ONLINE APPENDIX
The Political Boundaries of Ethnic Divisions

Samuel Bazzi*
Boston University, CEPR, NBER

Matthew Gudgeon†
U.S. Military Academy

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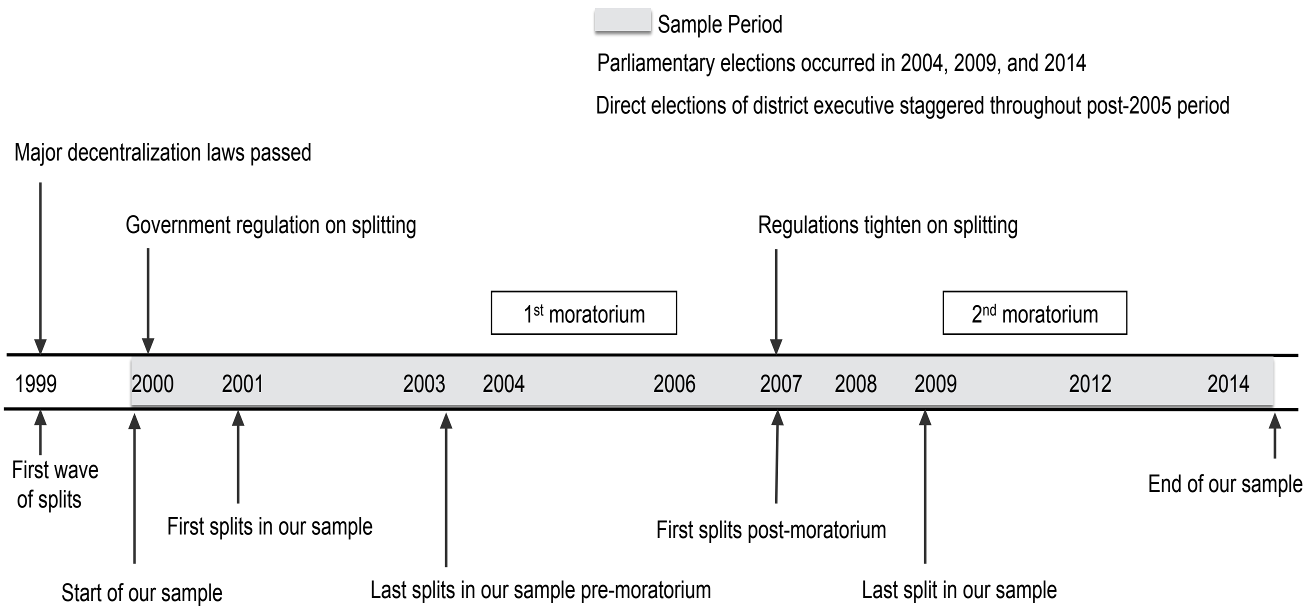
*Department of Economics. 270 Bay State Rd., Boston, MA 02215. Email: sbazzi@bu.edu.
†Department of Social Sciences & OEMA. 607 Cullum Rd., West Point, NY 10996. Email: matthew.gudgeon@westpoint.edu.

A Further Background on District Proliferation

Figure A.1 provides a timeline of events over our study period, including major decentralization, splitting, and electoral reforms. Below, we provide further details on the implications of splitting discussed in Section I.B.

Figure A.1: Timeline of Events



Size of Government. In the typical district, between 1,200 and 2,000 new jobs are created (according to interviews and province-level yearbooks). We have found no evidence that the total number of offices and jobs decrease in the parent district. Thus, the overall number of civil servants per capita increases substantially, and these newly created jobs are important for setting and executing public policy.

In addition, there are apportionment gains to splitting due to the step function rule used to determine the seat-to-population ratio. Seats in local parliament always weakly increase with splitting. For example, an original district with 400,000 people initially would have 40 seats. If it split into two equally sized districts, each would have 30 seats for a total of 60 compared with 40 originally.

Fiscal Resources. Splitting also leads to an increase in transfers from the central government. We show this in our sample using the within-district identification strategy detailed in Section III.[1] Once new funds for the child district start flowing in approximately two years after the split, real transfers at the original district level increase by 18–25 log points off a mean of roughly USD 200 (Table A.1, Panel (a), Column 1).[2] These revenue increases pass through to significant increases in local government expenditures in the following year.

We can also show that child districts experience relatively larger post-split increases in transfers than parent districts. To do this, we need to deal with the fact that we do not observe how transfers were divided between child and parent areas before splitting. However, one natural benchmark is to assume that pre-split transfers (T) were allocated according to population with the parent receiving $\left(\frac{N_{parent}}{N}\right) T$

[1]Initial population is absorbed in the fixed effect, and while including time-varying population does little to change the point estimates, it introduces unnecessary noise as the data is incomplete and requires estimation and imputation.

[2]Note that the decline in transfers in the year after splitting reflects a short adjustment period when child district transfers have only slowly started to flow into the new public coffers while parent district transfers have begun to adjust downward to account for their now smaller population.

and the child receiving $\left(\frac{N_{child}}{N}\right)T$. We use this benchmark to perform two exercises that clarify the overall fiscal benefits of splitting and the differential gains to child districts. First, we take the original district transfers as given and compare realized transfers post-split to the expected transfers if they had continued to be allocated proportional to population. Second, we assume that parents and children receive their population shares of the original district transfers pre-split (and in the year of the split when nothing yet changes). Then, we continue this time-series post-split using the actual, observed transfers at these lower administrative units. This allows us to re-estimate regressions like that in column 1 of Panel (a) in Table A.1 at the smaller units.

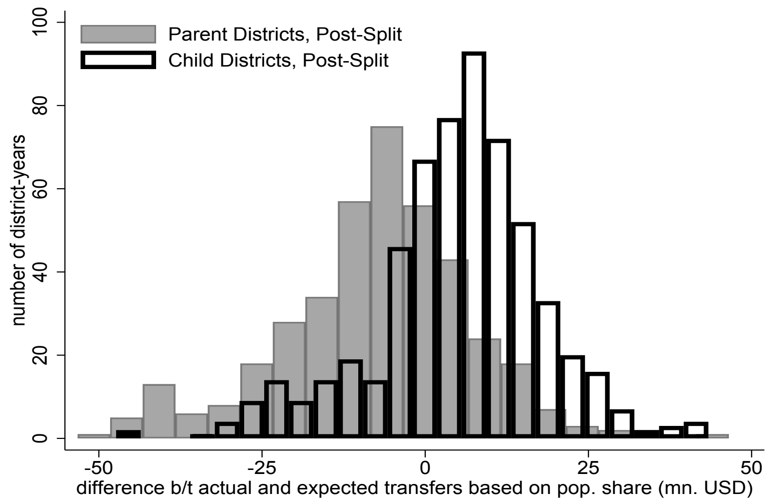
First, we simply compare realized transfers in post-split years at the parent/child level to expected transfers based on population shares of the realized original district level transfers in all post-split years. Figure A.2 plots the distribution of this difference between actual and expected transfers (based on population shares of the realized original district transfers). This shows the difference (in USD) for all post-split years and districts in our sample but looks comparable if plotted year-by-year. It is evident that children receive more than expected based on population shares and, consequently, parents less. In the average post-split year, parents receive USD 7.4 million less than expected (USD 16 per capita) and children receive USD 5.1 million more (USD 58 per capita). This strongly suggests that the gains from splitting accrue disproportionately towards children. This finding is in line with the upfront costs of establishing new government institutions. For example, around 40–50 percent of expenditures go towards staff, which expanded greatly in the child but not the parent.

Note that while children gain disproportionately from splitting, parents nevertheless tend to see an increase in transfers as well. To see this, suppose that parents received their population share of original district transfers pre-split. While post-split parents receive a lower share of the total transfer 'pie', the 'pie' is also larger. In practice, this still results in an increase in transfers per capita at the parent level as made clear next.

Second, columns 2–4 of Panel (a) in Table A.1 make these patterns even clearer by showing that both parents and children benefit from splitting in terms of real transfers, but children clearly benefit more. Parent districts experience roughly a 19 log point increase in long-run transfers ($\geq$ 5 years post-split) relative to the pre-split period (column 3), whereas child districts experience a 59 log point increase (column 4). While these results are subject to strong assumptions about the pre-split allocation of transfers, different assumptions are unlikely to explain away the main takeaways that (i) overall transfers increase in both parent and child districts, and (ii) child districts benefit relatively more than parent districts.

Proximity to Government. In addition to receiving increased transfers, child district residents experience a significant reduction in the average distance to government institutions. Panel (b) of Table A.1 shows how reported travel distance to the capital (in kilometers) changed after splitting. These estimates are based on reports by the village head in 2000 and 2011 from *Podes*, which we aggregate to 2010 district borders using population weights. While parent districts experienced little change in distance to the capital, child districts register an average reduction of around 55 km off of a pre-split mean of 100 km.

Figure A.2: Comparing Fiscal Transfers Between Parent and Child Districts



Notes: This figure plots the density of the difference in actual versus expected fiscal transfers for parent and child districts post-split under the assumption that the expected transfers are allocated proportional to population share of the original district.

Table A.1: Splitting-Induced Changes in Transfer Revenue and Distance to Capital

Panel (a): Effects on ln(total fiscal transfers)

Administrative Unit	Original District (1)	Parent Child (2)	Parent (3)	Child (4)
$\leq$ 2 Years Pre-split	0.073	-0.005	0.028	-0.017
	(0.041)	(0.032)	(0.030)	(0.038)
1 Year Pre-Split		reference period		
Year of Split	-0.029	-0.022	0.002	-0.035
	(0.023)	(0.026)	(0.021)	(0.035)
1 Year after Split	-0.113	0.073	0.252	-0.047
	(0.059)	(0.041)	(0.051)	(0.061)
2 Years after Split	0.093	0.314	0.211	0.368
	(0.057)	(0.047)	(0.051)	(0.060)
3 Years after Split	0.180	0.474	0.263	0.596
	(0.058)	(0.042)	(0.051)	(0.052)
4 Years after Split	0.246	0.500	0.290	0.620
	(0.064)	(0.038)	(0.056)	(0.047)
5+ Years after Split	0.207	0.444	0.187	0.593
	(0.053)	(0.050)	(0.058)	(0.064)
Number of District-Years	765	1,965	765	1,200
Dep. Var. Mean	27.3	26.4	26.7	26.1

Panel (b): Effects on Distance to District Capital (kilometers)

	Pre-Split Mean	Mean Change	Median Change
Parent Districts	48.9	-5.7	-1.14
	[33.3]	[18.2]	
Child Districts	99.8	-55.5	-38.5
	[79.5]	[8.04]	

Notes: Panel (a) reports a regression of log transfer revenue in real 2010 IDR (see Appendix F) on dummies pre- and post-split as well as district fixed effects, year fixed effects, and district-specific time trends. Details on the transfer time series are discussed in the text above. Standard errors are clustered at the original district level. Panel (b) reports the average change in distance to the capital in kilometers, constructed from the *Podes* 2002 and 2011 administrative censuses, for parent (and child districts separately). We are missing data for a small number of the districts in Aceh in 2002. Standard deviations in brackets.

Table A.2: Timing of Splitting

	Dependent Variable:	
	no. months until split mean: 53	1(post-moratorium split) mean: 0.31
Panel (a): Diversity	Standardized Coefficient	
original district ethnic fractionalization	-1.175	-0.014
	(4.178)	(0.067)
original district Δ ethnic fractionalization	4.662	0.050
	(3.077)	(0.057)
child district ethnic fractionalization	0.693	-0.006
	(4.064)	(0.066)
parent district ethnic fractionalization	1.503	0.028
	(4.062)	(0.065)
original district ethnic polarization	-3.503	-0.019
	(2.708)	(0.045)
original district Δ ethnic polarization	2.533	0.041
	(1.906)	(0.027)
child district ethnic polarization	-3.667	-0.018
	(2.618)	(0.040)
parent district ethnic polarization	-0.077	0.033
	(3.696)	(0.068)
original district religious polarization	-0.671	-0.039
	(4.017)	(0.063)
original district Δ religious polarization	1.087	0.040
	(2.223)	(0.032)
child district religious polarization	-2.187	-0.070
	(3.969)	(0.059)
parent district religious polarization	0.919	0.001
	(4.271)	(0.067)
Panel (b): 65 Potential Confounders		
expected number of significant predictors at 5% level by chance	3.3	3.3
actual number of significant predictors at 5% level		
all original districts	4	6
above median Δ polarization districts	3	5
below median Δ polarization districts	5	8
above median Δ fractionalization districts	7	3
below median Δ fractionalization districts	5	3

Notes: Each cell is a different bivariate OLS regression of the timing of the first split on initial district characteristics, each of which is measured in 2000 before the onset of splitting. The dependent variable in column (1) counts the number of months between January 2000 and the month in which each original district split, and in column (2) is an indicator for whether the split happened after the moratorium from 2004–6. Coefficients are based on standardized variables. Panel (a) looks at ethnolinguistic and religious diversity, including the Δ measure capturing differences between parent/child and original district diversity levels. Panel (b) looks at the 65 controls capturing a broad array of confounders associated with proximity to security forces, economic development, public goods, demographics, natural resource intensity, political factors, economic structure, geography/topography, and remoteness. See Appendix D.4 for a discussion of the variables and Appendix F for further details. We repeat this exercise for all original districts and then those with above and below median $\Delta fractionalization$ and $\Delta polarization$. The sample size is the 52 original districts in our main analysis, and HC3-robust standard errors are in parentheses.

B Conceptual Framework: Further Details

In this appendix, we make explicit the general points made in Section II using a special case of Esteban and Ray's (2011a) model.

An Esteban and Ray (2011a) Framework. Esteban and Ray (2011a) model groups contesting a budget with per-capita value $\pi + \mu$, some of which can be distributed privately while the rest is public with the winning group choosing their preferred mix of public goods. For large N and for the isoelastic cost function $c(r) = (1/\theta)r^{\theta}$ with r denoting resources expended by a typical member of any group, per-capita conflict is given by $\frac{V}{pop} \approx (\alpha[\pi P + \mu F])^{1/\theta}$, where α is within-group cohesion, π (μ) is the population-normalized public (private) payoff of the conflict prize, P is ethnic polarization, and F is ethnic fractionalization. The paper explains the sense in which this is an approximation.

Effects of Splitting at the Original District Level. We trace out the implications of changing borders on conflict in this model under the assumption that splitting creates new, separate contests in parent and child districts. Conflict within each of the new districts will now be a function of the diversity *within* each new area. Let $\mathcal{O}$ denote the original district boundaries, $\mathcal{P}$ denote the parent district, and $\mathcal{C}$ the child district. Further assume that per-capita payoffs remain unchanged within each new area. Then, the change in total violence per-capita at the original district level is:

$$\frac{\Delta V_{\mathcal{O}}}{pop_{\mathcal{O}}} = \alpha^{1/\theta}\left(\frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}}([\pi P_{\mathcal{P}} + \mu F_{\mathcal{P}}])^{1/\theta} + \frac{pop_{\mathcal{C}}}{pop_{\mathcal{O}}}([\pi P_{\mathcal{C}} + \mu F_{\mathcal{C}}])^{1/\theta} - ([\pi P_{\mathcal{O}} + \mu F_{\mathcal{O}}])^{1/\theta}\right),$$

for original district population $pop_{\mathcal{O}} = pop_{\mathcal{P}} + pop_{\mathcal{C}}$. That is, the change in violence per capita is explicitly a difference between population-weighted functions of diversity within the new units relative to a function of diversity in the original district pre-split. In the event that the groups separate into perfectly homogeneous child and parent districts with P and F both equal to zero, all violence in the original district ceases.

Effects of Splitting at the Parent/Child District Level. It is also interesting to consider changes in violence *within* the new borders. This requires taking a stance on how violence is initially distributed across parent and child. Letting σ be the share of total pre-split violence occurring within the parent district, the change in conflict within the parent district is given by:

$$\frac{\Delta V_{\mathcal{P}}}{pop_{\mathcal{P}}} = \alpha^{1/\theta}\left(([\pi P_{\mathcal{P}} + \mu F_{\mathcal{P}}]^{1/\theta} - \sigma\frac{pop_{\mathcal{O}}}{pop_{\mathcal{P}}}([\pi P_{\mathcal{O}} + \mu F_{\mathcal{O}}])^{1/\theta}\right)$$

If violence is initially distributed according to population ($\sigma = \frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}}$), the change in per-capita violence within the eventual parent border is given by the simple difference in the diversity within that new unit and the overall diversity in the original district. This follows analogously for the child.

Changes in the Value of the Prize. The model also implies that changes in the value of the prize (π, μ), social cohesion (α) or the costs of violence (which vary with θ) will change conflict. Splitting is accompanied by an influx of government resources as well as reductions in the distance to the new capital, which could affect conflict costs. In particular, since the local government budget increases with splitting, we expect the value of the public prize π to increase. This means π above would no longer be constant and instead be higher in the newer units, effectively putting more weight on polarization in the newer units (relative to original district polarization) in explaining changes in per-capita violence.

Towards our Empirical Specification. This conceptual framework directly motivates our empirical strategy. In our linear difference-in-difference setup, we explore how violence changes post-split as a function of ΔP and ΔF. At the original district level, we define $\Delta P = \left(\frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}}P_{\mathcal{P}} + \frac{pop_{\mathcal{C}}}{pop_{\mathcal{O}}}P_{\mathcal{C}}\right) - P_{\mathcal{O}}$.

When exploring changes within the smaller units, taking the parent district for example, we define $\Delta P = P_{\mathcal{P}} - P_{\mathcal{O}}$. We define ΔF analogously at each administrative level. Note that this departs from a fully structural interpretation of Esteban and Ray (2011a) by assuming that the changes in per-capita violence are *linear* functions of underlying diversity measures. This linearization can be justified for small changes in diversity. Our approach is also in line with Esteban, Mayoral and Ray (2012) who make a similar simplification in their cross-country OLS estimates of the static, cross-sectional equilibrium version of the Esteban and Ray (2011a) model. Like them, we effectively ignore θ and focus on estimating reliably signed coefficients on the diversity measures. Our generalized difference-in-difference framework recovers the causal effects of $\Delta\mathbf{diversity}$ so defined. This linear approach also enables one to more easily distinguish between ΔF and ΔP.

C Measuring Conflict: Background and Robustness

C.1 Indonesia's National Violence Monitoring System (SNPK)

Indonesia's National Violence Monitoring System (NVMS) or SNPK by its Indonesian acronym (*Sistem Nasional Pemantauan Kekerasan*) is among the world's largest single-country, geospatial conflict databases. After compiling several million images from over 120 carefully screened local newspapers, data entrants classify the nature of violence underlying each reported event into one of the 10 categories listed below in Table C.1.[1] There are further subcategories within each category of conflict. For example, when available, each event also includes information on the number of deaths, injuries and buildings destroyed.

Table C.1: Violence Categories in the SNPK

Resource Conflict	Violence triggered by resource disputes (land, mining, access to employment, salary, pollution, etc.).
Governance Conflict	Violence is triggered by government policies or programs (public services, corruption, subsidy, region splitting, etc).
Popular Justice Conflict	Violence perpetrated to respond to/punish actual or perceived wrong (group violence only).
Elections and Appointment Conflict	Conflict Violence triggered by electoral competition or bureaucratic appointments.
Separatist Conflict	Violence triggered by efforts to secede from the Unitary State of the Republic of Indonesia (NKRI).
Identity-Based Conflict	Violence triggered by group identity (religion, ethnicity, tribe, etc).
Other Conflict	Violence triggered by other issue.
Violence During Law Enforcement	Violent action taken by members of formal security forces to perform law-enforcement functions (includes use of violence mandated by law as well as violence that exceeds mandate for example torture or extrajudicial-shooting).
Violent Crime	Criminal violence not triggered by prior dispute or directed towards specific targets.
Domestic Violence	Physical violence perpetrated by family member(s) against other family member(s) living under one roof/same house including against domestic workers and violence between cohabiting couples.

As discussed in Section III.B, we rely on this rich, human-led classification system to isolate social conflict as opposed to (unorganized) interpersonal violence or crime. Of course, the lines between categories are often fuzzy.[2] Nevertheless, in a robustness check in Appendix C.2, we effectively show that our core results are not driven by the particular measure of social conflict.

[1]The data report other information about each event such as the actors involved, the organizational form of violence (e.g., riot, kidnapping), weapons used, and outcome of external intervention. While potentially useful, this information is much less systematic and comprehensive than the categorization into types of violence, which is the most directly related to the conceptual framework and broader interest in the paper.

[2]This description from the data manual provides further background that may be illustrative: "According to NVMS system, violent crime comprises acts of violence that occur without any prior dispute between parties. The motivation behind a criminal act can be monetary, for example, robbery or abduction; or personal pleasure, for example, rape or serial killings. In contrast, violence in the context of conflict occurs due to pre-existing disputes between those involved such as dispute over land, election, religion or other such matters. As such, in the NVMS system, an act of killing can be coded as 'Conflict' if there is a dispute behind it, e.g., in a killing of a certain group figure by other groups, or can be coded as 'Crime' if there is no pre-existing dispute between parties, for example, serial killings."

Event Descriptions. Later in this section, we provide several examples of events in the "elections and appointment" conflict category. Below, we provide examples from a few of the other categories beginning with "governance".

1. Pontianak City, 24 July 2006: *Hundreds of residents from 6 villages came to the office of Sungai Kunyit Subdistrict. They protested the perceived unfair distribution of the unconditional cash transfer (BLT) funds. They then threw a chair at the sight of a BPS (Central Statistical Agency) representative. Some community leaders and the subdistrict head calmed the masses.*

2. Kotawaringin Timur District, 21 June 2012: *People burnt a temporary bridge in Seruyan Hilir subdistrict because they argued that the government took too long to build the main permanent bridge.*

3. Singkawang District, 5 December 2008: *Protests led by Front Pembela Islam (FPI), Front Pembela Melayu (FPM), and Aliansi LSM Perintis Singkawang. They argued that dragon statue is a religious symbol, and hence a public road is not the proper place to build that symbol. In addition, the dragon statue is perceived as Chinese symbol. FPI claimed that symbols for particular ethnic groups cannot be placed in public places.*

Note that the last example above could clearly have also been classified as 'identity-based conflict', pointing to the fuzziness across categories as noted earlier.

A few other illustrative examples come from the "resource conflict" category:

1. Aceh Singkil District, 30 May 2011: *Two hundred people demonstrated in front of the mayor's office of Aceh Singkil in relation to land disputes with companies of Malaysian origin. They also demanded a fair and fixed land [compensation].*

2. Halmahera Tengah, 30 Jan 2012: *Hundreds of East Halmahera residents burned tires and blocked roads at the PT Kemakmuran Pertiwi Tambang (PT Harita Grup) nickel mining site in Loleba village.*

Comparison to Other Conflict Data. The SNPK data offer several advantages over two alternative sources of information on violence in Indonesia. First, it offers more comprehensive temporal coverage than the triennial *Potensi Desa* (or *Podes*) data, which records information on the violent events at the village-level over the prior three-year period. This coarse coverage would not allow for the systematic generalized difference-in-difference identification strategy we deploy here. Moreover, *Podes* accounts are based on the self-reports of village leaders as opposed to the plausibly more objective, cross-validated newspapers reports in the SNPK.

Second, the SNPK offers significantly more comprehensive coverage compared to a widely used, cross-country, subnational data source. The Uppsala Conflict Data Program (UCDP) Georeferenced Event Data (GED) (Sundberg and Melander, 2013) has been fruitfully deployed in a range of subnational conflict studies and with particular success in sub-Saharan Africa alongside the widely used Armed Conflict Location & Event Data Project (ACLED) data. The UCDP-GED is available for Indonesia whereas the ACLED is not (yet). Mapping the UCDP-GED events to our original district monthly panel, we find very limited coverage of social conflict events in Indonesia. While SNPK covers 223 of the 230 original district–month incidents in the UCDP-GED data, there are 4,795 additional district–months with social conflict incidents in the SNPK. Together, these violent events involve nearly 5,000 deaths over a 15 year period. The more limited coverage by UCDP-GED is explained by both its more narrow focus on large-scale conflict and by its reliance on international news sources and/or English-based ones in Jakarta. The SNPK offers much deeper coverage precisely because it digitized millions of old newspapers from outlying regions of the country that allowed for coverage of violence that may have otherwise missed the attention of international reporters. Barron, Engvall and Morel (2016) offer a more systematic comparison (for all of Indonesia) by applying particular restrictions in the SNPK that more closely match those applied in the UCDP-GED. Their conclusion is similar to ours; the UCDP-GED cover around one-third of the events and and deaths reported in the SNPK.

Costs of Conflict. The violent episodes in SNPK can be costly. Even if we examine the least violent years and restrict to social conflict, we observe around 500 annual deaths, 7,000 annual injuries, and 1,500 annual buildings damaged. Including crime and domestic violence more than doubles these numbers. Using a methodology due to Fearon and Hoeffler (2014), we estimate that the direct costs of social conflict in the post-2005 period range from 0.2–0.5% of GDP.

Electoral Violence in the SNPK. SNPK records point to various forms of political violence—protests over voter eligibility, clashes between supporters, direct targeting of candidates and government offices overseeing elections—often related to local, mayoral elections. Such violence often involves building damage and injuries rather than deaths. Nevertheless, such incidents can and do escalate. Consider for example these incidents from the districts of Kota Subulussalam and Maluku Tenggara Barat: (i) "(November 2, 2013): Demonstrations involving hundreds of supporters of candidates for mayor and vice mayor. The masses demanded an explanation from the Independent Election Commissioner. [7 injured]." (ii) "(May 30, 2002): The chaos of the mayoral election of West Southeast Maluku district is bad. Supporters of Heri Kadubun who were riding in boats were attacked by supporters of the Taher Hanubun group [3 killed, 8 injured]."

Harish and Toha (2017) use the SNPK data to identify three salient types of electoral violence in Indonesia: (1) *voter-targeting* is "any kind of election-related violence that affects voters' preferences participation in elections", (2) *candidate-targeting* directs violence towards "candidates themselves and those around them by intimidating them into withdrawing and/or physically and forcefully removing them from the race", and (3) *government-aimed* is "violence mounted against a government agency responsible for monitoring and enforcing rules of elections." The authors use SNPK data combined with supplementary reporting to categorize over 1,000 episodes of local election violence in Indonesia since 2005. Attacks targeting candidates are the most common, occurring on 35 percent of the days in a six month window centered on the election. Voter-targeting occurred in 25 percent of those days, and agency-targeting on 17 percent of days. Not surprisingly, most candidate-targeting is concentrated in the lead-up to the election with attacks on election-related government agencies occurring thereafter.

Drawing upon the same SNPK data, we provide some concrete examples of incident reports that clarify the types of electoral violence underlying these patterns. The following are district-specific examples that we translate from the SNPK:

1. Aceh Singkil District, 2 November 2013: *Protest at Komisi Independen Pemilihan (KIP, Independent Commission for Elections) by supporters of Affan Alfian-Pianti Mala (Walikota-Wakil Walikota [mayor–vice mayor] candidate) regarding fraud in mayoral election.* Seven people were reported seriously injured. The election took place on 29 October.

2. Aceh Barat Daya District, 28 June 2012: *Supporters of FD (mayoral candidate for Aceh Barat Daya) were attacked by their competitors in Kuala Terubu Village and Alue Sungai Pinang village.* The election took place on 9 April 2012.

3. Halmahera Utara District, 16 April 2005: *Komisi Pemilihan Umum Daerah (KPUD, Local General Elections Commission) office and the house of the Partai Demokrasi Kebansaan (PDK) chairman were destroyed by people because one of the candidate was not selected in mayor–vice mayor ticket.* Two buildings were damaged and one destroyed. The election took place on 27 June 2005.

4. Kepulauan Sula District, 12 May 2005: *Molotov bombing of the local Electoral Commission office due to anger with the decision about four mayoral candidates.* The election took place on 27 June 2005.

5. Pulau Morotai District, 21 May 2011: *Mass supporters of RS and WP [mayoral candidate and running mate] who did not accept the decision of the Morotai Electoral Commission in the election took action in the Morotai air force base, South Morotai, northern Maluku, by trying to break. . .* Four people were injured, and one building was damaged. Subsequent violent incidents were reported on May 26 and 27. The election took place on 16 May 2011.

6. Kotawaringin Timur, 6 June 2005: *Incident between supporters of mayoral candidates Wahyu-Amrullah and Thamrina-Mullan Safri because one of them established billboard in the other candidates' area (Seruyan) K Timur: On Jalan Mayjen Suprapto, Seruyan Hilir subdistrict, billboard of mayoral candidate was destroyed, occurred around mayoral election time. In Danau Sembuluh subdistrict, AS (legislative member candidate for Dapil [electoral region] II) was attacked by people (one of them was legislative member candidate for Dapil [electoral districdt] II).* Two people were seriously injured. The election took place on 23 June 2005.

7. Bengakayang, 21 May 2010: *In the Local Electoral Commission office, demonstrations took place with rioters throwing stones at the building and officials out of anger over the election outcome.* One building was damaged. The election took place on 19 May 2010.

C.2 Alternative Categorizations of Conflict

Our main analysis considered a set of violence categories in the SNPK that aimed to capture group-based conflict. This section addresses two potential concerns with the measure of social conflict we use based on the SNPK groupings.

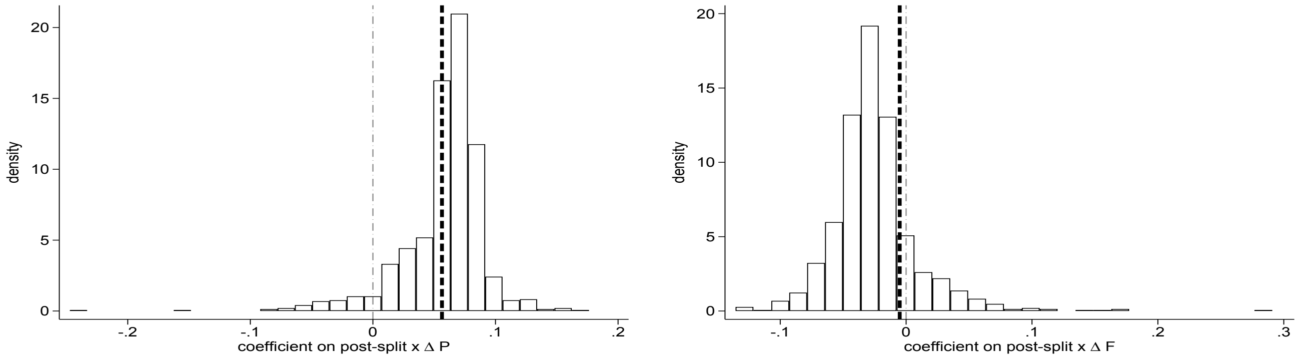
First, some of the crime-related categories of violence may be shaped by similar (changes in) ethnic divisions as other categories deemed to fall under conflict.[3] Hence, their omission may be deemed arbitrary at best and biasing at worst. Table C.2 shows that the main results in Table 1 are robust to not restricting the definition of violence. Indeed, the estimated effects of $\Delta diversity$ are very similar. The increase in precision may be due to the fact that the broader grouping reduces classical measurement error of the sort discussed in Appendix C.1.

Second, we further gauge robustness to event misclassification by re-estimating our regressions for all possible combinations of the ten main categories of violence in the SNPK. Figure C.1 presents the distribution of the estimated coefficients on $post\text{-}split \times \Delta P$ and $post\text{-}split \times \Delta F$ for these 1,023 regressions with the given baseline estimate for social conflict indicated by the dashed, vertical black line. For both our baseline and each separate regression, we scale the reported coefficient by the mean of the given dependent variable, which varies across groups of categories. The magnitudes are therefore standard deviation $\Delta diversity$ effect sizes relative to the mean outcome over the sample period. Note that we are not using this data mining approach for inference purposes but rather to address concerns that our particular designation of categories as conflict was somehow spuriously generating our results. Figure C.1 helps to dispel such concerns and shows that our core estimated effect of ΔP on social conflict appears to be around the middle of the distribution of effect sizes across all possible combinations of violence categories. Moreover, the distribution of these coefficients seems to lie mostly above zero, which again points to the fact that changing ethnic divisions shifts most types of violence in the same direction. The takeaways are similar for ΔF.

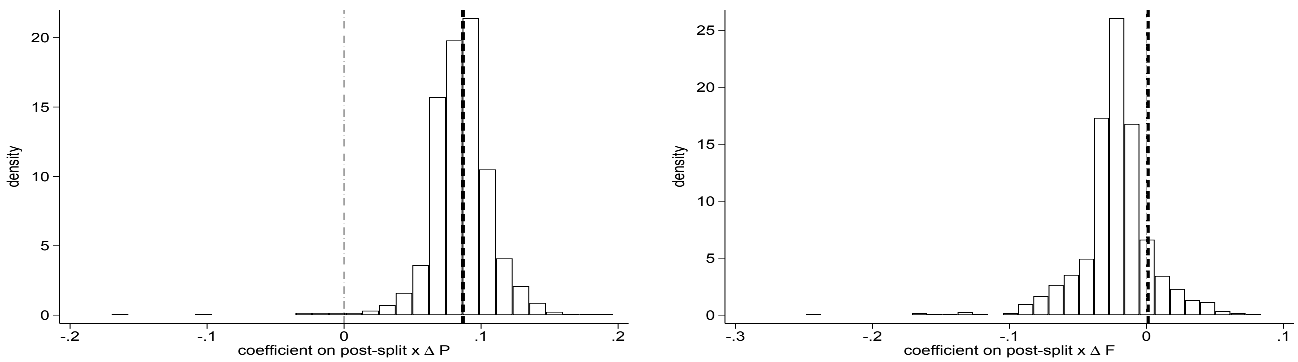
[3] Echoing this interpretation, one of the architects of the SNPK notes in a later reappraisal that "What may appear to be local violence (crime, interpersonal clashes over land) is often linked in complicated ways to the broader conflict" (Barron, Engvall and Morel, 2016, p. 25). This would be consistent with the ethnic-related criminal gangs documented at length in the Wilson (2015) book that we cite in the paper. Indeed, many of these gangs are often mobilized for conflict by political actors during times of instability around elections. Another, broader interpretation of this concern would be that changes in ethnic divisions further undermine local state capacity that helps to forestall a breakdown in social order and prevent various types of crime.

Figure C.1: Distribution of Estimated Effects of Δ**diversity** across All Possible Groupings of Violence Categories in SNPK

(a) Original Districts



(b) Parent and Child Districts



Notes: These graphs present the distribution of estimated effects of $\Delta diversity$ across all possible groupings of the violence categories reported in the SNPK. The estimates are rescaled by the mean of the dependent variable such that the effects are standard deviations relative to the mean violence in the given grouping. The dashed line is our baseline estimate from Table 1, also rescaled by the mean of the dependent variable.

Table C.2: Effects are Similar When Not Restricting to Social Conflict

Administrative Unit	Original District	Parent & Child	Parent	Child
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.007	0.018	-0.008	0.036
	(0.021)	(0.021)	(0.021)	(0.027)
post-split $\times$ Δ ethnic polarization	0.049	0.043	0.054	0.028
	(0.016)	(0.015)	(0.020)	(0.011)
post-split $\times$ Δ ethnic fractionalization	-0.013	-0.008	-0.002	0.001
	(0.028)	(0.019)	(0.025)	(0.027)
post-split $\times$ Δ religious diversity	0.006	-0.008	-0.055	0.000
	(0.012)	(0.019)	(0.026)	(0.023)
Number of District-Months	7,956	20,220	7,956	12,264
Dep. Var. Mean, Pre-Split	0.76	0.52	0.69	0.42

Notes: This table re-estimates our baseline specification but for all violence reported in the SNPK.

C.3 Alternative Measures of Conflict Intensity

SNPK records injuries, deaths, and property damage. We show in Table C.3 that our results are robust in panel (a) to redefining any social conflict to include only the roughly 90% of incidents that record at least one of these outcomes, and in panel (b) to redefining any social conflict to include only those events with any injuries or property damage.

Table C.3: Effects are Similar When Restricting to Social Conflict Events with an Injury, Death, or Property Damage

Administrative Unit:	Original District **(1)**	Parent & Child **(2)**	Parent **(3)**	Child **(4)**
	Panel (a): Only events with an injury, death, or property damage			
post-split	-0.005	0.001	-0.007	0.004
	(0.026)	(0.021)	(0.028)	(0.023)
post-split × Δ ethnic polarization	0.029	0.032	0.031	0.044
	(0.017)	(0.017)	(0.012)	(0.022)
post-split × Δ ethnic fractionalization	0.003	-0.008	0.050	-0.025
	(0.015)	(0.013)	(0.025)	(0.021)
post-split × Δ religious diversity	0.018	-0.008	-0.003	-0.010
	(0.014)	(0.011)	(0.022)	(0.013)
Number of District-Months	7,956	20,220	7,956	12,264
Number of Districts	52	133	52	81
Dep. Var. Mean, Pre-Split	0.53	0.30	0.43	0.22
	Panel (b): Only events with an injury or property damage			
post-split	-0.003	-0.002	0.004	-0.005
	(0.029)	(0.022)	(0.029)	(0.023)
post-split × Δ ethnic polarization	0.034	0.037	0.029	0.051
	(0.019)	(0.016)	(0.010)	(0.022)
post-split × Δ ethnic fractionalization	-0.002	-0.006	0.033	-0.020
	(0.024)	(0.013)	(0.024)	(0.021)
post-split × Δ religious diversity	-0.004	-0.007	-0.018	-0.006
	(0.015)	(0.010)	(0.025)	(0.013)
Number of District-Months	7,956	20,220	7,956	12,264
Number of Districts	52	133	52	81
Dep. Var. Mean, Pre-Split	0.49	0.26	0.40	0.18

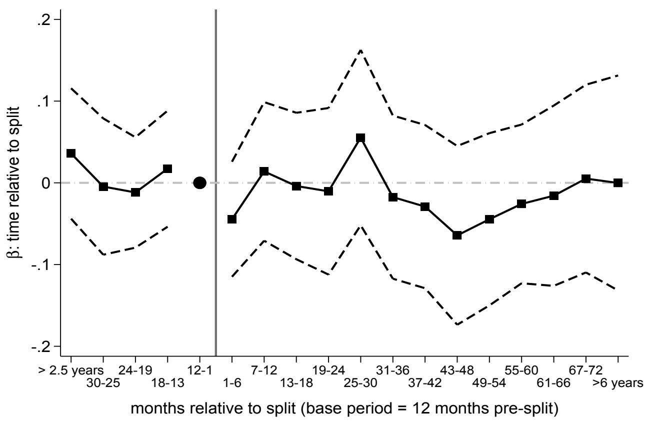
Notes: Panel (a) re-estimates our baseline specification only counting social conflict events with at least one recorded injury, death, or property damage. Panel (b) re-estimates our baseline specification only counting social conflict events with at least one recorded injury or property damage.

D Robustness Checks on the Main Results in Section IV

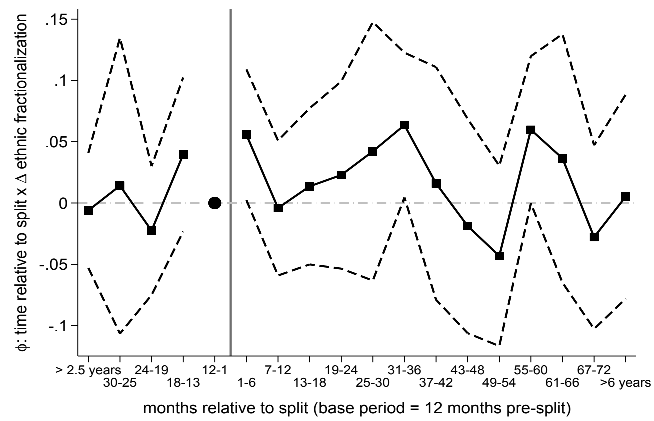
D.1 Event Study Specifications

Figure D.1: Event Study Excluding District-Specific Time Trends

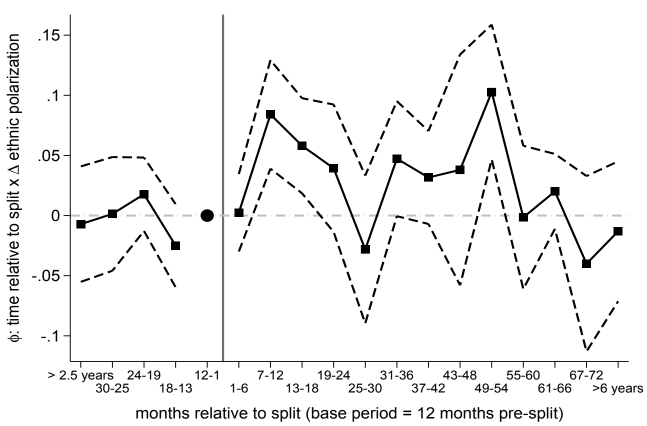
(a) Average Effects: Original District



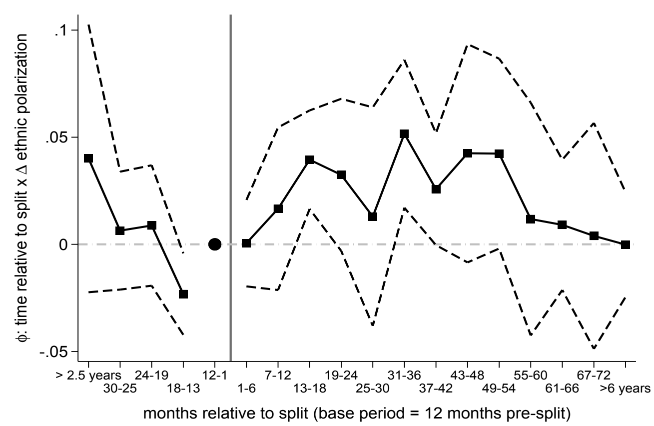
(b) Effects by Δ Fractionalization: Original District



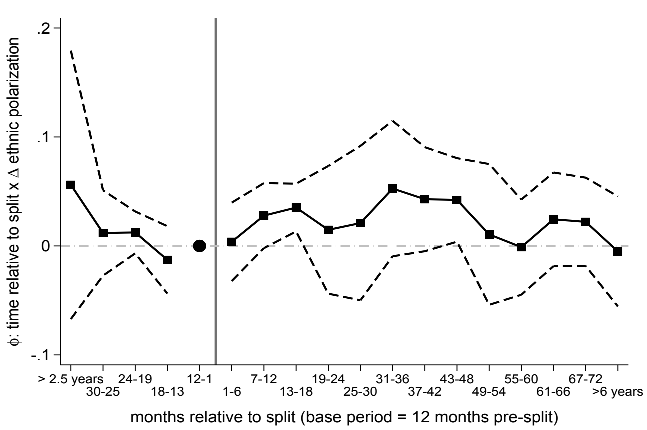
(c) Effects by Δ Polarization: Original District



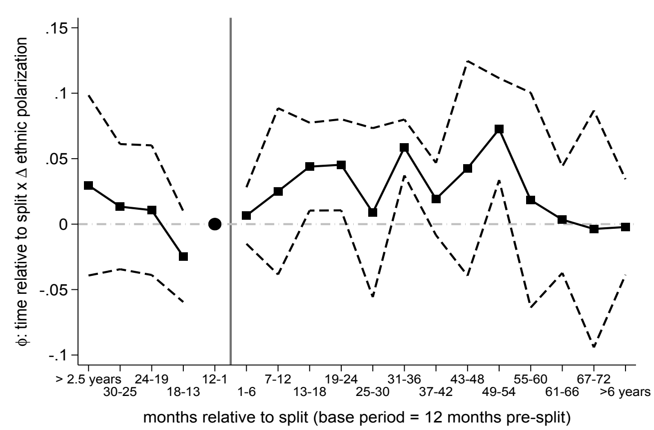
(d) Effects by Δ Polarization: Parent and Child District



(e) Effects by Δ Polarization: Parent District

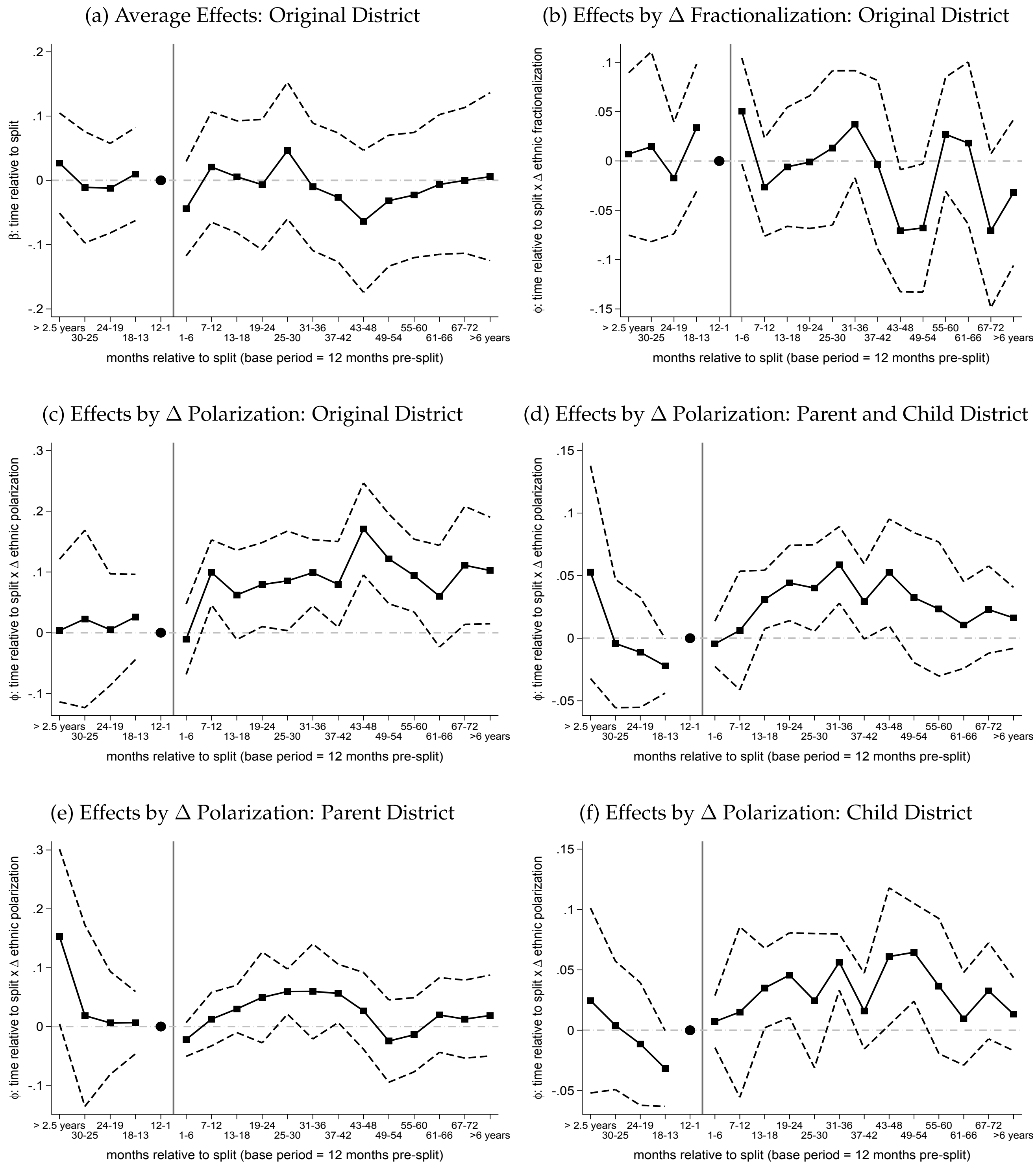


(f) Effects by Δ Polarization: Child District



Notes: These figures report event study specifications as in Figure 7 but omitting district-specific time trends as in column 9 of Table 2.

Figure D.2: Event Study Excluding Extreme Outlier and District-Specific Time Trends



Notes: These figures report event study specifications as in Figure 7 but omitting district-specific time trends and the extreme outlier in ΔP as in column 10 of Table 2.

D.2 Identification Checks in Table 2

Tables D.1–D.4 below report the full set of robustness checks in Table 2 for all administrative levels. Section IV.E provides a detailed discussion of several checks. Appendix D.3 provides further details on column 2, Appendix D.4 on column 3, and Appendix D.5 on column 5.

Table D.1: Identification Checks on Core Original District Results

	Baseline **(1)**	Feasible **Δdiversity** **(2)**	Lasso Controls **(3)**	$\Delta resources$ $+\Delta distance$ **(4)**	Google Trends **(5)**	Exclude $\Delta Relig$ **(6)**	Add Lag Dep. Var. **(7)**	Exclude Outlier **(8)**	Exclude d-Trends **(9)**	Exclude Outl., Trends **(10)**
post-split	-0.012	-0.015	-0.013	-0.006	-0.011	-0.012	-0.014	-0.012	-0.035	-0.026
	(0.025)	(0.027)	(0.026)	(0.027)	(0.025)	(0.025)	(0.024)	(0.025)	(0.030)	(0.027)
post-split × Δ ethnic polarization	0.036	0.053	0.028	0.038	0.040	0.033	0.032	0.058	0.015	0.082
	(0.018)	(0.023)	(0.013)	(0.014)	(0.018)	(0.017)	(0.017)	(0.023)	(0.016)	(0.028)
post-split × Δ ethnic fractionalization	-0.003	-0.021	-0.024	-0.006	-0.005	-0.001	0.001	-0.015	0.008	-0.023
	(0.019)	(0.017)	(0.020)	(0.022)	(0.019)	(0.020)	(0.018)	(0.018)	(0.037)	(0.026)
post-split × Δ religious diversity	0.014	0.009	0.019	0.013	0.015		0.012	0.022	0.027	0.045
	(0.013)	(0.022)	(0.013)	(0.013)	(0.013)		(0.012)	(0.014)	(0.016)	(0.018)
post-split × Δ distance to capital				-0.002						
				(0.019)						
post-split × Δ transfer revenue				0.037						
				(0.028)						
Google Trends					0.125					
					(0.067)					
Number of District-Months	7,956	7,680	7,956	7,836	7,956	7,956	7,904	7,776	7,956	7,776
Number of Districts	52	50	52	51	52	52	52	51	52	51
Dep. Var. Mean, Pre-Split	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.58	0.57	0.58

Notes: This table reproduces the estimates in Table 2 including the suppressed coefficients in column 4 and 5. Standard errors are clustered by original district.

Table D.2: Identification Checks on Core Parent and Child District Results

	Baseline	Feasible Δ**diversity**	Lasso Controls	$\Delta resources$ $+\Delta distance$	Google Trends	Exclude $\Delta Relig$	Add Lag Dep. Var.	Exclude Outlier	Exclude d-Trends	Exclude Outl., Trends
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	-0.003	-0.010	-0.001	-0.001	-0.004	-0.002	-0.002	-0.000	-0.006	-0.003
	(0.021)	(0.022)	(0.017)	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.022)	(0.021)
post-split $\times$ Δ ethnic polarization	0.032	0.032	0.032	0.032	0.033	0.031	0.029	0.038	0.009	0.021
	(0.019)	(0.014)	(0.016)	(0.017)	(0.019)	(0.019)	(0.018)	(0.015)	(0.012)	(0.010)
post-split $\times$ Δ ethnic fractionalization	0.000	-0.009	-0.003	0.006	0.001	-0.001	0.001	0.003	-0.004	-0.001
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.009)
post-split $\times$ Δ religious diversity	-0.009	-0.009	-0.005	-0.013	-0.009		-0.007	-0.007	-0.012	-0.008
	(0.011)	(0.013)	(0.012)	(0.012)	(0.011)		(0.010)	(0.011)	(0.010)	(0.009)
post-split $\times$ Δ distance to capital				-0.012						
				(0.013)						
post-split $\times$ Δ transfer revenue				0.027						
				(0.012)						
Google Trends					0.071					
					(0.041)					
Number of District-Months	20,220	18,540	20,220	19,980	20,220	20,220	20,087	19,680	20,220	19,680
Number of Districts	133	121	133	131	133	133	133	130	133	130
Dep. Var. Mean, Pre-Split	0.33	0.34	0.33	0.33	0.33	0.33	0.32	0.33	0.33	0.33

Notes: This table estimates the specifications in Table D.1 for parent and child districts. There are 19 additional interactive controls included in column 3. Standard errors are clustered by original district.

Table D.3: Identification Checks on Core Parent District Results

	Baseline	Feasible Δ**diversity**	Lasso Controls	$\Delta resources$ $+\Delta distance$	Google Trends	Exclude $\Delta Relig$	Add Lag Dep. Var.	Exclude Outlier	Exclude d-Trends	Exclude Outl., Trends
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	0.001	-0.005	-0.017	0.002	0.003	-0.001	0.001	0.004	-0.027	-0.023
	(0.026)	(0.027)	(0.024)	(0.027)	(0.026)	(0.027)	(0.026)	(0.026)	(0.029)	(0.029)
post-split $\times$ Δ ethnic polarization	0.027	0.046	0.079	0.023	0.032	0.029	0.026	0.027	-0.002	-0.007
	(0.013)	(0.017)	(0.016)	(0.015)	(0.013)	(0.016)	(0.013)	(0.014)	(0.014)	(0.030)
post-split $\times$ Δ ethnic fractionalization	0.035	0.016	0.017	0.035	0.035	0.035	0.034	0.035	0.006	0.006
	(0.026)	(0.021)	(0.040)	(0.027)	(0.026)	(0.027)	(0.025)	(0.027)	(0.025)	(0.024)
post-split $\times$ Δ religious diversity	-0.031	-0.012	-0.026	-0.031	-0.030		-0.029	-0.031	-0.018	-0.017
	(0.021)	(0.026)	(0.022)	(0.021)	(0.021)		(0.019)	(0.021)	(0.027)	(0.027)
post-split $\times$ Δ distance to capital				0.010						
				(0.016)						
post-split $\times$ Δ transfer revenue				-0.004						
				(0.021)						
Google Trends					0.145					
					(0.073)					
Number of District-Months	7,956	7,680	7,956	7,836	7,956	7,956	7,904	7,776	7,956	7,776
Number of Districts	52	50	52	51	52	52	52	51	52	51
Dep. Var. Mean, Pre-Split	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.48	0.47	0.48

Notes: This table estimates the specifications in Table D.1 for parent districts. There are 14 additional interactive controls included in column 3. Standard errors are clustered by original district.

Table D.4: Identification Checks on Core Child District Results

	Baseline	Feasible Δ**diversity**	Lasso Controls	$\Delta resources$ $+\Delta distance$	Google Trends	Exclude $\Delta Relig$	Add Lag Dep. Var.	Exclude Outlier	Exclude d-Trends	Exclude Outl., Trends
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	-0.005	-0.011	-0.003	-0.002	-0.007	-0.005	-0.005	-0.002	0.005	0.010
	(0.025)	(0.026)	(0.022)	(0.024)	(0.025)	(0.024)	(0.024)	(0.025)	(0.023)	(0.022)
post-split $\times$ Δ ethnic polarization	0.043	0.031	0.040	0.034	0.043	0.043	0.039	0.049	0.015	0.029
	(0.025)	(0.014)	(0.026)	(0.020)	(0.025)	(0.025)	(0.022)	(0.020)	(0.016)	(0.010)
post-split $\times$ Δ ethnic fractionalization	-0.011	-0.019	0.016	0.005	-0.011	-0.012	-0.010	-0.006	-0.001	0.004
	(0.019)	(0.016)	(0.019)	(0.017)	(0.019)	(0.019)	(0.018)	(0.018)	(0.014)	(0.014)
post-split $\times$ Δ religious diversity	-0.005	-0.001	-0.010	-0.014	-0.005		-0.004	-0.001	-0.011	-0.004
	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)		(0.013)	(0.014)	(0.010)	(0.009)
post-split $\times$ Δ distance to capital				-0.033						
				(0.020)						
post-split $\times$ Δ transfer revenue				0.038						
				(0.012)						
Google Trends					0.042					
					(0.039)					
Number of District-Months	12,264	10,860	12,264	12,144	12,264	12,264	12,183	11,904	12,264	11,904
Number of Districts	81	71	81	80	81	81	81	79	81	79
Dep. Var. Mean, Pre-Split	0.25	0.25	0.25	0.25	0.25	0.25	0.24	0.25	0.25	0.25

Notes: This table estimates the specifications in Table D.1 for child districts. There are 12 additional interactive controls included in column 3. Standard errors are clustered by original district.

D.3 Constraints on Splitting and Changes in Ethnic Divisions

This section provides further background on and additional results related to the "Feasible Splitting" exercise in SectionIV.E.

We construct the distribution of feasible Δ**diversity** based on splitting schemes that satisfied the legal restrictions in terms of the minimum number of subdistricts (3) and basic viability, proxied by contiguity. This "NP-hard" problem is challenging given the large number of possible splits.[1] In order to make headway, we use a heuristic, randomized approach. Specifically, we randomly partition the district and then check to ensure the partition satisfies the contiguity requirements.[2] We repeat this process until we get 1,000 valid partitions for each original district, which we achieve for all but two original districts. Within each of the valid partitions, we then compute the corresponding ΔP and ΔF, creating a distribution of feasible ΔP and ΔF for each split. When constructing $\Delta diversity$ for parent and child districts separately, we simply assign the simulated partition with the original district capital to the parent and the residual partition(s) to the child(ren).[3] This procedure should provide a reasonably unbiased estimate of various moments of the distribution of $\Delta diversity$, taking the number of splits as given.

While some districts have relatively few feasible options, or many that result in very similar $\Delta diversity$, others have a range of feasible $\Delta diversity$. It is not obvious, in such cases, which moment of the feasible $\Delta diversity$ distribution is most appropriate. Column 3 of Table 2 (and Tables D.1–D.4) used the mean. Results hold with the minimum or maximum.

More generally, though, the key insight we derive from this exercise is that the variation *across* districts in feasible $\Delta diversity$ swamps variation *within* districts. Indeed, stacking all random draws r for each district and regressing ΔP_{rd} on district fixed effects, θ_d, delivers a R^2 of nearly 0.9. While some districts certainly had choices that would result in different $\Delta diversity$, in general, regardless of their choice, their $\Delta diversity$ would differ from feasible changes in other districts. This can be seen graphically in Appendix Figure D.3, which plots the distribution of feasible ΔP for six districts across several major regions of Indonesia.

To formally develop this intuition, we re-estimate our baseline regressions randomly assigning each of the 50 original districts to either the minimum or the maximum of their simulated feasible $\Delta diversity$. We then repeat this a large number of times (50,000 in practice) and plot the distribution of resulting estimates for ΔP and ΔF.[4] If strategic border formation is driving our results, then the baseline estimates in Table 1 should look very different for at least some of these permutations.

Figure D.4 shows that this is not the case. In fact, the entire distribution of estimated effects of ΔP lies above zero and is roughly centered on our baseline estimate. This suggests that regardless of how local policymakers drew the borders, the constraints on splitting and underlying geography limited the extent to which splitting could reshape ethnic divisions.

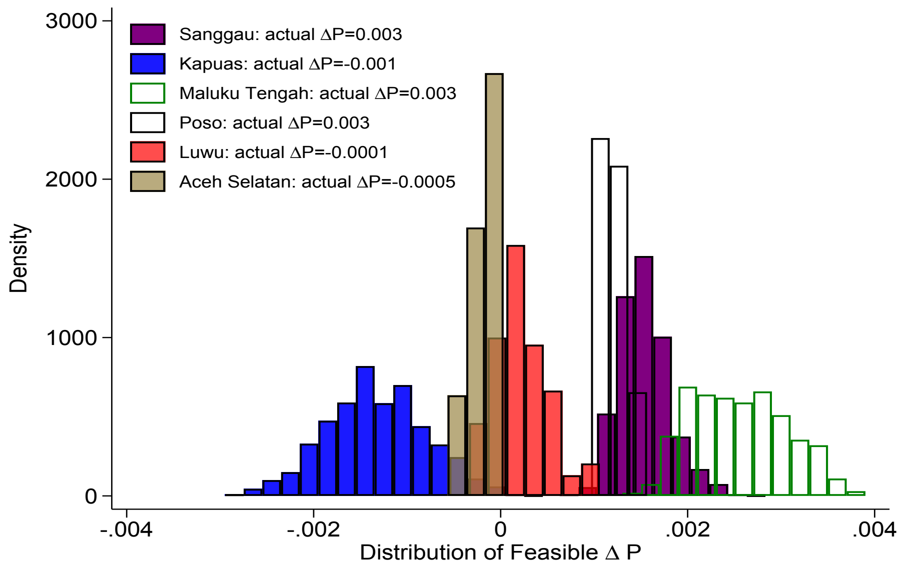
[1] The number of possible splits of n subdistricts (of a given original district) into k new districts given by the Stirling number of the second kind (see Fryer Jr. and Holden, 2011). For example, although Aceh Tenggara only has 255 possible partitions of its 9 subdistricts into the two new districts, Kotawaringin Timur has 4.236×10^{11} possible partitions into its three new districts (see Figure 4).

[2] Contiguity matrices are computed from shapefiles. We connect islands to the closest non-island in the same original district.

[3] If there are multiple children we use the location of the eventual capital to distinguish among them.

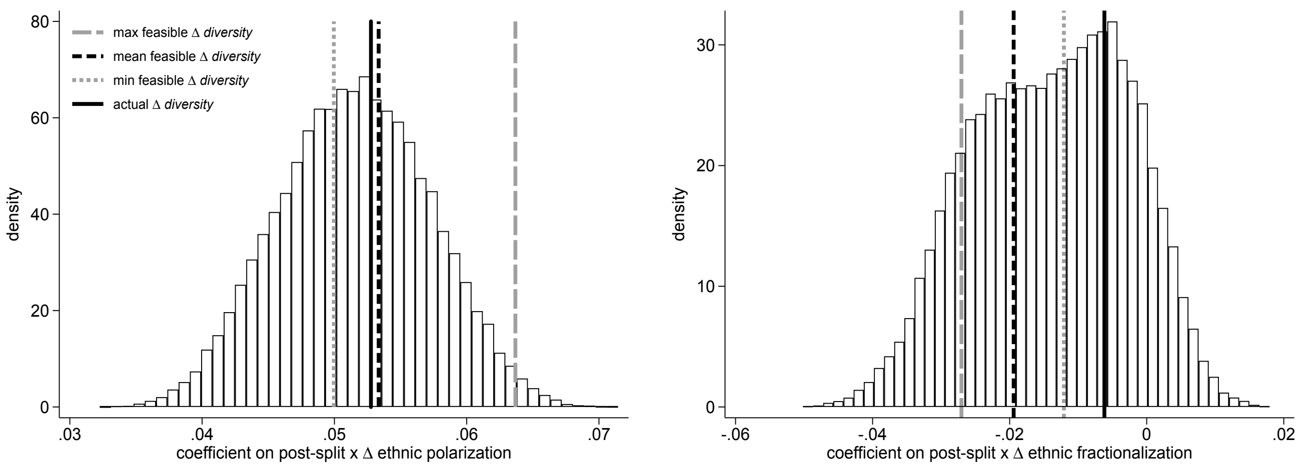
[4] There are 2^{50} possible ways to permute min and max $\Delta diversity$ across the districts in our regressions. Given computational constraints, we randomize this 50,000 times and appeal to the law of large numbers.

Figure D.3: Comparing Distribution of Feasible ΔP Across Districts



Notes: These figures plot the distribution of randomly drawn feasible ΔP for six original districts in our data.

Figure D.4: Distribution of Estimated Effects of Randomized Min or Max $\Delta diversity$



Notes: These figures plot the distribution of estimated effect sizes on $post\text{-}split \times \Delta diversity$ based on randomly assigning each district either its minimum or maximum feasible $\Delta diversity$ from the set of feasible partitions. We repeat this exercise 50,000 times and the bars reflect the density of each effect size (standard deviation change relative to mean outcome). The black solid line is our baseline effect size with actual $\Delta diversity$, the dashed line is based on the mean $\Delta diversity$ as reported in column 2 of Table 2, and the dashed lines are based on the observed min and max $\Delta diversity$.

D.4 Confounding Effects of Other Initial District Characteristics

This section presents results on omitted variables as discussed in Section IV.E. We follow the standard method of assessing omitted variable bias in heterogeneous effects DiD specifications, namely interacting treatment (post-split) with other factors besides the primary one(s) of interest ($\Delta diversity$) and assessing coefficient stability. The key question is how to select those variables. We consider two approaches: one, subjective and researcher-driven, and a second, more objective and machine-led. In both cases, we marshal a large set of variables across Census, administrative, and GIS-based data sources, mapping each measure to the district level of analysis in the given specification. All variables are time-invariant or predetermined as measured in 1999 or 2000.

First, we consider groups of variables plausibly correlated with diversity and conflict based on prior literature and intuition. After reproducing our baseline estimate in column (1), Tables D.5–D.8 present results based on variables broadly capturing: (2) proximity to security forces, (3) economic development, (4) public goods, (5) demographics, (6) natural resource intensity, (7) political factors, (8) economic structure, (9) geography/topography, and (10) remoteness. Across all specifications at different administrative levels, the estimated effects of $\Delta diversity$ are statistically indistinguishable from the baseline in column 1. While reassuring, these tables are nevertheless subject to researcher degrees of freedom in which variables we include and how we combine them across different columns.

Second, we pursue a more agnostic approach to variable selection based on the double-selection post-Lasso method of Belloni, Chernozhukov and Hansen (2014) to identify covariates that are particularly important in explaining both diversity and social conflict. We elaborate briefly on this method here.

We assume that $post\text{-}split \times \Delta P$ and $post\text{-}split \times \Delta F$ can be taken as exogenous, once one controls linearly for a relatively small number of variables—a simple sparsity assumption. The method uses a three-step approach to help the researcher determine which controls to include. First, we select, from the set of $post\text{-}split \times control$ variables, the covariates that predict $post\text{-}split \times \Delta P$, and separately, $post\text{-}split \times \Delta F$, conditioning on the usual baseline fixed effects and $post\text{-}split \times \Delta Relig$. This first step accounts for important confounding factors that are related to ΔP and ΔF. We use 65 $post\text{-}split \times control$ variables (detailed in Appendix F), drawn from key Indonesian data sources that cover 1999/2000 and are granular enough to construct controls at the eventual parent and child district boundaries. Selection is accomplished using Lasso. The Lasso penalty term λ is a choice parameter, so we consider a range of values that yield a reasonable number of controls in the final step. In the second step, we select variables that predict the incidence of social conflict from the same set of $post\text{-}split \times control$ variables, again conditioning on the baseline specification. This step, also operationalized using Lasso, helps capture any important predictors of changes in violence, which keeps residual variance small and can identify additional confounds. Finally, we estimate our baseline OLS equation including the union of selected controls from these two prior stages (hence "post-lasso"). Inference is uniformly valid for a large class of models under the assumed sparsity condition.

Column 3 of Tables D.1–D.4 showed that our main results are unchanged when including these machine-selected covariate interactions with $post\text{-}split$. The fact that these covariates do not alter our results provides some reassurance that the relationship between post-split changes in the incidence of violence are driven by cross-district variation in ΔP and not other observable, cross-district variation. Figure D.5 below shows further that these results are robust to varying the penalty parameter, λ, allowing for the inclusion of more or fewer additional covariates.[5] We see that the estimated effects of Δ**diversity** are fairly stable across λ despite large changes in the number of controls selected. In some cases, estimated effects drop and become noisier as we drop λ and grow the number of controls, which is to be expected.

[5] In practice, the variable selection tends to pick variables that predict $post\text{-}split \times \Delta P$ and $post\text{-}split \times \Delta F$, rather than social conflict. The full listing of included covariates in each specification, including the baseline, are available upon request.

Table D.5: Robustness to Additional Controls × Post-Split, Original District Level

+ controls for:	–	sec. forces	development	pub. goods	demog.	nat. res.	politics	occup.	geog.	remoteness
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	-0.012	-0.017	-0.017	-0.011	-0.014	-0.014	-0.014	-0.013	-0.012	-0.018
	(0.025)	(0.025)	(0.027)	(0.027)	(0.024)	(0.025)	(0.026)	(0.027)	(0.026)	(0.025)
× Δ ethnic polarization	0.036	0.037	0.034	0.036	0.028	0.039	0.036	0.036	0.030	0.034
	(0.018)	(0.018)	(0.017)	(0.016)	(0.018)	(0.018)	(0.018)	(0.019)	(0.014)	(0.018)
× Δ ethnic fractionalization	-0.003	0.005	0.000	-0.003	-0.021	-0.007	-0.010	-0.013	-0.022	0.004
	(0.019)	(0.018)	(0.021)	(0.021)	(0.018)	(0.020)	(0.019)	(0.021)	(0.017)	(0.017)
× Δ religious polarization	0.014	0.021	0.015	0.030	-0.000	0.017	0.009	0.014	0.026	0.023
	(0.013)	(0.017)	(0.013)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.019)	(0.018)
× log distance to security post		-0.009								
		(0.019)								
× log distance to police station		0.037								
		(0.024)								
× nighttime light intensity			-0.011							
			(0.018)							
× share with > primary education			-0.014							
			(0.024)							
× distance to public market				-0.007						
				(0.026)						
× share villages with electricity				-0.025						
				(0.025)						
× share villages with safe water				0.018						
				(0.026)						
× share villages with street light				0.019						
				(0.032)						
× share villages with transport center				0.055						
				(0.014)						
× health centers per capita				-0.015						
				(0.028)						
× high schools per capita				0.020						
				(0.019)						
× log initial population					0.027					
					(0.020)					
× population share, 5–14					0.063					
					(0.034)					
× population share, 15-49					0.052					
					(0.026)					
× nat. resource transfers per capita						0.020				
						(0.010)				
× cash crop share of total ag. output						0.025				
						(0.022)				
× share of land area with forest						-0.013				
						(0.016)				
× parliamentary vote polarization							-0.019			
							(0.019)			
× fiscal transfers per capita							-0.014			
							(0.016)			
× share in agriculture								-0.012		
								(0.044)		
× share in forestry/fishing								0.019		
								(0.044)		
× share in other								-0.007		
								(0.041)		
× land area									0.031	
									(0.015)	
× share villages on coast									-0.278	
									(0.131)	
× share villages in valley									-0.156	
									(0.076)	
× share villages on hill									-0.199	
									(0.104)	
× share villages on flatland									-0.239	
									(0.115)	
× shares villages in highlands									0.026	
									(0.043)	
× log elevation									-0.004	
									(0.026)	
× log distance to coast									0.020	
									(0.041)	
× log distance to river									0.025	
									(0.033)	
× log distance to subdistrict capital										0.020
										(0.030)
× log distance to district capital										0.003
										(0.037)
× log distance to major roads										0.019
										(0.028)
Num. of Observations	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956

Notes: This table augments our baseline specification from column 1 of Table 1 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.6: Robustness to Additional Controls $\times$ Post-Split, Parent/Child District Level

+ controls for:	–	sec. forces	development	pub. goods	demog.	nat. res.	politics	occup.	geog.	remoteness
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	-0.003	-0.007	-0.004	-0.001	-0.002	-0.003	-0.002	-0.004	-0.005	-0.009
	(0.021)	(0.021)	(0.022)	(0.019)	(0.022)	(0.020)	(0.021)	(0.023)	(0.020)	(0.021)
$\times$ Δ ethnic polarization	0.032	0.033	0.031	0.031	0.032	0.029	0.032	0.033	0.033	0.032
	(0.019)	(0.019)	(0.019)	(0.015)	(0.020)	(0.021)	(0.019)	(0.020)	(0.021)	(0.019)
$\times$ Δ ethnic fractionalization	0.000	-0.002	0.001	-0.001	0.001	-0.001	0.000	-0.000	-0.003	0.005
	(0.012)	(0.011)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)
$\times$ Δ religious polarization	-0.009	-0.004	-0.009	-0.006	-0.009	-0.007	-0.010	-0.008	-0.010	-0.013
	(0.011)	(0.010)	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
$\times$ log distance to security post		-0.031								
		(0.016)								
$\times$ log distance to police station		0.030								
		(0.017)								
$\times$ nighttime light intensity			0.003							
			(0.015)							
$\times$ share with $>$ primary education			-0.011							
			(0.017)							
$\times$ distance to public market				-0.004						
				(0.014)						
$\times$ share villages with electricity				-0.017						
				(0.015)						
$\times$ share villages with safe water				0.023						
				(0.016)						
$\times$ share villages with street light				0.001						
				(0.018)						
$\times$ share villages with transport center				0.053						
				(0.014)						
$\times$ health centers per capita				0.007						
				(0.015)						
$\times$ high schools per capita				-0.018						
				(0.016)						
$\times$ log initial population					0.003					
					(0.015)					
$\times$ population share, 5–14					-0.001					
					(0.016)					
$\times$ population share, 15-49					-0.005					
					(0.020)					
$\times$ nat. resource transfers per capita						-0.016				
						(0.011)				
$\times$ cash crop share of total ag. output						0.011				
						(0.016)				
$\times$ share of land area with forest						0.006				
						(0.012)				
$\times$ parliamentary vote polarization							0.002			
							(0.013)			
$\times$ fiscal transfers per capita							-0.007			
							(0.010)			
$\times$ share in agriculture								-0.008		
								(0.022)		
$\times$ share in forestry/fishing								0.013		
								(0.023)		
$\times$ share in other								-0.011		
								(0.024)		
$\times$ land area									0.008	
									(0.024)	
$\times$ share villages on coast									0.021	
									(0.076)	
$\times$ share villages in valley									0.019	
									(0.046)	
$\times$ share villages on hill									-0.038	
									(0.072)	
$\times$ share villages on flatland									0.009	
									(0.070)	
$\times$ shares villages in highlands									0.036	
									(0.031)	
$\times$ log elevation									0.005	
									(0.016)	
$\times$ log distance to coast									0.006	
									(0.030)	
$\times$ log distance to river									-0.013	
									(0.019)	
$\times$ log distance to subdistrict capital										0.018
										(0.020)
$\times$ log distance to district capital										0.030
										(0.024)
$\times$ log distance to major roads										-0.031
										(0.017)
Num. of Observations	20,220	20,220	20,220	20,220	20,220	20,220	20,220	20,220	20,220	20,220

Notes: This table augments our baseline specification from column 2 of Table 1 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.7: Robustness to Additional Controls × Post-Split, Parent District Level

+ controls for:	–	sec. forces	development	pub. goods	demog.	nat. res.	politics	occup.	geog.	remoteness
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	0.001	-0.006	-0.007	-0.018	-0.001	0.001	-0.004	-0.002	-0.006	-0.003
	(0.026)	(0.024)	(0.028)	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)	(0.024)	(0.026)
× Δ ethnic polarization	0.027	0.029	0.030	0.063	0.036	0.029	0.028	0.031	0.030	0.037
	(0.013)	(0.014)	(0.014)	(0.011)	(0.016)	(0.012)	(0.013)	(0.014)	(0.017)	(0.014)
× Δ ethnic fractionalization	0.035	0.044	0.031	0.056	0.032	0.041	0.040	0.033	0.045	0.038
	(0.026)	(0.024)	(0.027)	(0.020)	(0.024)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
× Δ religious polarization	-0.031	-0.021	-0.027	-0.012	-0.040	-0.029	-0.040	-0.035	-0.034	-0.032
	(0.021)	(0.022)	(0.021)	(0.018)	(0.020)	(0.019)	(0.022)	(0.023)	(0.022)	(0.023)
× log distance to security post		-0.028								
		(0.021)								
× log distance to police station		0.053								
		(0.023)								
× nighttime light intensity			-0.020							
			(0.021)							
× share with > primary education			-0.024							
			(0.030)							
× distance to public market				-0.060						
				(0.028)						
× share villages with electricity				-0.067						
				(0.025)						
× share villages with safe water				-0.010						
				(0.027)						
× share villages with street light				-0.012						
				(0.022)						
× share villages with transport center				0.076						
				(0.017)						
× health centers per capita				0.049						
				(0.017)						
× high schools per capita				0.019						
				(0.017)						
× log initial population					0.017					
					(0.026)					
× population share, 5–14					0.058					
					(0.027)					
× population share, 15-49					0.011					
					(0.033)					
× nat. resource transfers per capita						0.010				
						(0.009)				
× cash crop share of total ag. output						-0.005				
						(0.027)				
× share of land area with forest						-0.022				
						(0.024)				
× parliamentary vote polarization							-0.027			
							(0.019)			
× fiscal transfers per capita							0.017			
							(0.022)			
× share in agriculture								-0.019		
								(0.036)		
× share in forestry/fishing								0.008		
								(0.041)		
× share in other								-0.036		
								(0.038)		
× land area									-0.018	
									(0.025)	
× share villages on coast									0.006	
									(0.124)	
× share villages in valley									0.041	
									(0.083)	
× share villages on hill									-0.024	
									(0.128)	
× share villages on flatland									0.003	
									(0.105)	
× shares villages in highlands									0.032	
									(0.047)	
× log elevation									-0.029	
									(0.024)	
× log distance to coast									0.013	
									(0.033)	
× log distance to river									0.041	
									(0.039)	
× log distance to subdistrict capital										0.027
										(0.033)
× log distance to district capital										-0.012
										(0.039)
× log distance to major roads										0.030
										(0.029)
Num. of Observations	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956	7,956

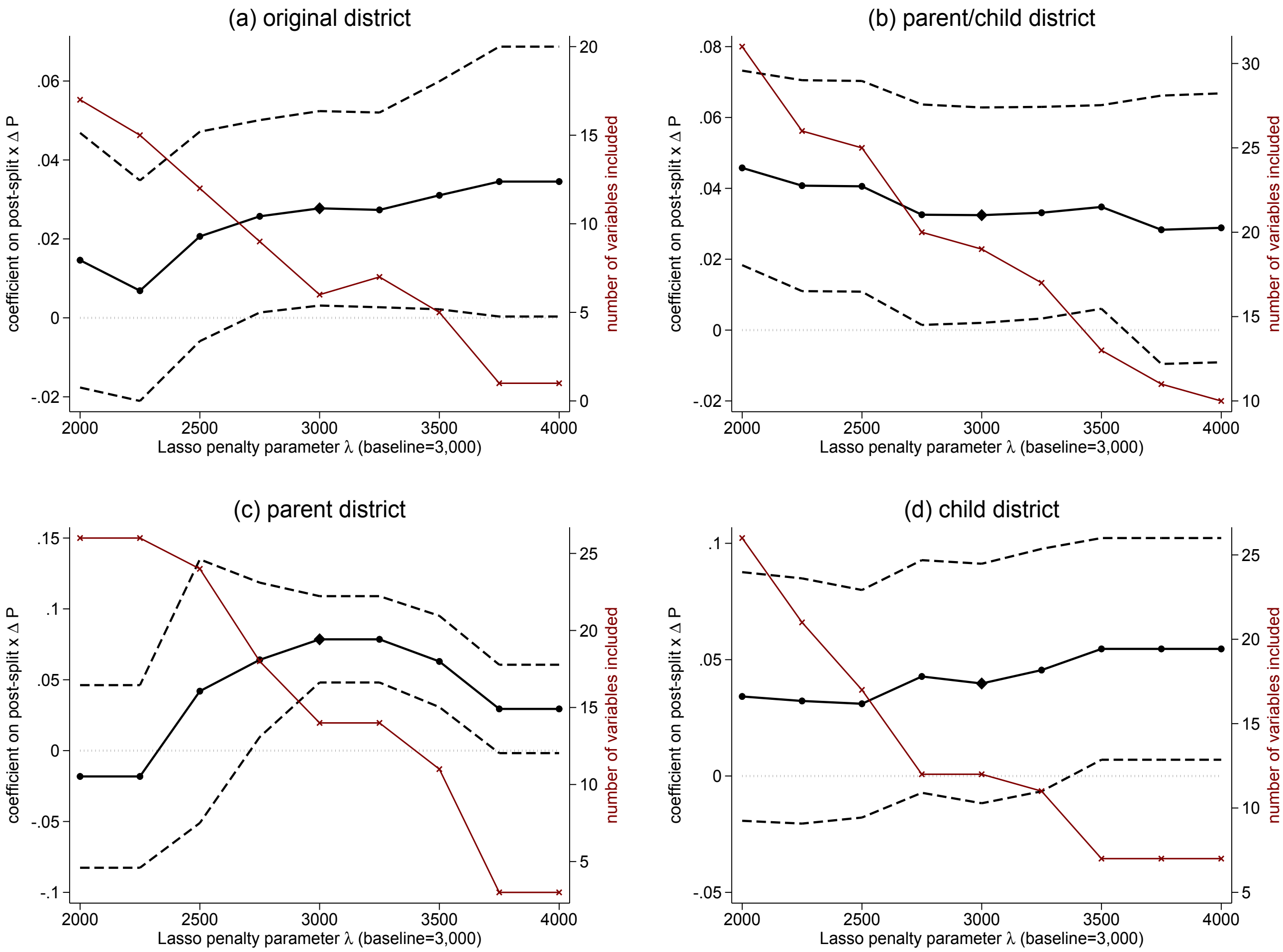
Notes: This table augments our baseline specification from column 3 of Table 1 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.8: Robustness to Additional Controls × Post-Split, Child District Level

+ controls for:	–	sec. forces	development	pub. goods	demog.	nat. res.	politics	occup.	geog.	remoteness
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
post-split	-0.005	-0.010	-0.004	-0.000	-0.004	-0.004	-0.005	-0.006	-0.010	-0.011
	(0.025)	(0.027)	(0.026)	(0.023)	(0.025)	(0.022)	(0.025)	(0.027)	(0.024)	(0.024)
× Δ ethnic polarization	0.043	0.048	0.042	0.027	0.045	0.035	0.046	0.044	0.055	0.049
	(0.025)	(0.024)	(0.023)	(0.026)	(0.025)	(0.027)	(0.023)	(0.026)	(0.028)	(0.019)
× Δ ethnic fractionalization	-0.011	-0.018	-0.012	-0.007	-0.007	-0.015	-0.006	-0.012	-0.016	-0.006
	(0.019)	(0.019)	(0.020)	(0.020)	(0.024)	(0.018)	(0.019)	(0.020)	(0.021)	(0.021)
× Δ religious polarization	-0.005	0.000	-0.006	-0.006	-0.004	0.002	-0.011	-0.004	-0.008	-0.020
	(0.014)	(0.012)	(0.014)	(0.016)	(0.016)	(0.014)	(0.015)	(0.014)	(0.017)	(0.015)
× log distance to security post		-0.034								
		(0.026)								
× log distance to police station		0.027								
		(0.022)								
× nighttime light intensity			0.013							
			(0.019)							
× share with > primary education			-0.004							
			(0.026)							
× distance to public market				0.007						
				(0.020)						
× share villages with electricity				-0.008						
				(0.024)						
× share villages with safe water				0.026						
				(0.024)						
× share villages with street light				0.011						
				(0.031)						
× share villages with transport center				0.044						
				(0.020)						
× health centers per capita				-0.002						
				(0.026)						
× high schools per capita				-0.019						
				(0.023)						
× log initial population					-0.005					
					(0.018)					
× population share, 5–14					-0.019					
					(0.019)					
× population share, 15-49					-0.012					
					(0.027)					
× nat. resource transfers per capita						-0.034				
						(0.018)				
× cash crop share of total ag. output						0.029				
						(0.021)				
× share of land area with forest						0.012				
						(0.015)				
× parliamentary vote polarization							0.019			
							(0.017)			
× fiscal transfers per capita							-0.012			
							(0.013)			
× share in agriculture								-0.006		
								(0.026)		
× share in forestry/fishing								0.013		
								(0.022)		
× share in other								-0.007		
								(0.037)		
× land area									0.006	
									(0.035)	
× share villages on coast									-0.001	
									(0.097)	
× share villages in valley									-0.025	
									(0.051)	
× share villages on hill									-0.072	
									(0.092)	
× share villages on flatland									-0.020	
									(0.087)	
× shares villages in highlands									0.061	
									(0.047)	
× log elevation									0.007	
									(0.024)	
× log distance to coast									0.011	
									(0.042)	
× log distance to river									-0.036	
									(0.029)	
× log distance to subdistrict capital										0.032
										(0.032)
× log distance to district capital										0.042
										(0.030)
× log distance to major roads										-0.066
										(0.027)
Num. of Observations	12,264	12,264	12,264	12,264	12,264	12,264	12,264	12,264	12,264	12,264

Notes: This table augments our baseline specification from column 4 of Table 1 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Figure D.5: Varying the Penalty Parameter in Lasso Robustness Procedure



Notes: This figure reports alternative estimated effects of $post\text{-}split \times \Delta P$ based on varying the penalty parameter λ used to discipline variable selection in the double Lasso procedure. Column 3 of Tables D.1–D.4 (and Table 2 in the paper) reported results for $\lambda = 3,000$ as a baseline. These figures vary that value from 2,000 to 4,000, leading to a range of variables included as seen in the red line and "x" points plotted on the right y-axis. The dashed lines are 95 percent confidence intervals on the point estimates from each individual regression.

D.5 Validating the Conflict Measures and Addressing Systematic Reporting Bias

Recall that the SNPK data is based on an exhaustive and carefully vetted set of local media sources across Indonesia. However, like other conflict event data, the SNPK still has the potential concern that it systematically underreports violence in certain areas of the country. While we control for the number of sources being used by coders in any given province–month, we can still not completely rule out the possibility that media outlets differentially report on events in (and hence reallocate resources and reporters to) more interesting locations. If "interesting" coincides with splitting and changes in ethnic divisions, then one might worry that we are over-estimating the effects of $\Delta diversity$ on conflict. Subjective reporting is a basic fact facing all conflict research.[6] We discuss here one important robustness check on our own results that might also be fruitfully applied to others using similar data.

In column 5 of Table 2 (and D.1–D.4), we draw upon Google Trends data in an attempt to rule out confounding effects of time-varying media intensity. The idea here is that the events taking place in any given district–month in our data should attract a baseline level of interest from the (internet-using) population, among whom are media actors trying to follow that interest. Once we partial out that general location-specific interest in that period, the SNPK conflict report is more likely to reflect the true likelihood of any incidents rather than just a general uptick in popular (media) attention. These Google Trends, which capture the relative frequency of searches for the given district name (original, parent, or child), are indeed highly correlated with major local events such as mayoral elections.[7] More importantly, though, our core results remain qualitatively and quantitatively unchanged when controlling for these Google Trends, which we measure on a $[0, 1]$ continuum.

[6] These concerns apply to nearly every study of conflict based on media reports, e.g. regions facing weather or commodity price shocks might draw media resources and reporters away from other areas of a given country. Studies at the country level suffer from similar concerns insomuch as they rely on either media reporting of deaths to define civil conflict/war or subjective assessments of conflict scholars as to the timing of conflict outbreaks and cessation (see Bazzi and Blattman, 2014).

[7] A fixed effects specification suggests that parent/child district names are around 10 percent more likely to be searched for during the six month window around the direct mayoral elections.

D.6 Outliers and Inference

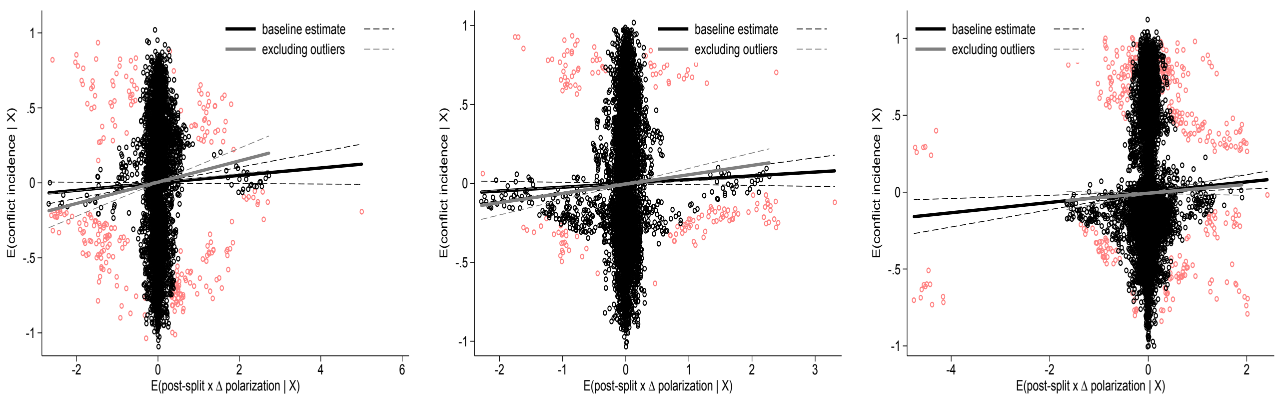
This section provides additional results on outliers that complement those in Table 2 as well as alternative approaches to inference.

Point Estimates. In Table 2, we removed one extreme outlier in ΔP six standard deviations below the mean. Here, we adopt the widely used approach of Belsley, Kuh and Welsch (2005) to identify observations with high influence as captured by a $dfbeta_i^k$ measure, which captures the difference between the regression coefficient β_k for variable k when the ith observation is included versus excluded, with the difference being further scaled by the estimated standard error on the regressor coefficient, β_k. Belsley, Kuh and Welsch (2005, p. 28) recommend as a rule-of-thumb to remove all observations for which $|dfbeta_i^k| > 2/\sqrt{N}$ where N is the number of observations. Other authors recommend weaker cutoffs of 1 (Bollen and Jackman, 1990).

To visualize outliers detected using this method, Figure D.6 plots the baseline partial regression coefficients and scatterplot of residuals for the original district, parent and child specifications in columns 1, 3, and 4 of Table 1. The red circles identify those residuals with high $|dfbeta_i|$ for ΔP. The black lines correspond to our baseline estimate, and the gray lines are estimates based on removing the influential observations. The only regression line that seems significantly affected by the inclusion of outliers is $post\text{-}split \times \Delta P$ at the original district level, which becomes more starkly positive when removing the high-influence observations. Panel (b) of Table D.9 presented the corresponding regression results alongside our baseline estimates for reference in Panel (a).

Figure D.6: Principled Removal of Outliers from Baseline Estimates of Table 1

(a) Original District (b) Parent District (c) Child District



Notes: These figures present the partial regression plots for $post\text{-}split \times \Delta P$ in our baseline regressions. The black regression line and 95 percent confidence interval are the results from columns 1 (a), 3 (b), and 4 (c) of Table 1. The red observations are district-months identified by the Belsley, Kuh and Welsch (2005) method for removing outliers described earlier. The gray regression line and 95 percent confidence interval are based on removing those observations and rerunning the baseline regressions.

Inference. Besides influencing point estimates and implied effect sizes, outliers and small sample sizes can also affect inference. Table D.9 presents several alternative approaches to inference in the generalized DiD panel setup. The baseline point estimates and standard errors clustered at the original district level are as suggested by the usual Bertrand, Duflo and Mullainathan (2004) motivation for clustering in fixed effects DiD designs. Below those, we present a series of standard errors or p-values. First, we consider the Conley (1999) spatial HAC estimator that allows for contemporaneous correlation in unobservables between all districts within 500 km in addition to the usual within-district correlation over time. Results are similar using other distance bandwidths. Second, we adopt the new "effective degrees of freedom" adjustment due to Young (2016), who adjusts standard errors by the effective sample size implied by the influence of each observation.[8] Third, we implemented a cluster wild bootstrap procedure with Webb weights and 9,999 draws (Cameron, Gelbach and Miller, 2008). Finally, we take seriously the quasi-random timing of splitting seen in Table A.2 and implement a randomization inference procedure that randomly reassigns the set of three $\Delta\mathbf{diversity}$ vector components across each of the districts in the given regression before estimation. We repeat this 10,000 times and recover the implied nearly exact p-values on our baseline estimates.[9]

Overall, the main finding of significant effects of ΔP remains fairly robust with the exception of the wild cluster bootstrap and the "effective degrees of freedom" adjustment. Nevertheless, as shown in Panel (b) of Table D.9, both of these inference procedures are sensitive to outliers. Indeed, the simultaneous removal of outliers and adjustment of inference to account for remaining high influence observations delivers the most consistent evidence that ΔP exerts a significant positive effect on social conflict. MacKinnon and Webb (2019) suggest that randomization inference may work better than the widely-used wild cluster bootstrap of Cameron, Gelbach and Miller (2008) given the imbalance in cluster sizes. We do not take a strong stand on which is the correct approach among the five considered in Table D.9 but believe that the weight of the evidence is in favor of statistically meaningful effects.

[8] This novel approach to inference delivers coefficient-specific degrees-of-freedom (DoF). For example, for ΔP, the DoF across columns 1–4 are 11.3, 4.7, 6.2, and 5.6.

[9] These are *nearly* exact as they do not recover the entire distribution of possible estimates as there 2^D possible ways to reassign $\Delta\mathbf{diversity}$ across D districts and with a relatively large number of $D > 50$ across all specifications, this would require far longer than necessary to identify the general shape of the distribution (and size of the tails) of estimated coefficient sizes.

Table D.9: Robust Inference and Outlier Removal

Administrative Unit	Original District (1)	Parent & Child (2)	Parent (3)	Child (4)
	Panel (a): Baseline			
post-split × Δ ethnic polarization	0.036	0.032	0.027	0.043
baseline: clustering on original district (OD)	(0.018)	(0.019)	(0.013)	(0.025)
spatial HAC, 500 km uniform bandwidth	(0.018)	(0.010)	(0.014)	(0.015)
effective degrees of freedom adjustment	(0.027)	(0.023)	(0.019)	(0.030)
wild bootstrap, clustering on OD [p-value]	[0.117]	[0.180]	[0.166]	[0.472]
randomization inference [p-value]	[0.090]	[0.017]	[0.032]	[0.003]
post-split × Δ ethnic fractionalization	-0.003	0.000	0.035	-0.011
baseline: clustering on original district	(0.019)	(0.012)	(0.026)	(0.019)
spatial HAC, 500 km uniform bandwidth	(0.021)	(0.012)	(0.018)	(0.016)
effective degrees of freedom adjustment	(0.022)	(0.023)	(0.019)	(0.030)
wild bootstrap, clustering on OD [p-value]	[0.879]	[0.982]	[0.214]	[0.587]
randomization inference [p-value]	[0.536]	[0.480]	[0.012]	[0.773]
Number of District-Months	7,956	20,220	7,956	12,264
Dep. Var. Mean Pre-Split	0.57	0.33	0.47	0.25
	Panel (b): Residual Outlier Removal			
post-split × Δ ethnic polarization	0.081	0.025	0.041	0.028
baseline: clustering on original district (OD)	(0.016)	(0.008)	(0.014)	(0.013)
spatial HAC, 500 km uniform bandwidth	(0.015)	(0.008)	(0.010)	(0.011)
effective degrees of freedom adjustment	(0.024)	(0.009)	(0.021)	(0.015)
wild bootstrap, clustering on OD [p-value]	[0.013]	[0.033]	[0.072]	[0.136]
randomization inference [p-value]	[0.051]	[0.100]	[0.027]	[0.082]
post-split × Δ ethnic fractionalization	-0.027	0.007	0.045	-0.007
baseline: clustering on original district (OD)	(0.018)	(0.013)	(0.025)	(0.018)
spatial HAC, 500 km uniform bandwidth	(0.020)	(0.012)	(0.018)	(0.015)
effective degrees of freedom adjustment	(0.020)	(0.009)	(0.021)	(0.015)
wild bootstrap, clustering on OD [p-value]	[0.255]	[0.547]	[0.063]	[0.727]
randomization inference [p-value]	[0.879]	[0.296]	[0.005]	[0.605]
Number of District-Months	7,696	19,753	7,788	11,918
Dep. Var. Mean Pre-Split	0.59	0.30	0.47	0.21

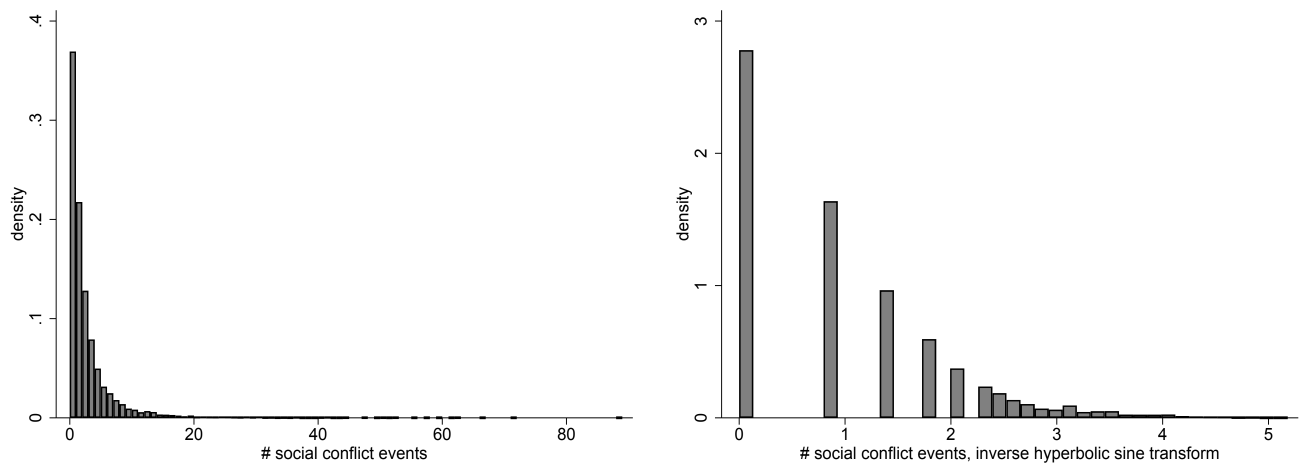
Notes: This table demonstrates robustness of the baseline results in Table 1 to alternative inference and outlier removal procedures. All regressions include $post\text{-}split$ and $post\text{-}split \times \Delta religious\ diversity$, but these coefficients are suppressed for presentational purposes. Panel (a) reports several alternative approaches to inference besides our baseline of clustering by original district: (i) the Conley (1999) spatial HAC estimator that allows for contemporaneous correlation in unobservables between all districts within 500 km in addition to the usual within-district correlation over time; (ii) a new "effective degrees of freedom adjustment" due to Young (2016), who adjusts standard errors by the effective sample size implied by the influence of each observation; (iii) a cluster wild bootstrap procedure due to Cameron, Gelbach and Miller (2008); and (iv) a quasi-randomization inference (RI) procedure that randomly permutes the $\Delta diversity$ vector across each of the districts in the given regression before estimation, repeating 10,000 times to recover the implied p-values. Panel (b) additionally removes outliers in $post\text{-}split \times \Delta P$ following the residual-influence approach in Belsley, Kuh and Welsch (2005). All specifications include month FE, district FE, district-specific time trends, and dummies for the number of papers used by coders for the given province–month.

D.7 Other Alternative Specifications

This section discusses additional robustness checks mentioned in Section IV.E.

Intensive Margin of Violence. Our baseline specification focused on the extensive margin of whether there are any social conflict events in the given district–month. This is a sensible baseline given that most district-months with any events have one or two events (see the left graph in Figure D.7 below). Even at the original district level—where 63 percent of district–months have any social conflict in column 1 of Table 1—80 percent of observations with any conflict have 5 or fewer events with a very long tail up to 89 events. The skewness is even starker at the more granular parent–child district level. While each of these separate event records is meant to capture a different incident, many are part of the same underlying conflict event, which means that the intensive margin specification might simply introduce noise. On the other hand, there may be substantive empirical content in this intensive margin variation.

Figure D.7: Number of Social Conflict Incidents by Original District-Month



Notes: This figure plots the distribution of the number of social conflict events by month at the original district level. The left figure is the raw data. The right figure is the inverse hyperbolic since transformation used in the regressions.

Table D.10 presents intensive margin specifications based on the widely used hyperbolic inverse sine transformation, $\log(\#events_{dt} + (\#events_{dt}^2 + 1)^{1/2})$, due to Burbidge, Magee and Robb (1988). This approach to dealing with zeros has much better properties than the usual method of adding a small constant inside the log and similarly can help mitigate the effect of skewness in the outcome distribution. It also allows us to maintain the basic fixed effects OLS specification. While interpreting magnitudes is less straightforward,[10] the main takeaway from Table D.10 is that the results look very similar to the baseline extensive margin specification albeit slightly less precise. We increase precision by winsorizing the top 5th percentile of $\#events$ to further deal with the extreme skew (see the right graphs in Figure D.7).

[10] Except for very small outcome values, the transformation can be interpreted in approximately the same way as a log dependent variable.

Table D.10: Intensive Margin Specification: Number of Conflict Events

Administrative Unit:	Original District (1)	Parent & Child (2)	Parent (3)	Child (4)
post-split	-0.035	-0.021	-0.049	-0.010
	(0.062)	(0.033)	(0.060)	(0.031)
post-split × Δ ethnic polarization	0.020	0.041	0.031	0.060
	(0.031)	(0.025)	(0.021)	(0.035)
post-split × Δ ethnic fractionalization	0.011	-0.018	0.061	-0.035
	(0.046)	(0.019)	(0.056)	(0.028)
post-split × Δ religious diversity	0.035	-0.006	0.009	-0.005
	(0.026)	(0.014)	(0.035)	(0.016)
Number of District-Months	7,956	20,220	7,956	12,264
Dep. Var. Mean, Pre-Split	0.98	0.44	0.73	0.30

Notes: The dependent variable is the hyperbolic sine transformation of the number of social conflict incidents in the given month. We winsorize at the 95th percentile of the outcome distribution. Otherwise, the specification is the same as in the baseline Table 1 with time and district FE, district-specific time trends, and standard errors clustered at the original district level.

Omitting Later Entrants to SNPK Data. Table D.11 omits districts that enter the SNPK data in 2005, thereby ensuring a balanced panel. The similarity in results is reassuring insomuch as these later entrants were selected on account of policy concerns about recent violence.

Table D.11: Alternative Time Restriction: Excluding 2005 Entrants to SNPK

Administrative Unit:	Original District (1)	Parent & Child (2)	Parent (3)	Child (4)
post-split	-0.015	-0.018	-0.013	-0.022
	(0.032)	(0.027)	(0.031)	(0.031)
post-split × Δ ethnic polarization	0.046	0.041	0.034	0.060
	(0.023)	(0.024)	(0.016)	(0.031)
post-split × Δ ethnic fractionalization	-0.006	-0.008	0.025	-0.024
	(0.022)	(0.015)	(0.026)	(0.025)
post-split × Δ religious diversity	0.017	-0.005	-0.025	-0.001
	(0.016)	(0.013)	(0.021)	(0.016)
Number of District-Months	5,196	13,020	5,196	7,824
Dep. Var. Mean, Pre-Split	0.52	0.31	0.43	0.24

Notes: This table drops all districts that entered the SNPK conflict data starting in 2005, thereby imposing a balanced panel. The specification is otherwise the same as in the baseline Table 1 with time and district FE, district-specific time trends, and standard errors clustered at the original district level.

E Additional Evidence Supporting Political Violence Results in Section V

Section I.C offered background on the changing role of ethnicity in Indonesian politics that could be broadly summarized in the following four takeaways: (i) ethnicity is an important organizing principle for political mobilization; (ii) ethnic-based clientilism and patronage networks are pervasive; (iii) decentralization and direct, majoritarian mayoral elections deepen (i) and (ii); and (iv) splitting further amplifies all of these forces. Here, we provide additional background from the political science literature as well as fresh empirical evidence consistent with this context.

Political Science Literature. Wilson (2015, p. 92) offers a helpful summary of views on ethnicity and patronage in the context of splitting: *"As local government and administrative boundaries were altered, 'local selfishness' was reinforced, resulting in conflicts and tensions at the local level (Firman 2013, 180). Just like national politics, local-level politics was an intense 'arena of contestation between competing coalitions of social interests' as networks that had relied upon central state patronage or been regime middlemen moved to establish new means to access resources (Hadiz, 2011a, 171). This contestation involved renegotiating the boundaries of collective identities, in doing so defining a social economy of who had to access to what, and under what circumstances. According to Klinken, from 1998 local elites throughout the country attempted to build 'an exclusive discourse of ethnicity', one that in its construction of group identity formed a 'language with which elites compete for power by mobilising supporters' (Klinken 2002, 68)."*

Kobayashi (2011) notes from personal interviews that *"A Dayak politician, a strong supporter of the creation of Bengkayang district, clearly explained that increase of Dayak government employees was one objective of* pemekaran *[splitting]. A Dayak department head admitted that* pemekaran *increased job opportunities for Dayaks in government by commenting that he himself would not have been promoted to the position of department head without creation of Bengkayang.*

Diversity and Close Elections. Table E.1 demonstrates that ethnic diversity is associated with closer mayoral elections. In particular, we regress the victory margin for the winning candidate on ethnic and religious diversity within the newly created parent and child districts. We consider both the first and second (when possible) quinquennial direct election after splitting.[1]

The strong positive correlation of diversity with closer elections is consistent with the importance of ethnic mobilization highlighted in recent literature. Column 1 shows this when pooling across both the first and second elections taking place in the new parent and child districts. Both polarization (P) and fractionalization (F) matter, though the former is more precisely estimated. The effect sizes, though, are not trivial. A one standard deviation increase in P or F is associated with 10 percent lower victory margin relative to a mean of around 0.14 across all elections from 2005–2014 in these new districts. Results look similar if not slightly more pronounced for second elections. Religious polarization also seems associated with lower victory margins but only for parent districts.[2]

Close Elections and Conflict. The first set of results in Table E.2 demonstrates that violence is more likely around new elections after splitting when those contests are closely contested. In particular, we interact the post-split$\times$election period indicator with the victory margin (ranging from 0.004 to 0.55). Panel (a) examines the baseline outcome of any social conflict, and Panel (b) examines the intensive margin number of conflict incidents transformed via the inverse hyperbolic sine used in baseline robustness checks in Appendix D.7. This latter specification allows for the possibility that the intensive margin

[1] As discussed in Appendix F, several newly created districts had not yet had their second election by the end of our study period, while others have missing data on election outcomes.

[2] It is also worth noting that we can estimate the relationship between $\Delta diversity$ and $\Delta victory\ margins$ for 22 parent and child districts with a direct election at the original district level prior to splitting. In particular, we find that a one standard deviation increase in ΔP (ΔF) is associated with a 2.2 p.p. (3.3 p.p.) reduction in $\Delta victory\ margin$ relative to its mean of 5.3 percent. There are only 10 prior elections and hence it is not meaningful to conduct inference, but the patterns are nevertheless supportive of the level results in Table E.1.

may be differentially more important around election periods, which may be generally more intense periods of violence. Together, these results are broadly consistent with the fact that victory margins are significantly lower in more diverse, newly created districts as seen in Appendix Table E.1.

Looking across specifications, the evidence in Table E.2 suggests that after splitting, violence is significantly more pronounced around close mayoral elections. These patterns are consistent with both (i) the qualitative background on election violence and incident descriptions discussed in Appendix C.1, and (ii) the conflict-amplifying effects of $\Delta diversity$ around elections seen in Table 3. While victory margins are potentially endogenous with respect to contemporaneous electoral violence, these results provide an important validation check on our interpretation. Together with the results linking ethnic diversity to closer elections, these findings paint a rich picture of how (changes in) ethnic divisions reshape conflict dynamics in settings with high returns to local political control.

Ethnic Divisions and Preferences for Mayoral Candidates. We draw upon the *Indonesia Family Life Survey* (IFLS) to provide some evidence in line with these claims as they relate to border-induced changes in ethnic and religious divisions. In particular, we draw upon the 2014 round of data, which asks individuals "What factors do you consider in electing a mayor?". We observe individuals in 40 of the parent and child districts in our main sample. In Table E.3 below, we control for basic demographics and relate $\Delta diversity$ to preferences over a large set of mayoral qualities. The results suggest that changes in ethnic divisions as a result of splitting are strongly associated with preferences for mayor's ethnicity as well as their provision of patronage. We find weaker correlations with mayoral experience, political affiliation and proposed program quality, among others. Note that this observation is at the end of the study period by which time many of these districts have had multiple mayoral elections, some of which may have been among those that witnessed violence of the sort identified in Section V of the paper.

Table E.1: Diversity and Close Elections After Splitting

	Dep. Var.: Victory Margin for Winning Mayoral Candidate in					
Administrative Unit	Parent/Child		Parent		Child	
Which Election?	1st	2nd	1st	2nd	1st	2nd
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ethnic polarization, new district	-0.013	-0.034	-0.001	-0.035	-0.016	-0.022
	(0.007)	(0.014)	(0.017)	(0.038)	(0.008)	(0.012)
ethnic fractionalization, new district	-0.003	-0.017	-0.011	-0.022	0.004	0.003
	(0.010)	(0.016)	(0.019)	(0.043)	(0.015)	(0.016)
religious polarization, new district	-0.024	-0.019	-0.039	-0.080	-0.016	0.012
	(0.010)	(0.015)	(0.017)	(0.046)	(0.012)	(0.014)
Number of Districts	115	67	46	25	69	42
Dep. Var. Mean	0.13	0.15	0.13	0.18	0.13	0.13

Notes: This table presents simple regressions relating ethnic diversity in the parent/child districts to the victory margin in the first and second direct mayoral elections post-split. Columns 1–2 pool parent/child districts, and columns 3–7 examine each separately. The $diversity$ measures are normalized, and standard errors are clustered at the original district level.

Table E.2: Differential Conflict Around Close Elections After Splitting

Administrative Unit	Parent Child (1)	Parent (2)	Child (3)
	Panel (a): Any Social Conflict		
post-split	0.024	0.009	0.026
	(0.031)	(0.039)	(0.037)
post-split × 1st election period	0.077	-0.027	0.096
	(0.053)	(0.066)	(0.038)
post-split × 1st election period × victory margin	-0.251	0.120	-0.449
	(0.177)	(0.203)	(0.250)
Number of Observations	17,580	7,056	10,524
Dep. Var. Mean	0.35	0.50	0.26
	Panel (b): # Social Conflict Events Hyperbolic Inverse Sine		
post-split	0.031	-0.013	0.053
	(0.063)	(0.108)	(0.053)
post-split × 1st election period	0.222	0.241	0.109
	(0.102)	(0.132)	(0.059)
post-split × 1st election period × victory margin	-0.681	-1.356	-0.286
	(0.385)	(0.523)	(0.441)
Number of Observations	17,580	7,056	10,524
Dep. Var. Mean	0.53	0.84	0.35

Notes: This table examines interactions of the first mayoral election period with the victory margin in that election. The interaction of post-split and that victory margin is included but not shown. The specification is otherwise similar to the one in Table 3.

Table E.3: Changes in Ethnic Divisions and Preferences for Mayoral Candidates

	Dep. Var. (binary): Respondent in 2014 Believes that the Mayor's . . . Is Important							
	Appearance (1)	Popularity (2)	Program Quality (3)	Political Affiliation (4)	Religion (5)	Ethnicity (6)	Experience (7)	Patronage (8)
Δ ethnic polarization	0.029	-0.010	-0.002	0.032	0.087	0.086	-0.012	0.045
	(0.013)	(0.014)	(0.010)	(0.020)	(0.037)	(0.023)	(0.009)	(0.012)
Δ ethnic fractionalization	-0.002	-0.029	0.013	0.014	0.056	0.044	-0.006	0.025
	(0.012)	(0.013)	(0.010)	(0.016)	(0.045)	(0.017)	(0.009)	(0.006)
Δ religious polarization	0.011	0.008	-0.003	-0.001	0.031	0.004	-0.013	0.002
	(0.009)	(0.017)	(0.009)	(0.014)	(0.026)	(0.012)	(0.005)	(0.004)
Number of Districts	1,887	1,887	1,887	1,887	1,887	1,887	1,887	1,887
Number of Districts	40	40	40	40	40	40	40	40
Dep. Var. Mean	0.75	0.76	0.93	0.70	0.77	0.60	0.93	0.46

Notes: The dependent variable in each column is a binary indicator that equals one if the respondent in the 2014 IFLS agrees that the mayoral candidates' given trait is an important factor in determining his/her vote. The regressions control for age, age squared, education level fixed effects, and gender. The $\Delta diversity$ measures are standardized, and standard errors are clustered at the district level.

F Data and Variable Construction

We describe here the key variables and data sources used in the paper.

Administrative Divisions

Indonesia's administrative divisions proceed down from the province to the district to the subdistrict to the village. These different levels of administration and our terminology for original, child and parent districts as defined below can be seen in Figure 3, which shows one of the districts in our study.

Original District: This administrative unit defines all areas based on the 2000 boundaries.

Child District: This represents the subdistricts that eventually become their own new district with an accompanying capital.

Parent District: This represents the subdistricts that stay with the original district capital after other subdistricts split off.

Post-Split: This is an indicator that turns on in the month that national parliamentary legislation first established a new district within the original district boundaries. In our main results, post-split equals one for the original district and parent district once the first child district splits off from 2000 onward. For child districts, the indicator equals one once it is ratified into law.

Conflict

The conflict data comes from the Indonesian National Violence Monitoring System, known by its Indonesian acronym SNPK, (see World Bank Indonesia, 2014).[1] The data are reported at or below the 2011 district level, and hence we can calculate conflict within both the 2010 and 2000 borders over the years 2000–2014. Our main conflict measures are binary indicators for any conflict in a given district–month, but we also consider the number of incidents as a robustness check. Coders read articles and then assign the incident to mutually exclusive categories based on the underlying trigger. The incidents are first coded as domestic violence, violent crime, violence during law enforcement, or conflict. Eighty-two percent of incidents record some property damage, injuries, or deaths.

Any Social Conflict: A dummy for whether SNPK recorded any non-crime and non-domestic violence incidents in the given month.

Active Media: Using data obtained directly from SNPK managers on newspaper availability and usage by province and month, we calculate the number of papers used in any given province-month. All conflict specifications control flexibly for media availability by including dummies for the number of active papers in any given province-month.

Entered 2005: SNPK coverage begins in 1998 for nine conflict-prone provinces and increases to 15 provinces plus parts of 3 provinces in greater Jakarta beginning in 2005. The data coverage is less complete and reliable for 1998 and 1999, and hence we focus on 2000–2014 for most results in the paper.

[1] We downloaded the data from `http://www.snpk-indonesia.com` in March 2015. This site is no longer active due to a recent contracting change. However, as of June 2016, the data is hosted on and available through the World Bank website.

Diversity

All measures are computed using the universal 2000 Population Census (see Badan Pusat Statistik, 2000). Since this contains data at the village level, metrics can be constructed at both the 2000 and 2010 borders.

Ethnic Fractionalization: Ethnic fractionalization in district d is given by $F = \sum_{j=1}^{\mathcal{N}_e} g_j(1-g_j)$, where $\mathcal{N}_e$ is the number of ethnic groups in the district, and g_j is the population share of group j as reported in the 2000 Census. We observe over 1000 ethnicities and sub-ethnicities speaking over 400 languages.

Ethnic Polarization: $P = \sum_{j=1}^{\mathcal{N}_e} \sum_{k=1}^{\mathcal{N}_e} g_j^2 g_k \eta_{jk}$, where $\mathcal{N}_e$, g_j, and g_k are as defined before, and η_{jk} is the distance between groups j and k. We map each ethnic group in the 2000 Census to a language in *Ethnologue*, which provides a full classification of the linguistic origins of each language (see the Online Appendix Section A.3 in Bazzi et al., 2016, for details). We set $\eta_{gh} = 1 - s_{gh}^{\delta}$, where s_{gh} is the degree of similarity between the languages spoken by g and h as given by the ratio of common branches on the language classification tree to the maximum possible (14), and δ is a parameter that selects the level of linguistic dissimilarity to be emphasized. We set $\delta = 0.05$ following others cited in the paper. Ethnicities with missing languages are given province-specific average pairwise distances (η's) between all other languages. Missing ethnic groups are necessarily grouped together, but separately from the "other" category, and also given province-specific average distances. We drop foreigners as they represent a minute fraction of the population, but we retain the ethnic Chinese.

Religious Polarization: Religious polarization, $Relig = \sum_{j=1}^{\mathcal{N}_r} \sum_{k=1}^{\mathcal{N}_r} g_j^2 g_k$, where $\mathcal{N}_r$ is the number of religious groups, and g_j (g_k) is the population share of group j (k). There are seven religions recorded in the Census, but in most districts, there is a single cleavage between a Muslim and a non-Muslim group.

Δ **Ethnic Polarization**: To examine changes in diversity at the original district level, we compute the population-weighted average polarization in the new units (children and parent district) and subtract the polarization in the original district. If original district $\mathcal{O}$ splits into parent $\mathcal{P}$ and child(ren) $\mathcal{C}_1$ ($\mathcal{C}_2$ if multiple), with populations $pop_{\mathcal{O}} = pop_{\mathcal{P}} + pop_{\mathcal{C}_1}(+pop_{\mathcal{C}_2})$ the change in ethnic polarization is $\Delta P = \left(\frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}} P_{\mathcal{P}} + \frac{pop_{\mathcal{C}_1}}{pop_{\mathcal{O}}} P_{\mathcal{C}_1} + \frac{pop_{\mathcal{C}_2}}{pop_{\mathcal{O}}} P_{\mathcal{C}_2}\right) - P_{\mathcal{O}}$. We construct changes in ethnic polarization at the child/parent level analogously as: $\Delta P = P_{\mathcal{P}} - P_{\mathcal{O}}$ for the parent and $\Delta P = P_{\mathcal{C}} - P_{\mathcal{O}}$ for each child.

Δ **Ethnic Fractionalization**: For original district $\mathcal{O}$ splitting into parent $\mathcal{P}$ and child(ren) $\mathcal{C}_1$ ($\mathcal{C}_2$ if multiple), with populations $pop_{\mathcal{O}} = pop_{\mathcal{P}} + pop_{\mathcal{C}_1}(+pop_{\mathcal{C}_2})$ the change in ethnic fictionalization is given by $\Delta F = \left(\frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}} F_{\mathcal{P}} + \frac{pop_{\mathcal{C}_1}}{pop_{\mathcal{O}}} F_{\mathcal{C}_1} + \frac{pop_{\mathcal{C}_2}}{pop_{\mathcal{O}}} F_{\mathcal{C}_2}\right) - F_{\mathcal{O}}$. We construct changes in ethnic fractionalization at the child/parent level analogously as: $\Delta F = F_{\mathcal{P}} - F_{\mathcal{O}}$ for the parent and $\Delta F = F_{\mathcal{C}} - F_{\mathcal{O}}$ for each child.

Δ **Religious Polarization**: For original district $\mathcal{O}$ splitting into parent $\mathcal{P}$ and child(ren) $\mathcal{C}_1$ ($\mathcal{C}_2$ if multiple), with populations $pop_{\mathcal{O}} = pop_{\mathcal{P}} + pop_{\mathcal{C}_1}(+pop_{\mathcal{C}_2})$ the change in religious polarization is given by $\Delta Relig = \left(\frac{pop_{\mathcal{P}}}{pop_{\mathcal{O}}} Relig_{\mathcal{P}} + \frac{pop_{\mathcal{C}_1}}{pop_{\mathcal{O}}} Relig_{\mathcal{C}_1} + \frac{pop_{\mathcal{C}_2}}{pop_{\mathcal{O}}} Relig_{\mathcal{C}_2}\right) - Relig_{\mathcal{O}}$. We construct changes in ethnic fractionalization at the child/parent level analogously as: $\Delta Relig = Relig_{\mathcal{P}} - Relig_{\mathcal{O}}$ for the parent and $\Delta Relig = Relig_{\mathcal{C}} - Relig_{\mathcal{O}}$ for each child.

Table F.1: Summary Statistics for Baseline Variables

	Mean	Std. Dev.	Min.	Median	Max.
	2000 Borders: 52 Original Districts				
any social conflict incidents	0.631	0.483	0.000	1.000	1.000
number of social conflict incidents	2.631	5.185	0.000	1.000	89.000
post-split	0.787	0.409	0.000	1.000	1.000
ethnic polarization	0.017	0.016	0.003	0.013	0.095
ethnic fractionalization	0.612	0.256	0.062	0.689	0.957
religious polarization	0.119	0.070	0.001	0.130	0.233
Δ ethnic polarization	-0.000	0.005	-0.035	0.000	0.008
Δ ethnic fractionalization	-0.059	0.083	-0.342	-0.032	-0.000
Δ religious polarization	-0.008	0.020	-0.129	-0.001	0.017
	2010 Borders: 133 Parent and Child Districts				
any social conflict incidents	0.364	0.481	0.000	0.000	1.000
number of social conflict incidents	1.035	2.941	0.000	0.000	76.000
post-split	0.768	0.422	0.000	1.000	1.000
ethnic polarization	0.017	0.016	0.003	0.013	0.095
ethnic fractionalization	0.609	0.258	0.062	0.682	0.957
religious polarization	0.122	0.067	0.001	0.131	0.233
Δ ethnic polarization	-0.000	0.011	-0.062	0.000	0.061
Δ ethnic fractionalization	-0.078	0.153	-0.677	-0.034	0.193
Δ religious polarization	-0.008	0.049	-0.192	-0.000	0.109

Notes: At the 2000 level, there are 52 districts and 7,956 monthly observations. At the 2010 level, there are 133 Districts (52 parents and 81 children) and 20,220 monthly observations. See Appendix F for variable definitions.

Voting and Elections

District elections occur every 5 years. Prior to 2005, district head elections were conducted by parliament and varied across districts in terms of timing. From 2005 onward, district and vice-district heads were directly elected by plurality vote contingent on that vote being at least 30 percent. If not, a second round between the top two candidates takes place. District heads directly appoint subdistrict heads. We collect data on the date of and vote shares in all direct elections from documents published by the General Election Commission (GEC), which are used in Martinez-Bravo, Mukherjee and Stegmann (2017) and also provided to us by Audrey Sacks who collected this information by hand from the GEC. Elections in child districts typically occur 1.5–2.5 years after the split. Elections in parent districts are determined by the pre-Suharto election cycles carried over into the democratic era (see Martinez-Bravo, Mukherjee and Stegmann, 2017).

Mayoral Election Period: Using the exact date of all direct elections, we construct an indicator that equals one in the 6 month window around the parent/childs first and second direct election dates. In the case of the latest splits, the first election can occur pre-split. There are some children (the latest splits) for which we do not observe a second election post-split.

Parliamentary Election Period: We construct an indicator that equals one in the 6 month window around the national DPR, DPRD-I, DPRD-II election dates in April 2004, April 2009, and April 2014.

Mayoral Election Victory Margins: Using the General Election Commissions records, we compute victory margins in the district head elections conducted after splitting. This continuous measure is simply equal to the vote share for the winner minus the vote share for the loser.

Control Variables

We list here the rich set of 65 variables from 1999 and 2000 that we interact with $post - split$ and use as controls to ensure that the cross-district variation picked up by $post - split \times Diversity$ is not picking up other observable differences across districts. These are carefully constructed from a variety of data sources, and are generally non-missing. Several variables are missing for at most one original district, and are imputed simply using the average across districts.

Podes Variables

We use the 2000 administrative village census (*Potensi Desa* or *Podes*) (see Badan Pusat Statistik, 2000, 2013, 2011) to construct a number of control variables relating to education, public goods provision, security, and development. Each of these measures are aggregated to the district level at both the original district level, and eventual, 2010 boundaries.

Health Variables: We construct a variable for the number of health care facilities (polyclinics and PHCs) per capita in 2000 at the 2000/2010 district levels. We construct the (population weighted) share of villages that say they have a midwife available. Further, we construct the (population weighted) share of villages that say they have a doctor or access to a PHC.

Education Variables: We construct the number of high schools per capita in 2000 at the 2000/2010 district levels. We also construct the number of Islamic schools per capita.

Public Goods: We construct the (population weighted) share of villages that have access to water from a pump or a water company; have a trash disposal system (bin/hole); have most households using gas/kerosene or electricity; and have road lighting. We also use the number of households per capita with electricity, with a telephone, and with a television.

Economy: We construct the number of permanent markets per-capita and the (population weighted) average distance to the nearest market. In addition we calculate the (population weighted) share of villages with a transportation hub (airport, seaport, or bus terminal). We also construct the (population weighted) share of villages reporting good or great economic conditions and the share of villages for which agriculture is the main source of income. Finally, we construct the (population weighted) average number of natural disasters in the past 3 years.

Security: We construct the (population weighted) mean distance to the nearest police post and office. We construct two variables: the logarithm of (one plus) the distance to the nearest police outfit and the logarithm of (one plus) the distance to the nearest police office (which is always larger).

Geography: We construct the (population weighted) share of villages on the shore, on the coast, in a valley, on a hill, on flat land, and at high altitude. We also construct the logarithm of total land area. Importantly, we also include the logarithm of (one plus) the (population weighted) mean distance from the village to the 2000 capital and the logarithm of (one plus) the (population weighted) mean distance from the village to the sub-district capital.

Census Variables

Using the 2000 Population Census (see Badan Pusat Statistik, 2000), we construct a number of additional demographic variables. We construct each of the below at both the original district and the eventual 2010 boundaries.

Population Shares: We use the Population Census in 2000 to compute the share of the population that is aged 5–14 and 15–29 at the original, child, and parent district levels. We also include the logarithm of total population and mean household size.

Education Shares: We compute the share of the population whose highest educational attainment is primary school, as well as the share of the population whose highest educational attainment is post-primary.

Migration: We compute the share of the population who arrived from a different province in the last five years and the share arrived from a different district in the last five years.

Geography: We include an indicator for the share of the population living in rural areas.

Sectors of the Economy: We compute the fraction of workers in agriculture, the fraction of workers in forestry, fishing and livestock, and the fraction of workers in other sectors (industry, trade, service, and transport).

Government Transfers

District Revenues: District revenue figures come from the World Bank's Indonesia Database for Policy and Economic Research also known as DAPOER (see World Bank, 2013), which in turn obtains data from the Indonesia Ministry of Finance. They are given for each district at the time of existence up to 2013. We add in the 2014 revenue data directly from the Ministry of Finance. Population data is taken from the same dataset. We construct all revenue and population variables at the original district level by aggregating up to the 2000 borders. Both the population and revenue data are missing in some cases. In our baseline, we impute these missing observations as described below, but our results are very similar if either or both variables are left as missing. Population data is missing in 2014 for all districts and in 2000 for 6 original districts. We impute population using the preceding/following year and the median growth rate of 1.5 percent. Revenue data is missing in 2000 for 4 of our original districts, and thereafter there are occasional within-district gaps in the data. These gaps occur between 2001–2005 and to a lesser extent between 2012–2013, never exceeding 8 missing districts. We impute missing revenues using annual median revenue growth rates. All revenue figures are adjusted for inflation using 2010 as the base year.

Total district revenue comes from the general allocation grant (Dana Alokasi Umum, DAU), the special allocation grant (Dana Alokasi Khusus, DAK), shared taxes, shared natural resource rents, as well as limited own revenue, and limited revenue from other sources. We construct 5 control variables, all using the information from year 2000, that account for all of district revenues while keeping information disaggregated: grants (DAU + DAK) per capita, shared taxes per capita, shared natural resource rents per capita, own revenue per-capita, and other revenue per capita. This allows natural resources, for example, to enter separately. These are necessarily only computed at the original district level, and are included at that level in the child/parent regressions.

When we examine how transfers evolve over time in Appendix A, we use the full time series of total revenues less own revenue, to capture total transfers from the central government. At the Original District level we simply use the logarithm of real total transfers.

At the parent and child level, we have to make an additional assumption, since we do not observe how parent and child districts shared transfers pre-split. Specifically, we assume that parent and child districts get their initial 2000 population share of the original district transfers and use these values up to and including the year of the split. For all subsequent years, we use actual realized transfers at the lower level, imputing any missing values using the prior years value and median growth rates.

Light Intensity

Fraction of District Area Covered by Lights: We use night lights in 2000 from (see National Centers for Environmental Information, National Oceanic and Atmospheric Administration, 2013) as a proxy for initial GDP (Henderson, Storeygard and Weil, 2012). We have data on the coverage of each village by any lights in 2000, and take the average percentage coverage across villages at the original district and eventual, 2010, borders.

Other Variables

Climate: We compute the population weighted average rainfall and temperature from 1948 to 1978 using village level information computed from the rainfall and temperature records produced by the UDEL team (see Willmott, Matsuura and Legates, 2012*a*,*b*).

GIS Data: We compute the logarithm of the population weighted average distance to the nearest road, to the coast, and to the nearest river. We also compute the logarithm of elevation (30 as), and the ruggedness of the terrain (RUGGED3). We include the population weighted average forest coverage in 2000. Finally we include detailed indicators for the slope of the terrain (slope 1–8). See Bazzi et al. (2016) for details on the underlying sources and construction.

Cash Crop Share: We use the 2003 *Podes* (see Badan Pusat Statistik, 2000, 2013, 2011) to calculate the value (price $\times$ quantity) of each crop produced within the 2000 and 2010 district borders. To proxy for agricultural resources, we compute the fraction of district agricultural output that is composed of nearly 30 cash crops, the most important among which include palm oil, rubber, coffee, and cocoa.

Party Vote Share Polarization: We use the 1999 parliamentary (proportional system) vote shares for all 48 political parties at the subdistrict level to construct a measure of party polarization at the original district and eventual 2010 borders level. The measure for a given district is given by $\sum_i \sum_j \text{share}_i^2 \text{share}_j$ over each party i and j. The underlying data was graciously shared by Audrey Sacks who collected this information by hand from the GEC.

Time Varying Transfers and Distance

Δ Distance: Using *Podes* 2002 and *Podes* 2011 (see Badan Pusat Statistik, 2000, 2013, 2011), we calculate the population-weighted average distance (in km) to the district capital across villages within the eventual parent and child units. At the child and parent level we construct Δ Distance as the difference in the natural logarithm of reported distance to the capital in 2011 less that in 2002. At the original district we take the average of these measures across parent and children, weighted by district population.

Δ Transfers: We use the information from DAPOER on total transfers less own revenue (which encompasses the general and specific allocation grants and all tax and natural resource sharing). As discussed above, we impute missing values using median annual growth rates and we adjust for inflation. At the original district level, we compute Δ Transfers as the change in the logarithm of real transfers post-split. We compare the average post-split to the average pre-split (including the year of the split).

We do not observe how parent and child districts shared transfers pre-split. So for the child and parent level we assume original district transfers were divided according to the child/parent's population share in all pre-split years and in the year of the split.Thereafter, we use actual realized transfers at the lower level, imputing any missing values using the prior years value and median growth rates. Similar to the original district level, we then construct Δ Transfers as the change in the average logarithm of real transfers post-split to that pre-split.

References

Badan Pusat Statistik. 2000. "Sensus Penduduk." Obtained from SMERU Research Institute through Data Sharing Agreement, March 2010.

Badan Pusat Statistik. 2000, 2013, 2011. "Potensi Desa." Obtained from SMERU Research Institute through Data Sharing Agreement, March 2010.

Barron, P., A. Engvall, and A. Morel. 2016. "Understanding Violence In Southeast Asia: The Contribution of Violent Incidents Monitoring Systems." *The Asia Foundation Working Paper*.

Bazzi, S., A. Gaduh, A. Rothenberg, and M. Wong. 2016. "Skill Transferability, Migration, and Development: Evidence from Population Resettlement in Indonesia." *American Economic Review*, 106(9): 2658–98.

Bazzi, S., and C. Blattman. 2014. "Economic shocks and conflict: Evidence from commodity prices." *American Economic Journal: Macroeconomics*, 6(4): 1–38.

Belloni, A., V. Chernozhukov, and C. Hansen. 2014. "Inference on treatment effects after selection among high-dimensional controls." *The Review of Economic Studies*, 81(2): 608–650.

Belsley, David A, Edwin Kuh, and Roy E Welsch. 2005. *Regression diagnostics: Identifying influential data and sources of collinearity.* Vol. 571, John Wiley & Sons.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. "How much should we trust differences-in-differences estimates?" *Quarterly Journal of Economics*, 119(1): 249–275.

Bollen, K. A., and R. W. Jackman. 1990. "Regression diagnostics: An expository treatment of outliers and influential cases." *Modern methods of data analysis*, 257–291.

Burbidge, J. B., L. Magee, and A. L. Robb. 1988. "Alternative transformations to handle extreme values of the dependent variable." *Journal of the American Statistical Association*, 83(401): 123–127.

Cameron, A. C., J. B. Gelbach, and D. L. Miller. 2008. "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics*, 90(3): 414–427.

Conley, T. G. 1999. "GMM estimation with cross sectional dependence." *Journal of Econometrics*, 92(1): 1–45.

Esteban, J., and D. Ray. 2011a. "Linking conflict to inequality and polarization." *American Economic Review*, 101(4): 1345–1374.

Esteban, J., L. Mayoral, and D. Ray. 2012. "Ethnicity and conflict: An empirical study." *American Economic Review*, 102(4): 1310–1342.

Fearon, J., and A. Hoeffler. 2014. "Benefits and Costs of the Conflict and Violence Targets for the Post-2015 Development Agenda." *Conflict and violence assessment paper, Copenhagen Consensus Center*.

Fryer Jr., R. G., and R. Holden. 2011. "Measuring the Compactness of Political Districting Plans." *Journal of Law and Economics*, 54(3): 493–535.

Harish, S. P., and R. Toha. 2017. "A New Typology of Electoral Violence: Insights from Indonesia." *Terrorism and Political Violence*, 1–25.

Henderson, J. V., A. Storeygard, and D. N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review*, 102(2): 994–1028.

Kobayashi, H. 2011. "Civic Associations, Local Governance and Conflict Prevention in Indonesia." PhD diss. University of Southern California.

MacKinnon, J. G., and M. D. Webb. 2019. "Wild bootstrap randomization inference for few treated clusters." In *The Econometrics of Complex Survey Data: Theory and Applications*. 61–85.

Martinez-Bravo, M., P. Mukherjee, and A. Stegmann. 2017. "An Empirical Investigation of the Legacies of Non-Democratic Regimes: The Case of Soeharto's Mayors in Indonesia." *Econometrica*, 85(6): 1991–2010.

National Centers for Environmental Information, National Oceanic and Atmospheric Administration. 2013. "Version 4 DMSP-OLS Nighttime Lights Time Series." https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html, Accessed June 11, 2013.

Sundberg, R., and E. Melander. 2013. "Introducing the UCDP georeferenced event dataset." *Journal of Peace Research*, 50(4): 523–532.

Willmott, C.J., K. Matsuura, and D. Legates. 2012*a*. "Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series (V 3.01)." http://climate.geog.udel.edu/~climate/html_pages/download.html, Accessed June 11, 2013.

Willmott, C.J., K. Matsuura, and D. Legates. 2012*b*. "Terrestrial precipitation: 1900-2010 Gridded Monthly Time Series (V 3.01)." http://climate.geog.udel.edu/~climate/html_pages/download.html, Accessed June 11, 2013.

Wilson, I. D. 2015. *The politics of protection rackets in post-New Order Indonesia: Coercive capital, authority and street politics.* Vol. 47, Routledge.

World Bank. 2013. "Indonesia Database for Policy and Economic Research." https://datacatalog.worldbank.org/dataset/indonesia-database-policy-and-economic-research, Accessed March, 2015.

World Bank Indonesia. 2014. "Sistem Nasional Pemantauan Kekerasan." https://microdata.worldbank.org/index.php/catalog/2626, Accessed May, 2019.

Young, A. 2016. "Improved, nearly exact, statistical inference with robust and clustered covariance matrices using effective degrees of freedom corrections." London School of Economics Unpublished Manuscript.