) oil palm expansion between 2001 and 2018 (Gaveau et al., 2022); and c) settlement expansion between 2001 and 2015 (Global Settlement Footprint data, Marconcini et al., 2021). For each source, we construct measures of the initial area extent in the year 2000, as well as annual expansion measures. Socioeconomic data are taken from Indonesia's village census PODES. Further district-level characteristics, such as ethnic composition, are obtained from the 2010 Indonesian national census. To proxy for the discontinuous treatment of villages at the newly established boundaries we calculate the bee-lines distance from village centroids to the border.[11] Additionally, we also calculate distances to the respective district capitals before and after the split. Summary statistics and a list of sources are outlined in Appendix Table A.1.

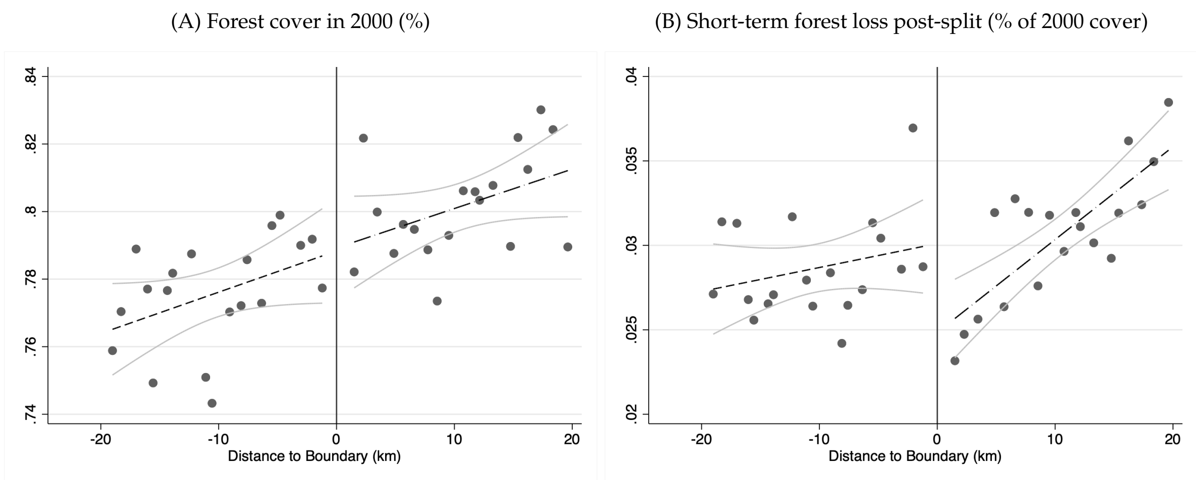
[10] We exclude splits where children do not share a physical boundary with the mother, including island splits (separated by water) and splits that involved several children at the same time and partially resulted in new boundaries only among the children. We further exclude areas where forest cover was relatively small to begin with by dropping splits of large urban centers into smaller administrative units, as well as splits that had less than 50% forest cover in 2000.

[11] On average, a mother district includes 172 villages and a child district includes 121 villages. Out of these, 64 and 60 villages are located "close" to—within 20km of—the newly established borders, respectively.

4.2 Econometric framework

To analyze whether the process of district splits changed deforestation dynamics, we employ a spatial regression discontinuity design (SRDD) strategy. This strategy relies on the main assumption that land-use change dynamics develop continuously in space and no systematic discontinuities arise across neighboring villages as long as they are located within the same district. If this identifying assumption holds, we can interpret all discontinuous jumps in deforestation on the two sides of a newly established (or soon-to-be established) district boundary as a causal effect of the district splitting process. As district administrations can adjust their decisions already in anticipation of an upcoming split, conceptually we expect changes in deforestation dynamics on the two sides of the boundary occurring after and also before a split has taken place; however only when the local government and economic actors could foresee along which lines the district will be splitting in the near future.

Figure 3: *Spatial RDD:* Initial forest cover and forest loss around new district boundaries



Note: Dots represent 20 binned means at each side of the cutoff (the new district boundary) for our sample of 115 splits. The left of each side displays villages located in mother districts, whereas the right side shows villages in the newly formed child districts. Short-term forest loss in panel B captures cumulative deforestation from the year of the split to three years after the split. Dashed lines are linear fits of the data with 90% confidence intervals.

In our SRDD strategy the newly established boundaries represent a sharp cutoff, and the running variables are defined by the villages' distance to the new boundary on each side of the border. Figure 3 visualizes our strategy by plotting initial forest cover against the distance to the new boundary in panel A, and total forest loss from the year of the split up to three years after the split against the same distance in panel B. Villages to the right of the cutoff are part of the new child district and thus are our treated units. As we move from the left to the right, towards the newly created districts, the distance to the original district capital increases monotonously and places become relatively more "remote" from the perspective of the original district administration. This leads to a monotonous increase in the initial forest cover, which simply reflects that more remote areas were generally more forested to begin with. More importantly, the forest cover is continuous across future boundaries in panel A and shows that future district splits were not linked to past discontinuities in forest cover (measured in 2000). This gives a first indication that the identifying assumption of variable continuity at the cutoff might hold, which we will support with further balance tests on a large number of topographical and socio-economic characteristics (reported below).

Panel B in Figure 3 shows that in the first three years after the district split, the extent of deforestation was generally increasing with remoteness, yielding a positively sloped linear fit at both sides of the boundary. Places that started with a larger forest cover also experienced on average more deforestation. However, in contrast to panel A, a sharp decrease in deforestation can be observed in the first three years after the split in the border area of the newly formed district. After the original district split up and a new child district was created, deforestation is substantially lower in villages that became part of the new child district than in their direct neighbors that remained part of the mother district. This can be taken as a first indicative evidence for a relative reduction in deforestation in the border regions of newly formed child districts.

We test this more formally by relying on an SRDD regression framework to assess whether deforestation dynamics developed smoothly in space across neighboring villages before and in the aftermath of the district split:

$$Deforest_{vs} \quad = \quad \eta \, Child_{vs} + f(Distance_{vs}, Child_{vs}) + \beta \, \mathbf{X}_v + \theta_s + \epsilon_{vs} \tag{1}$$

where $Deforest_{vs}$ measures forest loss in village v before or after the district split s occurred in a given period, $Child_{vs}$ indicates a village's location in the new district and $Distance_{vs}$—measuring the distance between a village's centroid and the respective split boundary—is the continuous forcing variable.[12] The function $f(Distance_{vs}, Child_{vs})$ includes either two linear or quadratic polynomials of distance, separately estimated on the two sides of the border. $\mathbf{X}_v$ is a vector of time-invariant village-specific controls, including village altitude and the initial share of the respective land-use type in 2000 that is being analysed in the regression (forest cover, oil palm, or human footprint area). Split fixed effects θ_s ensure that we only compare villages with their corresponding neighbors in our sample of pooled splits. Our main model is a pooled cross-section of 115 splits that took place at varying points in time between 2002 and 2014 (cf. Appendix Figure A.1). The split-level fixed effects θ_s further account for differential deforestation trends across the years, which we contrast with other, less strict, specifications.

[12] We exclude villages with a centroid in close proximity to the boundary (<1km) as they represent random shapefile artefacts.

We test our results based on fixed and optimal bandwidths. Our preferred specification uses a 20km window which eases the comparison across different estimations that rely on different outcomes. Results are robust to using robust-bias corrected (RBC) methods.[13]

To account for potential serial correlation due to some villages being included more than once (either as treatment or control units), we cluster standard errors at the split level (cf. e.g., Dube et al., 2010; Cantoni, 2020).[14] In our preferred specification, we fit our underlying outcome variable linearly on both sides of the cutoff, unless indicated differently. This helps to avoid overfitting and is supported by the visual examination of our data (cf. Figure 3) and by estimated information criteria (AIC/BIC).

Causal identification in the SRDD framework relies on two assumptions: a) Boundaries represent arbitrary thresholds across which all potential outcomes move continuously in the absence of treatment; and b) the absence of endogenous sorting, that is, villages cannot influence whether they end up as parts of the mother or the child district. While village boundaries are stable across time and space, new district boundaries are not randomly drawn in space but usually follow pre-existing sub-district borders. Our identifying assumptions require that the number of villages as well as topographical and economic characteristics are continuous across sub-district boundaries. If these assumptions are fulfilled, any differences in economic characteristics around the new borders must arise as a result of the decentralization process.

The assumption of no endogenous sorting can be assessed by a test of continuous density, for instance by estimating a local polynomial density function as proposed by Cattaneo et al. (2020). Figure A.2 in the Appendix shows visually that the density plot is fairly continuous around the cutoff. The formal test of a discontinuity can be rejected, but only with the relatively low p-value of 0.102. However, a battery of balance checks in Appendix Table A.2—applying our SRDD design from eq. (1) to village-level socio-economic and topographical variables—does not show any significant discontinuities around the future district boundaries.[15] All 22 reported variables develop smoothly across future district boundaries, reducing concerns about endogenous border location.

Finally, we acknowledge that the timing of and reasons for each district split are not exogenous. While this might bias a cross-sectional analysis, we believe this is not an issue in our setting: First, in our main specification we only compare neighboring villages

[13] We use Calonico et al.'s (2014) dedicated STATA package *rdrobust*.

[14] Within the bandwidth 20km at each side of the boundary, a total of 1,325 observations (<10% of our sample) are villages that are included more than once.

[15] We test the continuity of land-use characteristics in 2000 (forest cover, oil palm area, built-up settlement extent), geographic factors (altitude, coastal indicator, distance to nearest city by type), rural location, and initial conditions in 2000, including population size, socio-economic characteristics, and access to public services.

that appear on two sides of the same border before and after a split. Second, previous literature has shown that district-level correlates of deforestation such as forest cover in 2000, GDP and ethnic conflicts are not significantly related to the exact timing of the split, alleviating concerns regarding structural differences across time (Burgess et al., 2012; Alesina et al., 2019). And lastly, endogenous differences across the two districts resulting from a split, for example in their ethnic composition (Fitrani et al., 2005; Pierskalla, 2016; Bazzi and Gudgeon, 2021), are less of a concern. Results from balance checks discussed above lead us to assume continuity along unobserved dimensions (like village-level ethnic composition) as well.

5 Results

5.1 Main results

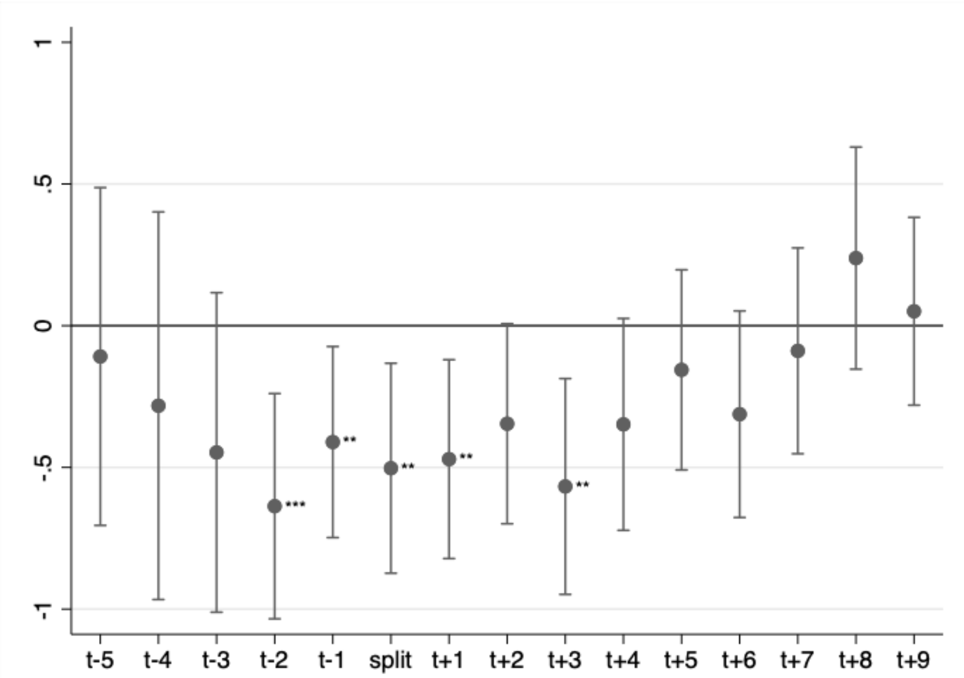
To investigate the dynamic effects of the district splitting process, we rely on yearly deforestation rates before and after each split as dependent variables in equation (1).[16] Figure 4 plots the estimates from 15 individual regressions, assessing deforestation starting five years before administrative splits occurred to up to nine years after. The results are based on our preferred specification relying on a linear fit, split-ID fixed effects, and controlling for initial ecological conditions. The results show that deforestation starts to significantly decrease in future child districts already up to two years before the split was actually implemented. Decreases in deforestation persist until up to three years after the split, but estimates get closer to zero over time, showing no statistical difference between mothers and children four years after the split. Thus, the pace of deforestation picks up in child districts in the long-run and catches up with that of mother districts over time.[17]

Table 1 collects these results by focusing on the years around the official district split—from three years before up to three years after the split. It shows SRDD results that estimate the difference between average deforestation rates among neighboring villages located in a child and a mother district before the split (in panel A) and after the split (in panel B). The results again rely on a linear fit but introduce fixed effects and controls step-wise. While column 1 reports the basic SRDD without any further controls, column 2 absorbs all macro-region-level shocks over time by introducing island-split-year fixed effects. Column 3 relies instead on split ID fixed effects, which restricts the com-

[16] Early and late splits lack information for pre- and post-split years, respectively, reducing the sample size at lags or leads of higher order (cf. Appendix Figure A.1).

[17] Table A.3 in the Appendix aggregates deforestation into three-year intervals and shows no significant differences between neighboring villages from the fourth year after the split, nor in forest cover at the end of our sample period in 2018.

Figure 4: *Dynamic SRDD effects:* Deforestation



Note: The figure displays treatment coefficients η from separate regressions (eqn. 1) that pool village observations based on their temporal distance to the district split year (denoted by "split"). The dependent variable measures deforestation in that given year, transformed by the inverse hyperbolic sine. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD relies on a linear fit. The graph displays 90% confidence intervals with standard errors clustered at the split level. Significance at or below 1% (***), 5% (**) and 10 percent (*).

parison to villages that are located in the neighborhood of each split, controlling away all spatio-temporal variation at a district scale, whereas columns 4 and 5 also control for initial forest cover and altitude. Across all specifications, child villages consistently experience statistically significantly lower deforestation rates than mother villages before as well as after the split. This difference is also considerable in economic terms: In our preferred specification in column 4, villages in child districts deforest 32–38% less than neighboring villages in mother districts.[18] Compared to the mean annual deforestation rate of 1.5% in our sample, it implies that the deforestation rate is around 0.5 percentage points lower in child districts. Results in this specification are based on a fixed bandwidth of 20km. Alternative specifications that rely on RBC-based bandwidths (in column 5) yield larger estimates.

The results are robust to using different specifications and outcome definitions. Estimates remain significant with somewhat larger effect sizes when fitting the data with a local quadratic polynomial (cf. Table A.4 in the Appendix). Results are furthermore

[18] Percentage changes in the outcome variables after regressing on binary variables are equally interpreted as in Log-Dummy regressions: $e^{\beta} - 1$ (Halvorsen and Palmquist, 1980; Bellemare and Wichman, 2020).

Table 1: *SRDD effects:* Deforestation in child vs. mother districts

	(1)	(2)	(3)	(4)	(5)
	Panel A: Dep.: asinh *Pre-split mean deforestation*				
Child	−0.816***	−0.549***	−0.498***	−0.483***	−0.652***
	(0.271)	(0.199)	(0.187)	(0.166)	(0.175)
Bandwidth	20	20	20	20	15 (42)
Observations	14,320	14,320	14,320	14,319	10,617
Adj. R^2	0.004	0.165	0.297	0.396	
	Panel B: Dep.: asinh *Post-split mean deforestation*				
Child	−0.566**	−0.405*	−0.404**	−0.390**	−0.568***
	(0.237)	(0.211)	(0.200)	(0.151)	(0.172)
Bandwidth	20	20	20	20	13 (35)
Observations	14,320	14,320	14,320	14,319	9,670
Adj. R^2	0.004	0.215	0.355	0.472	
Island-year FE	No	Yes	No	No	No
Split-ID FE	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

Note: The dependent variable is the average deforestation within three years before (Panel A) and from to three years after (Panel B) the split, transformed by the inverse hyperbolic sine. Child is a binary indicator for villages located in the new child district. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The bandwidth in column 5 is determined using an RBC estimator (Calonico et al., 2014). The SRDD relies on a linear fit. Controls include village altitude and forest cover in 2000. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).

robust when choosing alternative fixed bandwidths (cf. Appendix Figure A.3), as estimates remain significant at the 10% level for distances between 5 to 30km. Lastly, we run placebo regressions, artificially shifting borders up to 40km away from the actual boundaries. If the new administrations influence deforestation discontinuously only at the realized border, choosing other cutoffs in close neighborhood should lead to zero effects. Figure A.4 in the Appendix confirms this by showing insignificant and close to zero estimates for all placebo cutoffs.

5.2 Mechanisms

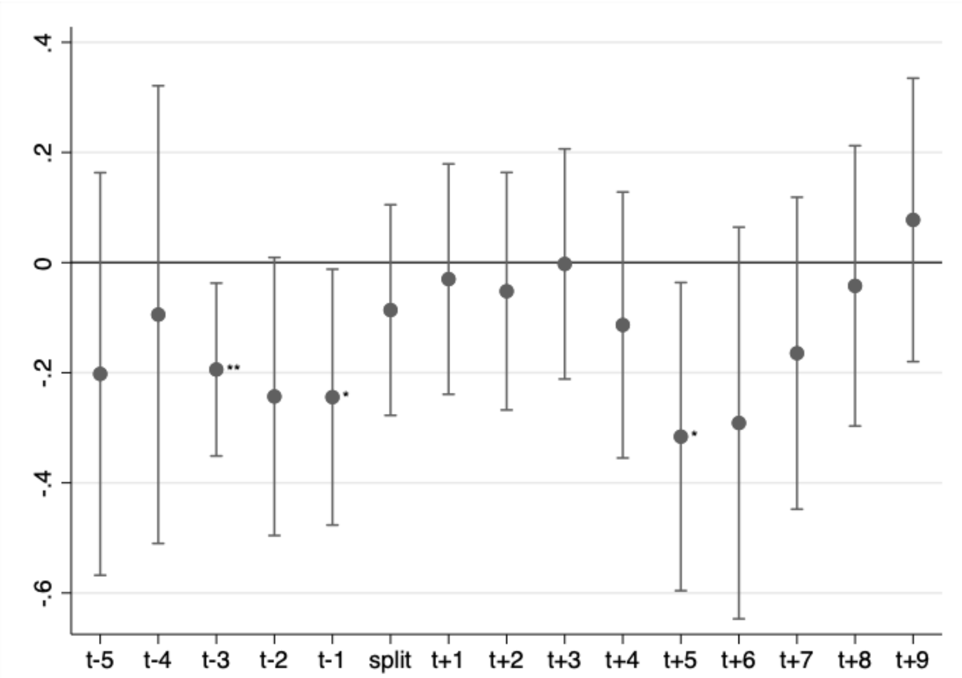
Our results document a temporary deceleration of deforestation in child districts as compared to mother districts, identified by a discontinuity at the newly established boundary. After splits, neighboring villages fall under the sphere of influence of new district administrations, so that these differences might reflect changing incentives to protect the remaining forest. However, our results show very similar decreases in the deforestation rate already in anticipation of district splits, which cannot yet be attributed to decisions made by the new district administrations. In this section, we analyze the interplay of different incentives induced by altered cost-benefit considerations before and after the split, focusing on how they affect the behaviour of both mother and child governments with regard to land-use decisions.

Immediate land-use rents Theory suggests that if forest conversion yields large immediate rents—e.g., through the sale of land-use licenses (Burgess et al., 2012) or wood products—mother governments have an incentive to try to extract as many resources as they can from the soon-to-be-lost areas. This would lead to a surge in deforestation rates on the area of the child district as soon as a district split is expected, which usually precedes the actual split by a few years. The results observed in Figure 4 speak against this hypothesis: Deforestation in areas that will belong to child governments after the split decelerates already before the jurisdictional change, showing no evidence for mother governments overusing the future child district's forestry resources in anticipation of a split. From the moment the split actually materializes, the rights to exploit forestry resources shift to the new child government for the same area. However, we also do not observe increased deforestation rates in the immediate aftermath of the split. Taken together, the deceleration of deforestation both before and after the split suggests that prospective benefits from short-term resource rents are overcompensated by other factors.

Medium-term land-use rents If deforestation is mainly driven by investments to expand agricultural production instead, then administrative decisions to support deforestation must follow a medium-term cost-benefit analysis. In consequence, the mother district's government will abstain from fostering land-use change in the soon-to-be lost areas and prefer to support agricultural development within its own remaining area. Starting when the wish for a new split is announced, medium-term rent considerations will create a gap in land-use dynamics between mothers and child districts.

Indonesia's decentralization reforms were accompanied by massive land-use change that shaped medium-term land-use rents: Triggered by a global palm oil boom, plantation area of oil palm increased from about 6% of village area in 2000 to 9.2% in 2018. This expansion was among the major drivers of deforestation in Indonesia. As oil palms take about three years to become productive after planting, remotely sensed oil palm expansion data offers us a useful opportunity to assess the role of medium-term agricultural rent considerations. To verify whether changes in oil palm expansion contribute to our findings, we rerun our main model in equation (1) with oil palm area expansion as the dependent variable. Figure 5 displays how oil palm area developed around the time of the splits. Estimates mirror the trends observed for deforestation closely around the time of the district split as oil palm expansion decelerates by around 20% in child villages already up to three years before the split took place. This suggests that the mother districts' unwillingness to promote agricultural development in

Figure 5: *Dynamic SRDD effects:* Expansion of oil palm area



Note: The figure displays treatment coefficients η from separate regressions (eqn. (1)) that pool village observations based on their temporal distance to the district split year (denoted by "split"). The dependent variable measures new oil palm area in that given year, transformed by the inverse hyperbolic sine. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD relies on a linear fit. The graph displays 90% confidence intervals with standard errors clustered at the split level. Significance at or below 1% (***), 5% (**) and 10 percent (*).

the soon-to-be-lost areas contributes to forest protection in the short run, because costs associated with such investment fall short of obtainable rents. Once the split has taken place, the difference between villages at either side of the cutoff loses significance and the pace of land-use change in villages located in the child district catches up with that of the mother district. One explanation is that the new child governments now face the incentive to promote oil palm conversion for rent-extraction on their area as well.

Constituencies' preferences While the pre-split decline in land-use change points toward strategic divestment on the side of the mother district, the post-split decline could also result from socio-political considerations. For the period after the split, decreases in deforestation could have been especially pronounced in places where decentralization has led to a better matching of preferences between district administrations and their constituencies. In this scenario, excess deforestation would come at a political cost for elected leaders. To verify this hypothesis, we investigate the role of decreasing ethnic heterogeneity, which has been proposed as a main mechanism behind the improvements of public service delivery and deforestation reductions in Indonesia (Alesina et al., 2019). Using data from the 2010 national census, we construct ethnic fractionalization measures, as proposed by Alesina et al. (2003), both in the mother and child district. In our sample, average fractionalization is 0.57—a comparably large value, mirroring Indonesia's ethnically diverse population. This value decreases on average by about 1.1 points or 2% in the child districts after the splits. Table 2 augments our main model with a binary variable identifying splits that resulted in a more homogeneous population in the child districts.[19] If the theory holds, we would expect deforestation to decrease by more in the aftermath of a split if it resulted in a more homogeneous population. Although the interaction term is negative, we do not find statistically significant differences between child districts that became ethnically more homogeneous after the split. It therefore seems that, in contrast to Alesina et al. (2019), the decline in forest losses after a district split cannot be linked to the mechanism of constituencies' preferences. This is also in line with results presented in column 6, which do not show long-term improvements in forest conservation that would corroborate such a mechanism.

Table 2: *SRDD effects:* Heterogeneities by ethnic composition

Dependent:	*ln Mean deforestation*					*Forest cover*
Period	Pre 6-4	Pre 3-1	Post 0-3	Post 4-6	Post 7-9	in 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Child	−0.148	−0.319	−0.337	0.112	0.101	−0.132
	(0.439)	(0.251)	(0.214)	(0.216)	(0.189)	(0.084)
Child × Decrease in ethnic fractionalization	0.380	−0.226	−0.103	−0.429	−0.333	0.035
	(0.511)	(0.326)	(0.299)	(0.317)	(0.325)	(0.147)
Split ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,695	12,822	12,822	12,822	12,822	12,822
Adjusted R^2	0.410	0.385	0.460	0.453	0.462	0.635

Note: The dependent variable is average deforestation in the years indicated, transformed by the inverse hyperbolic sine. Child is a binary indicator for villages located in the new child district. *Decrease in ethnic fractionalization* identifies villages in which the child district's ethnic fractionalization is smaller than the fractionalization of the original district. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD relies on a linear fit. Controls include village altitude and forest cover in 2000. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).

Administrative incapacity A temporal administrative incapacity among new child districts could also influence land-use change dynamics after district splits. Monitoring and enforcement institutions might take some time to set up, which could increase illegal deforestation, especially in regions that are more remote and hence incur higher costs of monitoring and enforcement. However, deforestation could be also reduced if the new administrations are slow to start promoting regional development right after

[19] This is the case for 51 out of 99 splits. We cannot compute changes in ethnic composition for 16 splits for reasons of data availability.

the split. Again, remoteness could play a moderating role in this process. To test this mechanism we create a binary variable that identifies splits in which the distance of child villages to their new capital on average is reduced by more than the sample median.[20] Columns 1 and 2 in Table 3 display results from interacting the treatment variable in our main model with this measure. If monitoring and enforcement of forest conservation is the main driving force behind the differences in land-use change, we would expect an increase in deforestation in places that are relatively more remote from the perspective of the newly formed child districts as the costs of monitoring increase in distance. By contrast, we would expect relatively more favourable deforestation dynamics in areas that became less remote after the district split due to a larger ease of monitoring. There is no evidence for either of these hypotheses: (1) Deforestation does not increase but even significantly declines in the relatively more remote areas after the district split; and (2) the interaction effect is positive (and insignificant), which does not show more beneficial deforestation dynamics in places that become relatively less remote after the split.

Table 3: *SRDD effects:* Heterogeneities by closeness to the new political center

Dependent:	*ln Mean deforestation*		*ln Mean new settlement area*			
Period	Pre 3-1 (1)	Post 0-3 (2)	Pre 3-1 (3)	Post 0-3 (4)	Pre 3-1 (5)	Post 0-3 (6)
Child	−0.626***	−0.559***	−0.280	−0.243	−0.510*	−0.521**
	(0.211)	(0.198)	(0.216)	(0.164)	(0.288)	(0.200)
Child × Large decline in distance to capital	0.278	0.373			0.757*	0.893***
	(0.351)	(0.290)			(0.403)	(0.334)
Split ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,319	14,319	14,299	14,299	14,299	14,299
Adj. R^2	0.399	0.474	0.398	0.456	0.399	0.456

Note: The dependent variable in columns 1 and 2 (3 to 6) is average deforestation (expansion in settlement area) in the years indicated, transformed by the inverse hyperbolic sine. Child is a binary indicator for villages located in the new child district. *Large decline in distance to capital* is a split-level binary variable measuring whether the villages' average decline in distance to their capital cities lies above the median. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD is relies on a linear fit. Controls include village altitude and forest cover in 2000. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).

The formation of new economic and political centers In addition to the new orientation to political centers, villages in some splits also find themselves close to quickly developing and increasingly urbanizing centers, while others move towards the new peripheries of the district, resulting in diverging deforestation pressures. Columns 3 to 6 in Table 3 investigate the relationship between district splits and urbanization using

[20] On average, the distance to the new capital in the child district is 42km closer than that to the original mother district (cf. Appendix Table A.1).

remotely sensed yearly human settlement expansion measures. On average, we do not observe significant discontinuities in settlement dynamics across villages at the new boundary (columns 3–4). However, interacting the treatment indicator with a binary variable that distinguishes between splits in which villages ended up closer than the median to their new capital than before, reveals divergent effects (columns 5–6). While these dynamics appear already in anticipation of the district split, the relationship is only marginally significant. After the split, villages in districts that are not experiencing a larger reduction in the distance to their administrative centers—and hence remain similarly peripheral as they were before—experience a substantially smaller relative decline in urbanization than their immediate neighbors. By contrast, urbanization increases in villages that move relatively closer to an administrative center—and hence become more central. These results lend further empirical support to the argument that new capitals trigger localized economic booms (Fitrani et al., 2005; Grossman and Lewis, 2014; Thung, 2019; Bluhm et al., 2021). In summary, while new political centers accelerate urbanization in their close proximity, administrative incapacity could be delaying the same process in more remote areas, resulting in a reduction in deforestation. Close to cities, the economic effects of a new political center push deforestation pressures up, cancelling out the unintended forest conservation impacts of administrative incapacity.

6 Conclusion

In recent decades, Indonesia underwent wide-sweeping decentralization reforms that led to a considerable sub-national government fragmentation. Relying on a spatial regression discontinuity design, we show that the creation of over 100 new districts temporarily slowed down deforestation in the newly formed jurisdictions. An analysis of deforestation dynamics around the time of the splits suggests considerable anticipation effects that also translate into relatively lower deforestation rates in new districts up to three years before administrative splits. In the medium run, however, deforestation rates equalize at the boundary of mother and child districts, resulting in no differences in the remaining forest cover on both sides of the boundary in the long run.

The results point to a strategic investment behavior by existing governments that maximize medium-run revenues. Deforestation and oil palm area expansion both slow down in areas that will become part of the new jurisdiction even before splits officially take place, suggesting that local governments in the mother districts decelerate land-use change in these areas in expectation of losing the future economic rents from this process. However, deforestation rates at the boundaries of newly formed districts equalize over time once the new child districts build up enough capacities to foster agricultural expansion of their own. In addition, we do not find evidence for lower deforestation in more ethnically homogeneous child districts, and thus cannot confirm that the mechanism of better matching constituencies' preferences translated into sustained long-term forest protection.

Such anticipatory land-use decisions before jurisdictional adjustments have not yet been empirically documented. This mechanism thus provides another perspective on the process of government fragmentation at the sub-national level, adding an unintended positive consequence for the protection of forests. Even a temporal decline in deforestation rates holds the potential to transform a local economy and make it more environmentally sustainable. Central governments, NGOs, and other policy makers might consider offering additional incentives for new district administrations to protect natural forests, before they build up a development strategy that relies on agricultural expansion.

Our study focuses on deforestation in a narrow bandwidth around new administrative boundaries. By that we precisely identify localized and temporary decreases in deforestation, which arise in a context of massive increases in deforestation linked to more inter-district competition (Burgess et al., 2012), as well as some improvements in the alignment of constituencies' and politicians' preferences (Alesina et al., 2019). Our results also pose questions that are beyond the scope of this paper: Given that political budget cycles play a major role in Indonesia (Sjahrir et al., 2013; Kis-Katos and Sjahrir, 2017; Cisneros et al., 2021), an analysis of the interplay of the observed effects with local elections could provide additional insights. This is particularly relevant as public office is seen as a means to capitalize on successful but costly election campaigns (Pierskalla, 2016), whereby medium-run land development can help to generate the needed revenues. Finally, our results raise the question about anticipatory strategies and administrative incapacity effects that go beyond land-use decisions. District splits could also yield negative externalities in other policy areas. The quality of public services—impacting among others education, health, infrastructure, or social equity outcomes—could similarly worsen before and after the splits. Additional research in this area could help to better understand the potential dynamic effects of district splits. Such further analyses could especially highlight further the trade-offs of the district splitting process as its short-term and long-term effects may not be fully aligned.

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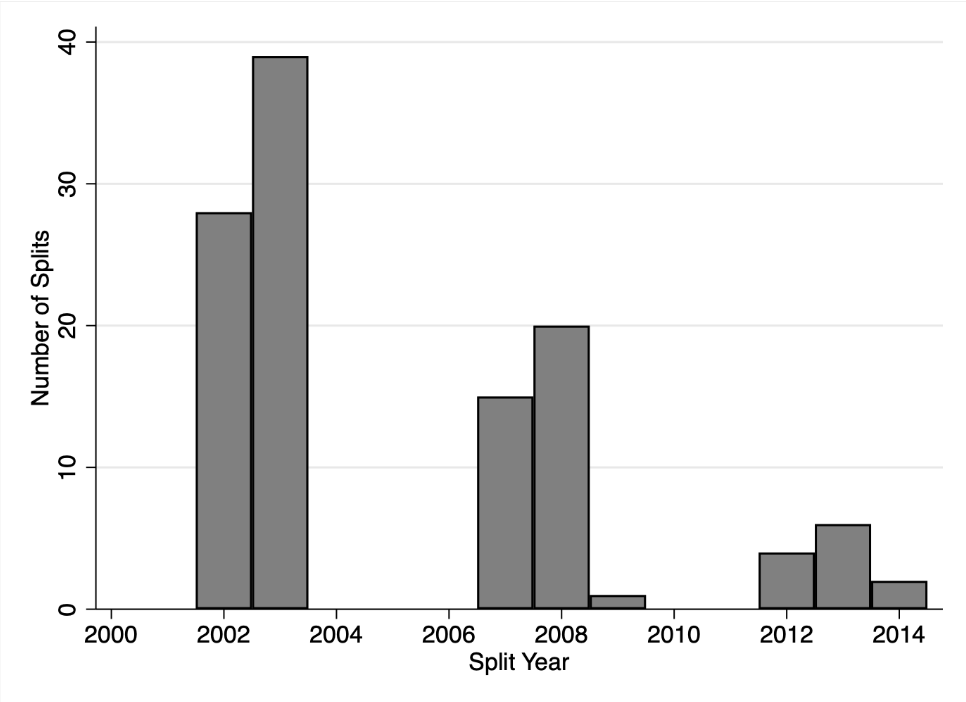
A Online appendix: Additional tables and figures

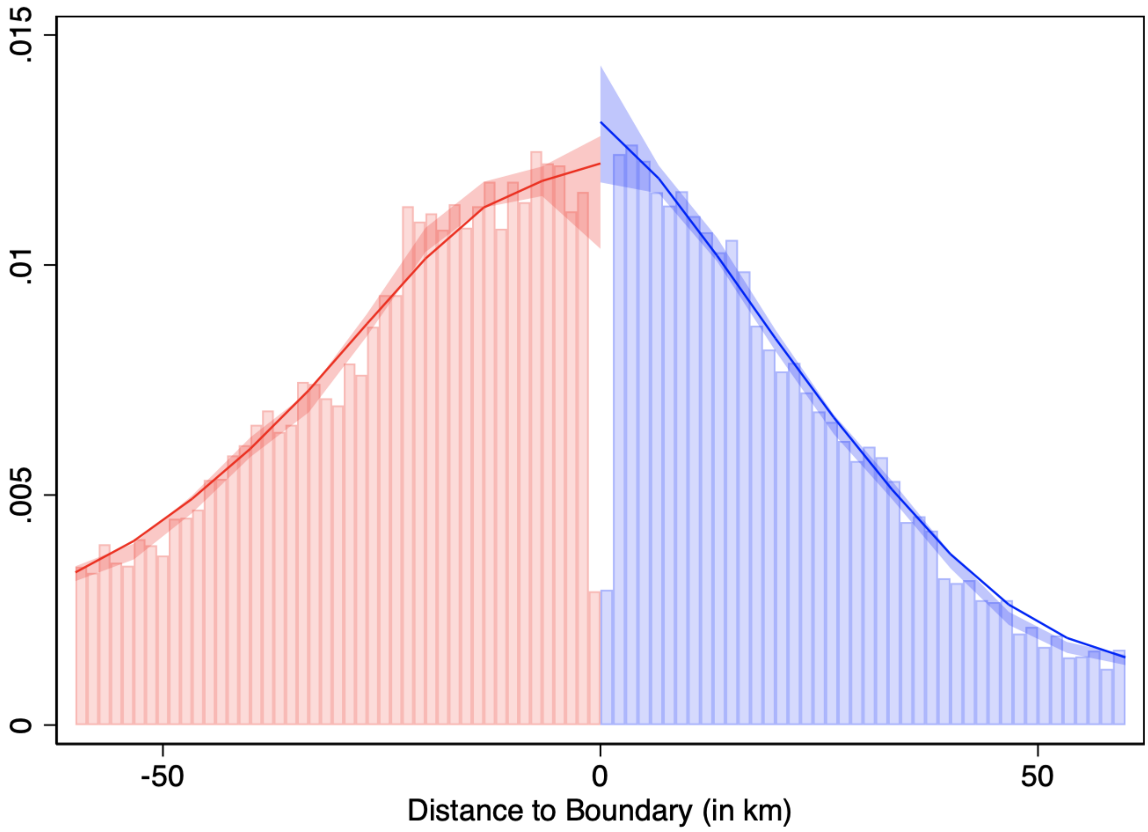
A.1 Figures

Figure A.1: *Descriptives:* Frequency of splits



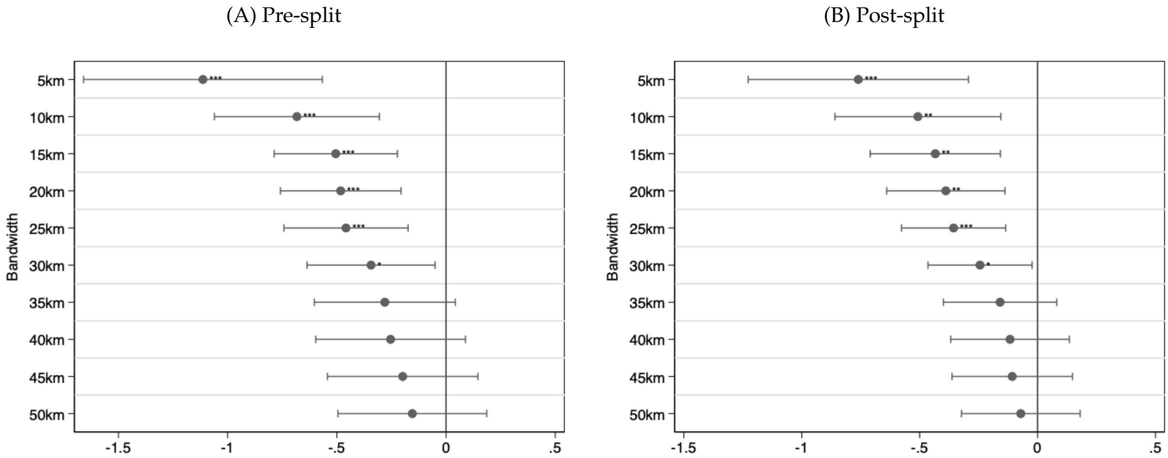
Note: The figure displays the number of district splits in our sample by year they were legislated in.

Figure A.2: *Identification check:* Density of the forcing variable



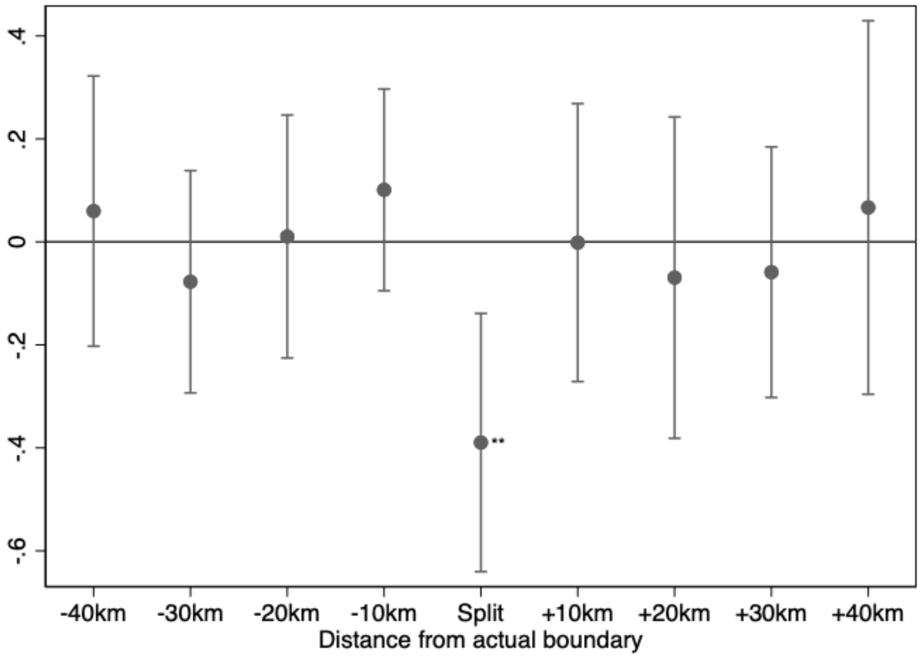
Note: Density of villages around the new district boundaries, measured in km. Figure constructed using *rdrobust* Stata package by Cattaneo et al. (2020). The corresponding local polynomial density estimator with quadratic fit is based on a 20km bandwidth, yielding a p-value of 0.102. The sample consists of villages whose centroids lie within the indicated bandwidth around the 115 district split boundaries.

Figure A.3: *Robustness:* Deforestation effects for varying bandwidths



Note: The figure displays coefficients from individual estimates of the binary child indicator for villages located in the new child district (eqn. (1)), with the dependent variable measuring average deforestation within three years before (Panel A) and from to three years after (Panel B) the split, transformed by the inverse hyperbolic sine. The sample consists of villages whose centroids lie within a fixed bandwidth indicated on the y-axis around the 115 district split boundaries. The SRDD relies on a linear fit. Controls include village altitude and forest cover in 2000. The graph displays 90% confidence intervals with standard errors clustered at the split level. Significance at or below 1% (***), 5% (**) and 10 percent (*).

Figure A.4: *Robustness:* Shifting boundaries in space



Note: Displayed coefficients represent estimates of the binary child indicator for villages located in the new child district. The dependent variable is average deforestation from to three years after the split, transformed by the inverse hyperbolic sine. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries for the coefficient labeled as "Split". All other coefficients are based on samples that artificially moved the boundary up to 40km away from the actual split boundary. The SRDD relies on a linear fit. Controls include village altitude and forest cover in 2000. The graph displays 90% confidence intervals with standard errors clustered at the split level. Significance at or below 1% (***), 5% (**) and 10 percent (*).

A.2 Tables

Table A.1: *Descriptives:* Summary statistics

Samples:	Entire sample		Bandwidth 20km	
	Mother (1)	Child (2)	Mother (3)	Child (4)
Split characteristics				
Number of villages	19,867	13,920	7,369	6,951
Distance to split (km)	39.7	29.1	10.3	9.9
	(37.8)	(31.1)	(5.4)	(5.3)
Distance to capital	39.7	34.0	28.7	26.6
	(38.9)	(31.5)	(26.6)	(23.1)
Distance to capital change (km)	-	42.0	-	22.7
	(-)	(45.8)	(-)	(30.0)
Length of split (km)	108.4	108.4	108.4	108.4
	(72.4)	(72.4)	(72.4)	(72.4)
Land use metrics				
Village size (sqkm)	40.7	45.1	26.6	27.9
	(109.0)	(128.3)	(76.3)	(75.9)
Forest cover 2000 (%)	79.2	80.1	77.6	80.1
	(23.0)	(23.4)	(23.0)	(23.1)
Forest cover 2018 (%)	66.6	69.0	66.1	68.1
	(24.3)	(25.6)	(23.5)	(24.7)
Oil Palm area 2000 (%)	5.4	7.0	5.8	5.8
	(15.7)	(18.6)	(17.0)	(16.7)
Human footprint area 2000 (%)	3.5	2.3	4.8	3.0
	(8.9)	(6.1)	(10.5)	(7.4)
Village topography				
Altitude (in meters)	396.3	454.7	449.5	537.2
	(598.2)	(670.3)	(592.2)	(720.6)
Located on shore (%)	17.8	18.3	12.4	13.6
	(38.2)	(38.6)	(32.2)	(34.2)
Distance to sub-district capital	20.0	23.6	16.9	18.4
in 2000 (km)	(32.5)	(50.1)	(31.6)	(30.6)
Distance to district capital	169.6	182.3	133.6	150.4
in 2000 (km)	(191.4)	(198.8)	(147.8)	(165.1)
Socio-economic composition (in 2000)				
Population	1,650	1,529	1,763	1,670
	(1,921)	(1,813)	(2,054)	(2,010)
Rural (%)	94.0	96.8	92.7	96.4
	(23.6)	(17.4)	(25.8)	(18.5)
Main income agricultural (%)	96.1	97.7	95.7	97.5
	(19.2)	(14.9)	(20.2)	(15.3)
Ethnic fractionalization	0.511	0.477	0.511	0.477
(at district-level)	(0.19)	(0.20)	(0.19)	(0.20)

Note: Distance to capital change is not available for mother villages because they retain their original capital as part of district splits. Forest cover, oil palm area and human footprint area relate the respective extent to village area. Standard deviations reported in parentheses.

Table A.2: *Placebo checks*: Continuity of topographic and socio-economic characteristics in 2000

	Panel A: Land-use characteristics in 2000						
	Forest cover	Oil palm area	Settlement area				
	(1)	(2)	(3)				
Child	−0.003	−0.004	0.007				
	(0.019)	(0.005)	(0.009)				
Obs.	14,320	14,300	14,320				
Adjusted R^2	0.340	0.267	0.483				
	Panel B: Socio-geographic characteristics (in 2000)						
	ln Pop.	% Rural	% Agricult. Income	Subdist. city distance	District city distance	% Coastal location	Altitude
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child	0.038	0.024	0.006	−2.360	7.702	0.025	1.274
	(0.046)	(0.015)	(0.007)	(1.828)	(6.728)	(0.016)	(24.745)
Obs.	13,568	14,227	13,568	13,568	13,568	13,568	14,319
Adjusted R^2	0.503	0.075	0.070	0.166	0.670	0.260	0.787
	Panel C: Socio-economic characteristics in 2000 (1)						
	No. Poverty card	No. health card	% Phone	% Radio	% Hospital	% Sub-hospital	% Kinder-garten
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child	5.840	8.568	0.002	0.004	−0.003	0.0179	0.006
	(4.916)	(7.207)	(0.005)	(0.021)	(0.004)	(0.005)	(0.002)
Obs.	13,569	13,569	13,569	13,569	13,569	13,569	13,569
Adjusted R^2	0.141	0.271	0.052	0.143	0.007	0.116	0.242
	Panel D: Socio-economic characteristics in 2000 (2)						
	% Primary school	% Bank index 1	% Bank index 2	% Market index 1	% Market index 2	# State electr. access	# Private electr. access
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child	−0.005	−0.001	0.003	0.011	0.016	3.979	3.116
	(0.004)	(0.017)	(0.017)	(0.019)	(0.010)	(19.160)	(4.062)
Obs.	13,569	13,569	13,569	13,569	13,569	13,569	13,569
Adjusted R^2	0.251	0.047	0.073	0.065	0.064	0.400	0.149
Split ID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: % rural, agricult. income, coastal location, phone, radio, (sub-) hospital, kindergarten, primary school, bank, and market capture binary village access variables. Poverty and health cards, state and private electr. access capture the number of inhabitants with access. See section 4 for the source of the respective outcome variable used. Child is a binary indicator for villages located in the new child district. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD relies on a linear fit. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).

Table A.3: *Robustness:* Dynamic SRDD effects on deforestation

Dependent:	ln Mean deforestation					Forest cover
Period:	Pre 6-4	Pre 3-1	Post 0-3	Post 4-6	Post 7-9	in 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Child	−0.208	−0.483***	−0.390**	−0.190	−0.0625	−0.109
	(0.296)	(0.166)	(0.151)	(0.160)	(0.170)	(0.069)
Split ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,148	14,319	14,319	14,319	12,958	14,319
Adjusted R^2	0.435	0.396	0.472	0.457	0.462	0.628

Note: The dependent variable is average deforestation in the years indicated, transformed by the inverse hyperbolic sine. Child is a binary indicator for villages located in the new child district. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The SRDD relies on a linear fit. Controls include village altitude and forest cover in 2000. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).

Table A.4: *Robustness:* SRDD effects on deforestation using quadratic fit

	(1)	(2)	(3)	(4)	(5)
	Panel A: Dep.: ln *Pre-split mean deforestation*				
Child	−1.065***	−0.880***	−0.704**	−0.627***	−0.670***
	(0.384)	(0.292)	(0.275)	(0.234)	(0.221)
Bandwidth	20	20	20	20	30 (66)
Observations	14,320	14,320	14,320	14,319	19,848
Adj. R^2	0.004	0.165	0.297	0.396	
	Panel B: Dep.: ln *Post-split mean deforestation*				
Child	−0.743*	−0.704**	−0.610**	−0.530**	−0.558***
	(0.381)	(0.288)	(0.268)	(0.223)	(0.214)
Bandwidth	20	20	20	20	26 (55)
Observations	14,320	14,320	14,320	14,319	17,746
Adj. R^2	0.004	0.215	0.355	0.472	
Island-year FE	No	Yes	No	No	No
Split-ID FE	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

Note: The dependent variable is average deforestation within three years before (Panel A) and from to three years after (Panel B) the split, transformed by the inverse hyperbolic sine. Child is a binary indicator for villages located in the new child district. The sample consists of villages whose centroids lie within a fixed bandwidth of 20km around the 115 district split boundaries. The bandwidth in column 5 is determined using an RBC estimator (Calonico et al., 2014). The SRDD is fitted relying on a quadratic trend. Controls include village altitude and forest cover in 2000. Standard errors are clustered at the district split ID. Significance at or below 1% (***), 5% (**) and 10 percent (*).