The Political Boundaries of Ethnic Divisions*

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Abstract

Policymakers in diverse countries face the persistent challenge of managing ethnic divisions. We argue that redrawing subnational political boundaries can fundamentally reshape these divisions. We use a natural policy experiment in Indonesia to show that changes in the political relevance of ethnic divisions have significant effects on conflict in the short- to medium-run. While redistricting along group lines can increase social stability, these gains are undone and even reversed in newly polarized units. Electoral democracy further amplifies these effects given the large returns to initial control of newly created local governments in settings with ethnic favoritism. Overall, our findings show that the ethnic divisions underlying widely-used diversity measures are neither fixed nor exogenous and instead depend on the political boundaries within which groups are organized. These results illustrate the promise and pitfalls of redistricting policy in diverse countries where it is not feasible for each group to have its own administrative unit.

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1 Introduction

Ethnic divisions are a persistent source of instability in diverse countries. Interethnic tensions are widely associated with weak public goods provision and conflict (Alesina et al., 1999; Easterly and Levine, 1997; Esteban et al., 2012; Montalvo and Reynal-Querol, 2005). With few exceptions, the longstanding literature on diversity offers mostly pessimistic conclusions. As such, it remains unclear whether and how governments can use policy tools to reshape ethnic divisions.

The redrawing of subnational boundaries offers one compelling opportunity. Changing political boundaries can reshape incentives for group mobilization and hence the scope for certain ethnic divisions to matter more than others. Pioneering work on ethnicity and conflict recognized this possibility (Horowitz, 1985), and the global proliferation of administrative units over the last 30 years of decentralization offers a unique opportunity to provide some of the first empirical evidence on this hypothesis. This massive wave of redistricting constitutes perhaps the largest shift in the locus of politics since the creation of new nation states after World War II.[1] While policymakers often support political reorganization to placate interethnic grievances (see Brancati, 2009), both theory and case studies suggest that the implications for ethnic divisions and conflict are far from obvious.

The key contribution of this paper is to show that political boundaries endogenously determine ethnic divisions. We exploit a natural policy experiment in Indonesia to estimate the effects of redistricting on conflict. Where feasible, creating homogenous new political units reduces violence. Yet, in practice, redistricting along group lines is rarely so simple and may instead foster new divisions. Indeed, we show that the potential gains in stability are often undone and even reversed in areas where new group divisions become salient and polarizing.[2] Even without any changes in the local population, new local government boundaries reconfigure which ethnic divisions are politically relevant. This changes the way that different groups interact and compete. In newly polarized settings, the ensuing electoral contests to control valuable public resources further amplify incentives for violence and may give rise to fresh cycles of conflict lasting beyond the first few years after redistricting.

Indonesia offers a rich setting to study changes in ethnic divisions and conflict. First, like many other new democracies, political violence remains a major policy concern (Butcher and Goldsmith, 2017). After the fall of a highly centralized, authoritarian regime, many feared the diverse country would break apart as local conflicts tore at ethnic, religious, and regional seams. These large-scale internecine conflicts have subsided, replaced by more sporadic outbursts of low-intensity social conflict and recurring electoral violence. Amplified by decentralization, ethnic mobilization around elections and political patronage are pervasive.[3] Meanwhile, institutional constraints on violence remain relatively weak. While distinct from civil wars, these outbreaks of local conflict may accumulate over time and also exert lasting adverse

[1] Grossman and Lewis (2014) document the global pervasiveness of this phenomenon across all levels of administration. For example, from 1990 to 2010, Nigerian states increased from 22 to 37, Ugandan districts from 34 to 112, and Kenyan districts from 47 to 70. Czechoslovakia and Hungary increased their municipalities by 50 percent from 1989 to 1993. Brazilian municipalities increased from 3,974 in 1980 to 5,560 in 2000. Vietnam increased its provinces from 40 to 64 from 1996 to 2003.

[2] Consider, for example, two minority groups that break away to form their own district. Previously pitted together against a larger majority, these two groups now face fresh incentives for conflict in the newly polarized district.

[3] Aspinall (2011, p. 298) notes that, "Since the introduction of direct local government head elections, there has been a shift in favor of alignment between the ethnic identity of local government heads and the local populations they govern. Electoral winners tend to be drawn from the largest ethnic group in the district or province." We provide further qualitative context in Appendix F.1, which also shows that greater diversity within newly created district boundaries is associated with closer elections and stronger individual preferences for politicians' ethnicities and patronage.

effects by eroding trust in the political process (Dercon and Gutiérrez-Romero, 2012), by undermining local institutions (Michalopoulos and Papaioannou, 2013), by weakening social capital and deepening ethnic cleavages (Dower et al., 2017; Rohner et al., 2013a), and by planting the seeds for more serious, future conflict (Rohner et al., 2013b).

Second, the Indonesian context allows us to overcome a host of endogeneity and measurement challenges typically associated with identifying the effects of changing political boundaries. Decentralization reforms beginning in the late 1990s led to a dramatic increase in the number of district governments across the archipelago from 302 in 1999 to 514 in 2014 (see Figures 1 and 2). Motivated by a desire to reduce sociopolitical tensions, the central government created a very favorable environment for such redistricting.[4] This allows us to rule out first order concerns about strategic violence aimed at achieving or preventing certain types of partitions. Moreover, we show that an abrupt centrally-imposed moratorium between 2004 and 2006 generates plausibly exogenous variation in the timing of redistricting across locations.[5] We exploit this staggered process in a generalized difference-in-difference framework.

Using universal Population Census data from 2000, we construct measures of how homogenized the new, smaller districts are relative to the original district based on the same, initial populations. Indonesia is home to over 1,000 self-identified ethnic groups, allowing us to distinguish two key measures in the literature: fractionalization and polarization. Ethnic fractionalization (F), which captures the likelihood of meeting someone outside your group, declines substantially on average at the original district level. However, some of the newly drawn borders encompass fewer, large groups, thereby increasing ethnic polarization (P), which also captures differences in preferences across groups proxied by language. Indeed, while homogenization was an objective of redistricting in many areas, policy constraints directly limited the feasible changes in diversity. We isolate these constraints to show that the cross-district variation in feasible redistricting schemes drives the changes in diversity and conflict.

We estimate the effects of these changes in ethnopolitical boundaries on conflict using new data developed by the Indonesian National Violence Monitoring System. Based on systematic coding of print newspaper archives, the data capture over 230,000 violent incidents at a high spatial and temporal frequency from 2000 to 2014. While limited initially to high-conflict regions, these data offer much more comprehensive coverage than other conflict data for Indonesia and rival some of the richest geospatial event-based sources in sub-Saharan Africa and South Asia (e.g., ACLED) in terms of depth and detail. Reported events include, for example, attempts to influence the allocation of resources and express popular dissatisfaction with local governance (Barron et al., 2014). Vigilantism and public mobilization along ethnic lines are common (Wilson, 2015) as is strategic violence around elections (Harish and Toha, 2017).

Despite policymakers' goals, redistricting does not change the average incidence of social conflict. This somewhat surprising finding can be explained by heterogeneous changes in ethnic divisions. Reductions in conflict in newly homogenous units are offset by increases in newly polarized units. Our estimates suggest that political boundaries can explain around half of the endogenous long-run correlation between ethnic polarization and conflict in the cross-section.[6] These changes arise in both the *parent*

[4] Mietzner (2014, p. 62) notes that decentralization "was designed to secure the long-term survival of the nation-state by reconciling the regions with a capital that had systematically undermined their local identities since the 1950s." And Aspinall (2013, p. 39) notes that the policy "rationale for creating a new district out of an old one is to provide an administrative home for a local ethnic or sub-ethnic group that lives in a concentrated area and to ameliorate tension with other groups."

[5] We build upon Burgess et al. (2012) who use similar variation in their study of deforestation externalities due to redistricting.

[6] We discuss additional benchmarking exercises in Section 5.3.

district, which retains the original seat of government, and the *child* district, which acquires a new local government and capital (see Figure 3 for an example). Robustness checks rule out other confounding effects of redistricting and changes in media attention. Overall, the abrupt reconfiguration of the diverse electorate gives rise to fresh incentives for violence that are amplified in polarized settings.

These border-induced changes in ethnic divisions may have persistent effects on conflict as a result of political cycles. Violence ratchets up around the first mayoral elections, particularly where they are closely contested. New ethnic divisions, and polarization in particular, exacerbate violence around these initial elections, particularly in child districts where the stakes are high given the fundamental role of the initial administration in establishing the new government and its first budget. Moreover, this amplification effect persists into the next election five years later and also drives violence in intervening periods, pointing to new cycles of political conflict. The more pronounced cycles in child districts are consistent with differences in the scale of changes in contestable public resources but may also point to nascent differences in local state capacity. Ethnic favoritism helps rationalize electoral violence and perpetuate grievances, a mechanism we validate using nighttime light intensity to capture village-level changes in access to publicly-provided electricity after redistricting.

Our results line up nicely with case studies in Indonesia. Our case study of redistricting in West Kalimantan in Section 6.3 illustrates how border-induced changes in ethnic divisions can reshape conflict. Diprose (2009) offers similar insights on Central Sulawesi as do Nolan et al. (2014) on Papua, noting that "local elections in relatively new districts can exacerbate existing social fault lines." Wilson (2015, p. 33) nicely summarizes the general context, arguing that redistricting "created confusion regarding lines of authority" and "involved renegotiating the boundaries of collective identities" as "local government bureaucratic precincts were altered, and some networks of resource distribution that relied upon state agents were disrupted or excluded by these shifting boundaries." As a result, "ethnic identities have been politicised as clientilistic networks. . . mobilising support along communal lines." Of course, conflict is by no means a foregone conclusion. However, by localizing political contestation, redistricting may make it easier to solve collective action problems that might otherwise forestall violence.

Similar findings may be at play outside Indonesia as well. In Uganda, for example, Green (2008) argues descriptively that "the huge expansion in the number of new districts has led to local-level conflict by altering relations between local ethnic groups." Although dramatic, the wave of redistricting we study is comparable in scale and purpose to efforts across sub-Saharan Africa, Asia, and Eastern Europe (see Grossman and Lewis, 2014; Grossman et al., 2017). A small but growing political science literature examines this process, documenting similar institutional underpinnings (see Pierskalla, 2016a, for a survey). In diverse countries, as in Indonesia, the resulting shift in the locus of politics can fundamentally change relevant group boundaries. How these changes affect incentives for conflict is very much an open question to which the Indonesian setting is uniquely well suited to answer.

Related Literature. This paper makes several contributions to the political economy literature. Our central contribution is to show that subnational borders can reshape ethnic divisions and conflict. We argue that the ethnic divisions underlying widely-used diversity measures are neither fixed nor exogenous and instead depend on the political boundaries within which groups are organized. Case studies as well as lab and survey experiments across Africa find that interethnic preferences are context-dependent (Berge et al., 2015; Eifert et al., 2010; Habyarimana et al., 2007; Lowes et al., 2015; Posner, 2004), and

Blouin and Mukand (forthcoming) and Yanagizawa-Drott (2014) show that public media can manipulate these preferences. We show that subnational boundaries are a policy choice that can change ethnic cleavages by reorienting which groups are relevant to one's own.[7] While prior literature has recognized this political endogeneity of ethnic divisions (see Fearon, 2006), we provide the first empirical test using border changes. Our findings highlight important policy tradeoffs and demonstrate how electoral democracy may hasten the deepening of new ethnic divisions.

While Esteban and Ray (2011a) and Esteban et al. (2012) study the equilibrium relationship between diversity and conflict, we identify the transition path to a new equilibrium as underlying ethnic divisions change. In this respect, our findings are similar to Amodio and Chiovelli (forthcoming) who show that abrupt, migration-induced changes in local polarization exacerbate conflict in post-Apartheid South Africa. Our effect sizes are smaller. This is intuitive because their results are based on changes in the underlying population, which introduces new groups and non-ethnic divisions (e.g., immigrant–native). By comparison, we hold the underlying population fixed and simply reorient the relevant group divisions within new boundaries. This is important from a policy perspective because barriers to mobility often limit Tiebout (1956) sorting that might otherwise help neutralize social frictions linking local diversity to conflict.

We argue that redistricting provides a compelling setting to test the hypothesized distinction between fractionalization and polarization in new theories of diversity and conflict. Esteban and Ray (2011a) show that in conflict over public goods (e.g., political power), polarization should be relatively more important as it captures differences in intergroup preferences and the strength of in-group ties.[8] For conflict over private goods (e.g., natural resources), however, fractionalization should matter more as the per capita spoils are rival. Esteban et al. (2012) provide supportive cross-country evidence using rough proxies for the relative publicness of resources within countries. Redistricting and local government proliferation offer a more precise public resource shock. We find that polarization matters relatively more than fractionalization. We also find that polarization matters more in child than parent districts, consistent with differences in the scale of the local shock to public versus private resources.

On a practical level, we build on arguments for basing measures of diversity on group divisions relevant to the nature of contestation. Our results suggest that the growing number of studies exploiting subnational variation in diversity should use spatial boundaries at levels of aggregation that are outcome-relevant.[9] This echoes recent work arguing that local diversity can have different effects than diversity at the aggregate, country level given the different nature of interaction within and between

[7]In this respect, our identification strategy is somewhat akin to Hjort (2014) who uses the random assignment of workers to ethnically mixed teams to understand how diversity shapes productivity in a flower plant in Kenya around a period of national interethnic strife. Hence, our notion of time-varying diversity is distinct from variation due to migration or differential mortality and fertility, which may be confounded with a host of other factors whose effects on conflict are of separate interest.

[8]Spolaore and Wacziarg (2017) make similar points in a related setup with the additional insight that contests over rival goods may be more likely between groups with similar preferences, a prediction borne out empirically when examining international conflict, which typically involves contestation of private resources such as oil (Caselli et al., 2015; Spolaore and Wacziarg, 2016). Other models of conflict emphasize the conditions giving rise to mobilization along ethnic as opposed to other group lines (e.g., Caselli and Coleman, 2013; Esteban and Ray, 2008, 2011b). Consistent with some of these predictions, our results highlight the important role of ethnic markers in mobilizing around newly contestable local politics.

[9]As better data on subnational diversity become available (e.g., Gershman and Rivera, 2016), it is tempting to take the analysis to increasingly granular geography. This might be appropriate for questions about intergroup contact and preferences but perhaps less appropriate for studying conflict if the resources being contested are determined and allocated at higher levels of administration. This is in line with the warning by Michalopoulos and Papaioannou (2017) regarding the modifiable areal unit problem (MAUP) in the use of spatial data where results depend on the level of aggregation.

jurisdictions (Alesina and Zhuravskaya, 2011; Desmet et al., 2016; Montalvo and Reynal-Querol, 2017).

Furthermore, we add causal evidence to the literature on optimal borders. The unique policy context in Indonesia allows us to take the complex determinants of administrative boundaries as given and focus on investigating its consequences. Alesina et al. (2011) and Michalopoulos and Papaioannou (2016) identify adverse long-run effects of arbitrary, post-colonial partitioning of ethnic groups across national borders. In the era of democracy and decentralization, one remedy might be to allow for subnational borders to be formed from the bottom-up. Our findings suggest that if not designed properly, redistricting schemes may also have unintended adverse consequences for social stability.

Finally, we add to a large literature on ethnic divisions and public goods (e.g., Burgess et al., 2015; Miguel and Gugerty, 2005) by taking a step back to investigate conflict over control of the institutions that allocate those goods. Our results suggest that violence may be informative about the tradeoff between population homogeneity and scalable public goods provision in redistricting schemes.

Roadmap. Section 2 details the context of decentralization and district proliferation in Indonesia. Section 3 presents motivating evidence on diversity and conflict and a conceptual framework showing how redistricting can reshape ethnic divisions. Section 4 proposes measures of border-induced changes in diversity and presents the new conflict data. Section 5 develops the empirical strategy and core results. Section 6 identifies electoral mechanisms linking the changing ethnic divisions to new conflict dynamics. Section 7 concludes with a discussion of policy implications and future research.

2 Background: Local Government Proliferation

The number of districts in Indonesia increased by nearly 70 percent over a 15 year period. This background section details the central role districts play in government, key features of the redistricting process, and the fundamental changes in the scope of government that follow. For reference, Appendix Figure A.1 provides a timeline of key events discussed below.

2.1 Decentralization and the Transfer of Power to District Governments

Indonesia has four main tiers of government. The largest tier is the province, of which there were 34 in 2014. Provinces are divided into districts known as *kabupaten* in rural areas and *kota* in urban areas. In 2014, there were 514 districts. Districts are in turn divided into 7,094 subdistricts (*kecamatan*), which are further subdivided into more than 80,000 villages, the smallest unit of government.

The resignation of President Suharto in May 1998 ushered in a wave of decentralization reforms that shifted the balance of power away from the central government and provinces and towards the districts. Effective January 2001, districts assumed responsibility for nearly all public policy with the exception of the few areas naturally reserved for the central government (e.g., foreign affairs, fiscal and monetary policy). Accordingly, districts assumed extensive decision-making power over local expenditures.

District heads or mayors, known as *bupati* and *walikota*, supervise the budget process, amalgamating spending requests from lower levels of government and submitting the final budget to local parliament for approval. The district executive plays a significantly larger role than local parliament in determining the composition and allocation of public goods (see Lewis, 2017b; Martinez-Bravo et al., 2016).[10] While parliamentarians remain important, they tend to be less individually accountable than mayors and more beholden to national party politics than to the local population (Lewis, 2017a).

Major electoral reforms also accompanied decentralization. Previously appointed by the central government, district heads were now elected via majority vote by members of the local parliament, who were in turn popularly elected according to a closed-list proportional representation system. Democracy deepened further in 2005 as district heads and their running mates were now directly elected via plurality/majority voting. Given the power of the district executive, these quinquennial mayoral elections, which occur at different times across districts, are a focal point of local political contestation.[11]

2.2 Creating New Districts

Until the late 1990s, district boundaries were relatively stable (Booth, 2011). Many boundaries originated under colonial rule when the Dutch used local leaders for indirect rule. In practice, these administrative divisions spanned large swathes of territory with many different groups (Cribb, 2013). Post-independence, new districts arose with the goal of uniform population (Charras, 2005). However, due to imbalances in population density across islands, many districts continued to span large areas and multiple ethnic homelands. These expansive, arbitrary (post-)colonial boundaries remained largely in place until the fall of Suharto, when subsequent governments facilitated dramatic redrawing of the district map. The number of districts ballooned from 302 in 1999 to 514 in 2014 (see Figure 1) through a process known colloquially as *pemekaran* or blossoming.

Redistricting Process. Subdistricts break off from their original district to create new districts. After a split, the *original district* is divided in (at least) two: The single *parent district* contains the original district name and capital with pre-existing institutions. The *child* district(s) receives a new name, capital, district head, parliament, and government apparatus. Figure 3 provides an example of this distinction with the original district of Aceh Tenggara splitting into the parent of Aceh Tenggara and the child of Gayo Lues. This also highlights the fact that original districts split up along contiguous, pre-existing subdistrict lines.

Local elites and interest groups initiate the action to split in accordance with a redistricting law passed in 2000. The regulation stipulates that new districts must have: (i) at least three subdistricts, (ii) support among the original district mayor and parliamentarians, and (iii) demonstrated socioeconomic capacity in terms of basic public goods and economic infrastructure.[12] We discuss these policy constraints in Section 4.1 as they determined the scope of feasible changes in ethnic divisions.

For identification purposes, we focus on the wave of redistricting from 2001–3 and 2007–8.[13] The

[10]Mayors also appoint all subdistrict heads beginning in 2004 and have long appointed village heads in urban areas (Martinez-Bravo, 2014). These local officials play important roles in local public goods provision by navigating relations with the district government where the resources initially flow from the center (see, e.g., Section 6.2 on electricity). They also play an important role in mobilizing voters around elections, effectively greasing the patronage politics discussed in Section 3.

[11]As Aspinall (2011, p. 305) notes, decentralization "shifted state resources and hence the focus of political contestation down toward the base of the political system." Booth (2011, p. 46) argues, "Certainly the devolution of resources to the district level, where it has occurred has made the job of district head. . . very attractive to those who in the past had only managed to achieve lower-level positions in provincial or regional bureaucracies, or who had been largely excluded from official positions."

[12]Given the favorable returns to parent and child districts (see below), splitting proposals were generally widely supported by original district parliamentarians who represent constituencies in both areas prior to redistricting (Pierskalla, 2016b).

[13]The redistricting in 1999 occurred before the new government regulation on *pemekaran* and substantively differs from later

central government twice stopped the redistricting process via national moratoria, the first of which occurred from 2004–6 and the second from 2009–2012 as clearly seen in Figure 1.[14] In both cases, the duration and enforcement of the ban was uncertain. Indeed, applications for new districts continued to arrive at the national parliament with more than 100 proposals at various stages of completion awaiting consideration in 2005–6 (BAPPENAS, 2007). Our main empirical strategy, which builds on Burgess et al. (2012), exploits this first moratorium by comparing districts that split around this policy shock. What is crucial for our identification is that the timing of redistricting is not driven by trends in conflict or correlated factors therein.[15] Section 4 provides supportive evidence.

Changes in Local Government. To understand how redistricting reshapes local government, a brief timeline is instructive. After a new child district is ratified, an interim executive along with local parliamentarians oversee the transition process with a focus on the first mayoral election. On average, those quinquennial elections first take place within 21 months after redistricting. The mayor is then tasked with operationalizing and staffing up to 30 new local government agencies in the new capital. By this time, roughly two years after redistricting, central government transfers have begun flowing into child district coffers. Local public expenditures begin increasing shortly thereafter, taking similar shape as in other districts with around 40–50 percent of spending on personnel. In the parent district, elections take place on the same local, five-yearly timeline as they would have absent redistricting, but in the meantime, local institutions undergo restructuring as the governed area and populace change.

Taking the original district as a whole, there are considerable gains to redistricting in terms of political representation and public resources as shown in Appendix A. First, most child district residents experience a significant reduction in distance to government representatives and institutions in the district capital. Second, the number of legislators per capita always (weakly) increases with redistricting due to apportionment rules. Third, fiscal allocation rules imply a significant, roughly 20 percent long-run increase in annual transfers, relative to a base of around 200 USD per capita. While the scale of changes in local government may differ between parent and child districts, the significant shock to politically-relevant ethnic divisions is shared by residents of both. We describe these changes and their potential implications for violence in the following sections.

3 Conceptual Framework: The Political Boundaries of Ethnic Divisions

Implicit in much of the literature on diversity is the notion that ethnic divisions are shaped by political boundaries. The scope for ethnic mobilization and patronage networks depends on the size and cohesion of groups *within the electorate*. This suggests that by changing political boundaries, redistricting has the

rounds of redistricting. Several were long-standing requests from the Suharto era, and others were initiated by the central government (Fitrani et al., 2005). These areas only enter our main analysis if they later split again.

[14] The primary stated reason for the moratoria was the drain on fiscal resources and lack of capacity to meet the staffing needs of new child district governments. Upon lifting the first moratorium, the government tightened the law on redistricting by increasing the minimum number of subdistricts to five and requiring original districts to have existed for at least seven years.

[15] Note that this design does not exploit variation from districts that never split. This prioritizes internal over external validity, a tradeoff we discuss further in Section 5.5. Prior studies identify incentives for creating new districts, including efficiency gains in the provision of public goods, ethnic homogenization, and rent seeking (see Fitrani et al., 2005; Nolan et al., 2014; Pierskalla, 2016b). While we find similar evidence, what's important for identification is that these underlying incentives do not predict early versus later timing of redistricting.

potential to reshape these intergroup divisions and, in turn, social tensions and conflict. But whether this actually happens, and how quickly it happens in practice, is unclear and yet crucial for informing policy. In the remainder of this section, we provide motivating evidence on diversity and conflict in Indonesia and then propose a simple conceptual framework showing how redistricting can change the ethnic divisions underlying this relationship.

3.1 Motivating Evidence on Diversity and Conflict in Indonesia

Ethnic diversity has long been associated with adverse social consequences ranging from weaker social capital to greater conflict. Since the seminal book by Horowitz (1985), researchers have identified these relationships across many countries.

Similar patterns hold in Indonesia. Indeed, in the late 1990s, ethnic divisions were a factor in major conflicts across the archipelago, including, among others, separatist movements in Aceh and Papua, communal violence in Maluku and Central Sulawesi, and political violence in West and Central Kalimantan (Barron et al., 2014).[16] Consistent with these pervasive divisions, Mavridis (2015) shows that residents of more ethnically diverse districts exhibit lower generalized trust and less community participation. Even as many of the most intense conflicts subsided by the mid-2000s, ethnicity remained a key vehicle for political mobilization across the country (see Allen, 2014; Aspinall, 2011; Fox and Menchik, 2011). The introduction of direct majority/plurality elections for mayors reinforced this tendency.[17] Indeed, we show in Appendix F.1 that electoral competition is much stiffer in diverse districts, where fractionalization and polarization are associated with narrower victory margins, especially in newly created districts. Relatedly, clientelism and patronage pervade local politics, with patronage networks often based on local ethnic identities and intermediated by lower-level officials such as village heads (Aspinall, 2013; Aspinall and Sukmajati, eds, 2016).

As in other countries, these ethnic group dynamics occasionally manifest in conflict. Ideally, group-based contests over distributive goods occur peacefully through the political process. However, in settings with weak institutions (e.g., newly democratic countries), violence may be an effective means of influencing elections or the allocation of public resources. These low-intensity, localized bouts of violence are prevalent in modern Indonesia.[18] While distinct from full-blown civil war, these episodes of violence are a major policy concern given their potential to undermine efforts to build local state capacity and to snowball into more systematic, large-scale conflict.

Using new data detailed in Section 4.2, we document a strong positive correlation between ethnic

[16] Like Fearon (2006), we view ethnicity as determined by descent but subject to politics and history and not merely biological. In the Indonesian context, religious identity tends to be much more of a choice variable than ethnic identity. Some of the communal violence in the late 1990s and early 2000s was widely seen at the time as religiously grounded, but revisionist accounts increasingly view those conflicts as ethnically organized (Schulze, 2017).

[17] Ethnic or regional political parties are effectively banned in Indonesia due to a host of legal requirements implemented with democratization in 1999, mandating that political parties must have widespread geographic coverage—in terms of institutional presence—in order to be eligible to contest elections (see Hillman, 2012, for details). Nevertheless, mobilization along identity lines in local elections is widespread (see Aspinall, 2011, and associated quotes in the introduction). At the same time, class cleavages and family dynasties are less important in local politics than elsewhere in Southeast Asia (see Aspinall and Asad, 2016).

[18] For example, Tadjoeddin (2012) finds that violence occurred in 23 percent of the first direct mayoral elections between 2005–2007. Harish and Toha (2017) show that conflict around local elections is a persistent problem. They classify over 1,000 electoral violence episodes into voter-targeted, candidate-targeted, and government-targeted. We provide examples using our data in Section 4.2 and discuss their findings in Appendix B.2.

diversity—as measured by either fractionalization or polarization—and the incidence of conflict in Indonesian districts since 2000 (see Appendix C). Simple regressions suggest that a one standard deviation increase in fractionalization (polarization) is associated with a 15 (8) percent increase in the likelihood of conflict. We discuss similar correlations in other settings when benchmarking the causal effects of border-induced changes in diversity in Section 5.3.

3.2 A Simple Model

We present here a simple conceptual framework to clarify how redistricting can change the ethnic divisions linking diversity to conflict. We focus on what Ray and Esteban (2016) call *social conflict* that is often organized around groups. Esteban and Ray (2011a) formally model the equilibrium effects of diversity on group-based conflict over rival (private) and non-rival (public) goods. They note that political power is a leading example of contestable public goods, and, for exposition purposes, we emphasize as much given the implications of redistricting. They show that in a contest over a purely public resource, the level of per capita conflict is increasing in group polarization, the value of the resource, and within-group cohesion. We use a vastly simplified two-group model below to frame our discussion of how redistricting affects violence by changing political boundaries.[19]

Baseline Setup. Suppose an original district $\mathcal{O}$ is composed of two groups with population G_1 and G_2 and total population $G = G_1 + G_2$. Denote by g_i the share of group i in the population (e.g., G_1/G). These groups compete over a public prize. The prize, being non-excludable and non-rival, is not diminished by group size, but the winner of the contest gets to choose the mix of public goods that their group prefers. We assume the winner chooses a level that provides their own group with value R per person and the other group with 0. The leader of each group i chooses total violence V_i given its per unit cost γ. The probability of group i winning control over the public prize is given by the contest function $\frac{V_i}{V_1+V_2}$. Each group leader chooses V_i to maximize per capita payoffs. That is, each group i, taking as given the other's choices V_{-i}, maximizes $\left(\frac{V_i}{V_1+V_2}R - V_i\frac{\gamma}{G_i}\right)$.

The Nash equilibrium level of conflict per capita, $\frac{V}{G} = \frac{V_1+V_2}{G_1+G_2}$, is given by $\frac{V}{G} = g_1 g_2 \left(\frac{R}{\gamma}\right)$. Thus, total violence per capita in the district depends on the value of the public prize R, the costs of conflict γ and a measure of diversity, $g_1 g_2$, which is greatest when both groups are of equal size. For two groups, this measure equals $0.5\times$ a standard fractionalization measure.

Effects of Redistricting. Models of conflict over a public good implicitly assume that the boundaries of the contest are fixed. In practice, though, the boundaries of local government are a policy choice. If the primary source of conflict is over the control and distribution of local public resources, then changes in the borders of the electorate should have ramifications for conflict. Here we trace out the implications of changing borders on conflict under the assumption that splitting creates new, separate contests in parent and child districts.[20]

Under these assumptions, changes in conflict within the original district boundaries are directly linked to changes in diversity. Conflict within each of the new districts will now be a function of the

[19] We thank Enrico Spolaore for suggesting this setup.

[20] Consistent with this assumption, the conflict data detailed in Section 4.2 suggest very little cross-border violence before or after redistricting in our setting ($< 0.1\%$ of all events).

diversity *within* each new area. Assume for now that winning the prize continues to yield R per person within group and 0 otherwise and that the costs of conflict remain unchanged. Using $\mathcal{P}$ to denote the parent and $\mathcal{C}$ the child district, the change in total violence per-capita at the original district level is:

$$\frac{\Delta V}{G} = \left(\frac{G_{\mathcal{P}}}{G} g_{\mathcal{P},1} g_{\mathcal{P},2} + \frac{G_{\mathcal{C}}}{G} g_{\mathcal{C},1} g_{\mathcal{C},2} - g_1 g_2 \right) \frac{R}{\gamma}, \tag{1}$$

where $g_{i,j}$ is the share of group j in new district i, and $G = G_{\mathcal{P}} + G_{\mathcal{C}}$. That is, the change in violence per capita is explicitly a function of the difference in the population-weighted average of diversity within the new units relative to the diversity in the original district pre-split. In the event that the groups separate into perfectly homogeneous child and parent districts, all violence in the original district ceases.

This simple model does not attempt to distinguish between ethnic fractionalization and polarization. As written, it suggests using changes in fractionalization, which will always decline with splitting (in population-weighted terms). Yet, this is not the case for polarization. An original district with four equally different groups could split into two districts, each with two similarly sized groups contesting power. In this case changes in polarization would be positive. Esteban and Ray (2011a) show that it is precisely this feature of diversity that is relevant to the conflict over public goods, which can be tailored to the winning group's preferences but not fully excluded from losers. In practice, redistricting sometimes implies tradeoffs between changing fractionalizatioapn and polarization, and we will let the data speak by considering both measures.

It is also interesting to consider changes *within* the new borders. This requires taking a stance on how violence is initially distributed across parent and child. Letting α be the share of total violence falling in the parent district, the change in conflict within the parent district is given by:

$$\frac{\Delta V_{\mathcal{P}}}{G_{\mathcal{P}}} = \left(g_{\mathcal{P},1} g_{\mathcal{P},2} - \alpha \frac{G}{G_{\mathcal{P}}} g_1 g_2 \right) \frac{R}{\gamma}. \tag{2}$$

If violence is initially distributed according to population ($\alpha = \frac{G_{\mathcal{P}}}{G}$), the change in per-capita violence within the eventual parent border is given by the difference in the diversity within that new unit and the overall diversity in the original district.[21] The same holds for child districts.

The model also implies that changes in the value of the public prize (R) or the costs of violence (γ) will change conflict. Redistricting is accompanied by an influx of government resources (R) as well as reductions in the distance to the new capital, which could affect γ. If R/γ increases in the newer units, then this will exacerbate Δ conflict, particularly in newly diverse areas. Adapting the model to incorporate these changes, we find a similar link between changes in diversity and changes in conflict but one that puts greater than population-weight on diversity in the newer units. We opt not to take this simple model too far. Rather, we pursue a reduced form empirical approach that focuses on changes in ethnic divisions as a baseline while incorporating changes in proxies for R and γ for robustness. We also examine differences between parent and child districts, as child districts experience relatively larger changes in R and γ (see Appendix A).

[21]We can test this assumption in the data using the pre-split distribution of violence across parent and child districts. In general, the population weighted share of incidents in the original district is a very good predictor of the actual number of incidents. Children have slightly less incidents than would be expected based on population shares, and consequently parents have slightly more, but these differences are not very large.

4 Data: Measuring Changing Ethnic Divisions and Conflict

This section presents our granular data on ethnic diversity and conflict (see Appendix G for details).

4.1 Border-Induced Changes in Diversity

Indonesia is the fourth most populous country in the world and among its most diverse. More than 1,000 self-identified ethnic groups speaking more than 400 languages span the archipelago. Indonesians are predominantly Muslim (87 percent) with minority Christian, Hindu, and Buddhist groups. From a policy perspective, diversity manifests at different levels of governance but became especially salient at the district level with decentralization. This section shows how redistricting fundamentally changes which group divisions are politically relevant.

We measure diversity using microdata from the universal 2000 Population Census. This data allow us to link the initial subdistricts in 2000 to their final 2010 district boundaries, providing us with measures of diversity at the original, parent, and child district levels. These are all based on the initial population in 2000 and hence not subject to concerns about endogenous sorting in response to redistricting. The 2000 Census was the first since 1930 to record ethnicity, allowing respondents to report a single affiliation. This led to remarkable cultural distinction, capturing over 1,000 self-identified ethnic groups (Ananta et al., 2015).[22] The sub-ethnic variation within broader ethnic groups may be relevant for conflict (Desmet et al., 2017). We also capture deeper interethnic cleavages using linguistic differences (Fearon, 2003).

We focus on two widely-used measures of ethnic diversity. Ethnic *fractionalization* in district d measures the probability that two randomly chosen individuals belong to different groups: $F = \sum_{j=1}^{\mathcal{N}_e} g_j(1-g_j)$, where $\mathcal{N}_e$ is the number of ethnic groups in the district, and g_j is the population share of group j. Given the large number of self-reported ethnic identities, fractionalization is quite high and indeed above 0.5 in many districts we study. Adopting the Esteban and Ray (1994) metric, ethnic *polarization* is given by $P = \sum_{j=1}^{\mathcal{N}_e}\sum_{k=1}^{\mathcal{N}_e} g_j^2 g_k \eta_{jk}$, where η_{jk} is the distance between groups j and k. Polarization aims to capture the deeper cleavages in society and differs from fractionalization in two key respects. First, the squaring of the own-group term emphasizes that stronger within-group identification coincides with greater out-group alienation, which together exacerbate intergroup tensions. As such, polarization is maximized when there are two distinct, equally sized groups. Second, it formally incorporates distances between groups while the standard measure of fractionalization (F) does not. We use linguistic distances and adopt parameter values as in Desmet et al. (2009, 2012) and Esteban et al. (2012) (see Appendix D.7 for details). Although less pervasive, religious divisions may be important in some locations. In what follows, we focus on ethnic diversity but nevertheless incorporate religious diversity in our empirical analysis for robustness.[23]

Changes in Diversity. Prior to redistricting, these measures of diversity at the original district level demarcated the boundaries of politically-relevant ethnic divisions. After redistricting, diversity within

[22] In our average original district, there are 549 distinct ethnic groups with 21 having more than 0.1 percent of the population. Consolidating subgroups based on language reduces these numbers to 271 groups, 18 with more than 0.1 percent.

[23] We account for religious polarization, but lacking an obvious notion of distance, set $\eta_{jk} = 1\ \forall j, k$. Given that most religious diversity implies one sizable non-Muslim group, polarization is nearly identical to fractionalization (rank correlation≈0.99). By comparison, ethnic polarization and fractionalization exhibit lower correlation (<0.2) and are statistically independent.

the new parent and child district boundaries becomes salient. Motivated by our conceptual framework, we propose simple but generalizable measures to capture these changes in ethnic divisions.

We compute the difference between the population-weighted average diversity in the new units and diversity in the original 2000 district. For example, if original district $\mathcal{O}$ splits into parent $\mathcal{P}$ and child $\mathcal{C}$, the change in ethnic fractionalization, $\Delta F = \left(\frac{G_{\mathcal{P}}}{G}F_{\mathcal{P}} + \frac{G_{\mathcal{C}}}{G}F_{\mathcal{C}}\right) - F_{\mathcal{O}}$, where the first term captures the implied F within the new borders. This can be seen as a multi-group generalization of equation (1). By definition, ΔF (weakly) declines. However, the sign of ΔP is less clear, and sometimes, the new borders increase polarization.

On average, $\Delta F = -0.059$ (std. dev.$= 0.083$) while $\Delta P = -0.0002$ (0.005). Figure 5 compares the original district diversity to the implied diversity after redistricting with the distance to the 45 degree line capturing the Δ. Importantly, there is variation in $\Delta diversity$ across districts with similar initial diversity. Later, we link this variation to constraints imposed by redistricting regulations. Note also that Indonesia's remarkable diversity implies scope for differentiating between the two measures (the correlation between ΔF and ΔP is 0.38).[24] Moreover, these ΔP reflect sizable shifts in ethnic divisions.

To make these numbers concrete, consider two examples of redistricting in our setting. First, some areas, like the original district of Aceh Tenggara, were able to leverage the geographic distribution of groups across subdistricts to split along ethnic lines, and create homogeneous governing bodies. Aceh Tenggara split into one child with 93 percent ethnic Gayo while the parent comprised 47 percent Alas, 17 percent Batak, and 15 percent Gayo. This implied a significant reduction in diversity relative to the original district, which had 39 percent Gayo, 33 percent Alas, and 12 percent Batak. These changes led to $\Delta F = -0.180$ and $\Delta P = -0.003$ and can be seen in Figure 4(a), which plots the boundaries of villages (colored by ethnic majority), subdistricts, and districts, with the latter shown pre- and post-redistricting.

Other districts split in ways that thrust hitherto less salient divisions into the limelight. One interesting example comes from Kotawaringin Timur, once the largest district in Central Kalimantan province and a legacy of Dutch administration in the 1930s, which was comprised of six relatively large groups spanning 26 subdistricts. It was not feasible to homogenize in the way that Aceh Tenggara did (see Figure 4(b)). Instead, the original district split into two child districts and one parent. This reduced fractionalization $\Delta F = -0.068$ but increased polarization $\Delta P = 0.004$ as the new districts comprised similar or fewer groups in more equal proportions than the original district. Section 6.3 discusses at length another interesting case from Bengkayang in West Kalimantan that further clarifies why these border-induced changes in diversity matter politically.

Together, these examples point to the institutional constraints on feasible redistricting schemes. With multiple groups spanning the same subdistricts, creating completely homogenous new districts would have been unworkable given the policy regulations on economic viability, which required sufficient scale. Nevertheless, a menu of possible partitions was available in many districts, and in Section 5.4, we examine whether the effects of redistricting on conflict depend on where the actual $\Delta diversity$ falls within the set of feasible $\Delta diversity$.

[24]By comparison, the migration-induced measures of ΔF and ΔP in the less diverse South African context are correlated at 0.94 (Amodio and Chiovelli, forthcoming).

4.2 New Conflict Data

We estimate the effects of changes in ethnic divisions using new monthly data on conflict from the National Violence Monitoring System, referred to hereafter by its Indonesian acronym, SNPK (*Sistem Nasional Pemantauan Kekerasan*). Coverage begins in 1998 for nine conflict-prone provinces and increases to 15 provinces plus greater Jakarta beginning in 2005.[25] Crucially, conflict locations are recorded at administrative levels that allow us to link event locations to parent and child districts prior to redistricting.

Like other geospatial conflict databases such as the Armed Conflict Location & Event Data (ACLED), media reports of violence are the key input to the SNPK. Over a four-year period, project architects collected over 2 million images from the print archives of around 120 local newspapers, including multiple outlets for each province and excluding those with clear biases or no fact-checking (see Barron et al., 2009, 2014). Despite this rigor, as with all event-based conflict data, one may still worry about bias from selective reporting. We systematically address these concerns in two ways. First, we flexibly control for the number of papers available to coders for each province–month. Second, we use auxiliary Google Trends data to rule out confounding media attention due to redistricting.

Coders used a standard template to assign incidents to 10 mutually exclusive categories based on the underlying trigger. They first code incidents as domestic violence, violent crime, violence during law enforcement, or conflict. Within conflict, coders further categorize based on what is being violently contested: elections and appointments, governance, resource, identity, popular justice, separatist, and other (could not be classified). As a baseline, we exclude domestic violence and crime given our focus on group-based conflict. In Appendix D.6, we demonstrate robustness to misclassification. From 2000 to 2014, these social conflict events occurred in around 63 (36) percent of the district–months based on the original district (parent/child) borders. Further background can be found in Appendix B.1, which also highlights important advantages of the SNPK relative to other violence data.

Before proceeding to results, we offer a few illustrative examples of the types of conflict reported in the SNPK. The following translated incident descriptions in Maluku Utara district help fix ideas: "(July 13, 2010): In Galela Selatan, supporters of Djasa (a mayoral candidate) destroyed the office of Galela subdistrict, 2 official cars, and billboards of other candidates." "(August 18, 2011): Office of Morotai District Legislature was bombed; it is suspected as terrorism to prevent the inauguration of the elected mayor." 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 (see Harish and Toha, 2017, for a rich accounting). Such violence often involves building damage and injuries rather than deaths. Nevertheless, such incidents can and do escalate.[26] Moreover, violence is not limited to election periods. Many events capture groups violently expressing grievances over policy and resource allocation issues.[27]

[25] We show in Appendix D.8.7 that our results are not likely to be driven by this sample selection. While the data is not representative of Indonesia, it spans all major island groups and covers a majority of the Indonesian population. We omit districts in Papua due to problems with the underlying administrative and census data. Data coverage is less reliable in the earliest years, and hence we exclude 1998 and 1999.

[26] Consider these incidents from the districts of Kota Subulussalam and Maluku Tenggara Barat: "(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]." and "(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]."

[27] For example, "(April 14, 2008): Hundreds of villagers in Seram Bagian Barat district, demonstrated at the mayor's office and

5 Results: The Effects of Political Boundaries on Diversity and Conflict

This section presents our core empirical results linking changes in ethnopolitical boundaries to changes in conflict. We first provide simple difference-in-difference (DiD) estimates showing that boundary-induced changes in diversity are associated with conflict. We then estimate a rigorous, generalized DiD that, first, recovers the causal effects of redistricting and, second, identifies changes in ethnopolitical divisions on violence. We show that despite policymakers' goals, redistricting causes no change in the average incidence of conflict. We argue that this somewhat surprising finding can be explained by heterogeneous changes in ethnic divisions. In areas able to create homogenous new districts, conflict falls. However, conflict increases in areas where redistricting led to greater polarization among the newly defined electorate.

5.1 Simple Difference-in-Difference: Changes in Ethnic Divisions and Conflict

We begin with motivating evidence that changes in ethnic divisions are associated with changes in conflict incidence. Our main DiD analysis restricts to 52 original districts (d) in 2000 that split into 133 districts by 2014. Among these, 29 original districts are observed from 2000–14 in the SNPK while 23 enter the data in 2005. Nearly all redistricting occurs in the two years before and after the moratorium on splitting from 2004–6.[28]

We regress the change in the average monthly likelihood of social conflict before after and redistricting on the change in ethnic divisions implied by the new borders. Figure 6 presents results in graphical form, normalizing $\Delta diversity$ and including regression lines with robust 95 percent confidence intervals. In graph (a), a one standard deviation increase in $\Delta polarization\ (P)$ is associated with a significant 6.8 percentage point (p.p.) increase in group conflict after redistricting. Relative to a mean zero $\Delta conflict$, this is a large effect. As a benchmark, consider two districts with roughly one standard deviation difference in ΔP. In Kupang, $\Delta P = -0.001$, and conflict fell by 22.2 p.p., whereas in Kotawaringin Barat, $\Delta P = 0.002$, and conflict increased by 12.4 p.p.[29] Interestingly, the DiD estimate is similar to the cross-sectional correlation between initial polarization and the long-run incidence of conflict for all districts between 2000 and 2014 (see Appendix C). Meanwhile, graph (b) shows that conflict is less responsive to border-induced changes in fractionalization, despite the positive long-run correlation between initial fractionalization and conflict.

The data in Figure 6 suggests a strong relationship between the political boundaries of ethnic polarization and conflict.[30] Nevertheless, there are many reasons why these simple DiD estimates might

local parliament. The action continued by blocking Trans-Seram Street until the next day. This action is the result of their demands for development." See Appendix B for other examples.

[28]Only one area in our study splits again after 2008 (in January 2013), and for simplicity we drop observations in 2013 and 2014 for this district. Results are unchanged under other treatments. Four other areas split for the first time in late 2012–13. However, we exclude these from the analysis in order to focus on areas that were credibly affected by the moratoria. Section 5.5 explores the generalizability of our sample of 52 districts using a reweighting approach.

[29]Recall that these small changes in polarization often imply large changes in ethnic divisions. In Kupang, for example, $\Delta P = -0.001$ captures the split of an original district with three fairly large groups (38 percent Atoni Metto, 32 percent Rote, and 18 percent Sabu) into three homogenous new districts for each (parent with 63 percent Atoni Metto, one child with 93 percent Rote, and another child with 98 percent Sabu).

[30]As detailed in Appendix D.1, these descriptive results exclude one extreme outlier with ΔP six standard deviations below the mean, are robust to controlling for all three $\Delta diversity$ regressors simultaneously, estimating robust Huber (1973) regressions rather than OLS, and conducting small-sample inference.

not reflect causal relationships. The rest of the paper aims to rule out these concerns, to understand the dynamics of conflict after redistricting, and to offer a deeper interpretation of the underlying changes in group divisions and social tensions.

5.2 Average Effects of Redistricting

We use a standard generalized DiD specification to identify the effects of redistricting on conflict:

$$conflict_{dt} = \nu + \beta post\text{-}split_{dt} + \theta_t + \theta_d + \theta_d \times t + \varepsilon_{dt}, \tag{3}$$

where $post\text{-}split_{dt}$ is an indicator equal to one for all months after the original district's first redistricting was passed into law.[31] The month fixed effects, θ_t, sweep out shocks to conflict incidence that are common across all districts (e.g., parliamentary elections or religious holidays). The district fixed effects, θ_d, take out time-invariant level differences in conflict incidence across districts. Meanwhile, the district-specific time trends, $\theta_d \times t$, are important given differential regional trends in violence and are consistent with panel specifications in the conflict literature (e.g., Dube et al., 2016; Dube and Vargas, 2013; Miguel et al., 2004). We measure $conflict_{dt}$ as a binary indicator for any reported incident of social conflict and show robustness to intensive margin specifications in Appendix D.8. We estimate all specifications using linear probability models (LPM). The coefficient β identifies the average post-redistricting deviation from district-specific conflict trends. We further estimate versions of equation (3) that disaggregate the original districts d and identify separate β for parent and child districts, allowing each to have its own fixed effect and trend.

The monthly panel specification leverages the granularity of both the conflict data and the policy changes (split approvals vary at the month level). This allows us to capture episodic as well as recurring violence associated with discontent. This is especially useful for exploring political cycles of violence in Section 6, which vary at a sub-annual frequency. In addition, it may offer power benefits relative to a coarser annual frequency given the considerable within-year variation and relatively weak autocorrelation of conflict (see McKenzie, 2012). We cluster standard errors at the original district level as a baseline, and in Appendix D.1, we demonstrate robustness to a battery of alternative approaches to inference (and treatment of outliers).

Identifying Assumptions. Two key assumptions underlie the generalized DiD strategy: (i) the timing of redistricting is orthogonal to conflict and its determinants, and (ii) districts exhibit parallel pre-trends in conflict. We provide supportive evidence here and present further robustness checks in Section 5.5.

First, we show that the timing of redistricting is plausibly exogenous. Cross-sectional regressions in Table 1 relate a normalized x variable to the timing of the initial split in original district d—measured either as the number of months since January 2000 or an indicator for whether splitting occurred after the moratorium. There are no statistically or economically significant effects of initial diversity within

[31] Districts that split into three or more all at once pose no particular difficulty. Out of 52 original districts, 11 split at multiple points in time. Consider, for example, Manggarai district, which first created one child, Manggarai Barat in 2003, and then later the parent district was further subdivided to create Manggarai Timur in 2007. In our baseline, we code these using the first date of the split. Results are robust to dropping these multi-split areas or to assigning the date of the split to the month in which the most splits took place for the given original district. However, in all cases, $\Delta diversity$ is computed over the full period, taking the original district and final parent and child districts.

the original district borders in 2000, the eventual parent/child district borders in 2010, or the border-induced change, $\Delta diversity$. Although diverse districts are more likely to split, they are no more likely to do so earlier. Moreover, as seen in the bottom panel, we find similarly insignificant timing effects for a large set of 65 confounding variables considered in robustness checks in Section 5.5. Our results are consistent with Burgess et al. (2012) who present complementary evidence on exogenous timing.

Second, we provide evidence of parallel pre-trends. One might worry about spikes or dips in conflict prior to redistricting, particularly if such trends were differential with respect to (changes in) diversity. Event study specifications discussed below rule out these concerns.[32] Moreover, a standard hazard model specification further shows no systematic relationship between changes in prior conflict and the timing of redistricting.[33] Overall, this evidence is consistent with the favorable environment for redistricting and the arbitrariness of approval timing due to the moratorium and other factors.

Null Average Effects. Estimation results for equation (3) can be found in Table 2, which shows that redistricting does not change the local incidence of conflict. Column 1 shows a null effect of splitting on the likelihood of conflict incidents at the original district level. The point estimate and standard error are very small relative to the pre-split mean of around 57 percent of original district–months with any incidents. Nor are the null effects explained by differential pre-trends or countervailing ups and downs in conflict after redistricting. This can be seen in the event study specification in Appendix Figure D.3(a). The average likelihood of conflict is relatively flat pre- and post-split.

While informative about overall changes in violence, these original district level results may obscure the different implications of redistricting for child and parent districts. Nevertheless, estimating at this more granular level in column 2 leads to similarly null effects. Moreover, this is not due to differential, offsetting effects in parent or child districts as seen in columns 3 and 4. We discuss potential differences between parent and child districts below.

5.3 Differential Effects of Redistricting: New Ethnic Divisions Amplify Conflict

Next, we identify a much richer set of post-split conflict dynamics by explicitly considering how redistricting reshapes ethnic divisions. At the original district level, we therefore augment equation (3):

$$conflict_{dt} = \nu + \beta post\text{-}split_{dt} + \phi\,(post\text{-}split_{dt} \times \Delta\ diversity_d) + \theta_t + \theta_d + \theta_d \times t + \varepsilon_{dt}. \qquad (4)$$

The ϕ coefficients identify whether areas that split into more homogeneous and less polarized units experience a differential reduction in conflict. As outlined in Section 3.2, if original district diversity shapes conflict pre-split while diversity within parent and child districts shapes conflict post-split, then post-split changes in conflict incidence should be a function of $\Delta diversity_d$ ($\phi > 0$).

[32] That redistricting is a largely peaceful process here is likely a consequence of the limited and often favorable fiscal and legislative consequences for the parent, combined with these obvious benefits for child districts. While there are cases of violence perpetrated for and against redistricting, such episodes are limited and do not explain the timing of splitting. Indeed, the leading conflict watchdog group in Indonesia highlights a case of violent pressure for splitting in a district of West Sulawesi but notes that "In most cases, this fragmentation [redistricting] has taken part without violence and indeed without much opposition" (International Crisis Group, 2005).

[33] In particular, we estimate a Cox (1972) proportional hazards model for time to split and cluster standard errors by original district. Doing so yields a small and insignificant hazard ratio of 1.18 with a p-value of 0.8.

Importantly, the fixed effects, θ_d, absorb the time-invariant effects of initial diversity on conflict. Unlike the simpler DiD in Figure 6, equation (4) accounts for common shocks across districts, as well as differences in district-specific conflict trends. Recall that the timing of redistricting is uncorrelated with $\Delta diversity$, which also does not exhibit differential pre-trends in conflict (see Appendix Figure D.4). Moreover, we take several steps in Section 5.5, including a Lasso-based "post-double-selection" procedure (Belloni et al., 2014), to show that $\Delta diversity$ is not simply proxying for other initial district characteristics that amplify conflict after splitting.

Core Results. Table 3 reports estimates of equation (4) at different administrative levels and normalizing the $\Delta diversity$ measures. Column 1 demonstrates the conflict-enhancing effects of creating more polarized districts. A one standard deviation increase in ΔP implies a 3.6 percentage point (p.p.) increase in social conflict that is significant at the 5 percent level. This is smaller than the simple difference-in-difference estimate (Figure 6) and implies a 6.3 percent increase in the likelihood of conflict relative to the mean before redistricting.[34] Furthermore, while Δ religious polarization also enters positively, it is less precisely estimated, perhaps due to the more limited range of districts with significant religious divisions.[35] Meanwhile, ΔF has a weaker effect close to zero, albeit less precisely estimated and hence not statistically different from ΔP (p-value=0.17).

We note upfront a few key points of robustness, leaving details to Section 5.5. First, these results look similar when estimating equation (4) with each diversity measure on its own. Second, the results are more striking after the principled removal of outliers, which leads to a large increase in the effect size for ΔP in particular (see Appendix D.1). Third, the qualitative takeaways are robust to alternative (randomization) inference procedures accounting for the small effective sample size (Young, 2016) and spatial correlation in unobservables (Conley, 1999).

We consider several benchmarks to shed deeper light on these boundary-induced changes in ethnic divisions. First, the estimated effects of ΔP and ΔF are smaller than the large positive correlations between conflict incidence and diversity across all districts as discussed in Section 3. Hence, the causal component due to political boundaries is slightly smaller for polarization and significantly smaller if not null for fractionalization. Second, the effect of ΔP on conflict is around one-half of the cross-country correlation between ethnic polarization levels (P)—defined similarly based on *Ethnologue* definitions of ethnolinguistic groups—and low-intensity civil conflict in the Esteban et al. (2012) specifications.[36] Third, the effect of border-induced ΔP in Indonesia is roughly one-quarter as large as the effects of migration-induced ΔP within the black population of South Africa (Amodio and Chiovelli, forthcoming).[37] This large difference is plausibly due to the fact that changes in local diversity due to migration capture additional conflict-relevant group divisions besides solely ethnic ones, e.g., between native "sons of the soil"

[34] Note that unlike the simple DiD, the regression in column 1 is based on all districts including the extreme outlier in ΔP. Omitting that outlier here leads to a larger effect of 5.8 p.p. See Appendix D.1 for further robustness checks on outliers.

[35] We continue to control for Δ religious polarization in all subsequent tables but suppress it for presentational purposes.

[36] This is based on re-estimating column 1 of Table 4 in their paper and comparing normalized effect sizes. We omit the Greenberg-Gini index of diversity to maintain a stricter comparison to our results, but the effect sizes are similar when including it. Their estimates are based on pooled OLS panel regressions at the five-year frequency, and the dependent variable equals one if the country experiences more than 25 conflict-related deaths with a mean of 0.28. By comparison, this same threshold and five-year frequency in our data implies a mean of 0.29. Interestingly, they too find weaker effects of ethnic fractionalization on conflict (when using the full breadth of groups in *Ethnologue*), an issue we revisit in Appendix D.7.

[37] This is based on rescaling their estimate in column 5 of Table 3 by the standard deviation of ΔP, 0.09, in Table A.2.

and immigrants (Fearon and Laitin, 2011; Weiner, 1978). Together, these comparisons suggest that the causal component of the diversity–conflict relationship due to borders is important.

The strong effects of ΔP in column 1 of Table 3 highlight a potentially important unintended consequence of using redistricting to create homogenous political entities. In diverse settings with many groups, while it is possible to reduce the number of groups and hence F, it may not be feasible to simultaneously ensure that the new boundaries do not engender new polarizing divisions. The two districts of Maluku Utara (MU) and Bolaang Mengondow (BW) illustrate the importance of ΔP. While both significantly homogenized based on F ($\Delta F^{MU} = -0.125$ and $\Delta F^{BW} = -0.097$), the new borders generated new ethnic divisions and a larger increase in polarization in MU ($\Delta P^{MU} = 0.005$ and $\Delta P^{BW} = 0.002$). We observe a 36 p.p. increase in conflict in MU compared to a 7 p.p. decline in BW after redistricting.

Parent and Child District Results. To shed further light on the tradeoffs associated with redistricting, we estimate equation (4) at the smaller, child and parent district boundaries. As noted in Section 3.2, changes in violence within these smaller units should also be a function of $\Delta diversity$, specified here as the difference in diversity between the given child or parent district and the original district. As with specification (4), the goal is to identify how changes in the salience of local diversity affect conflict.

There are several advantages to running our specification at this lower geographic level. First, it leverages greater variation in $\Delta diversity$. Second, it allows us to analyze violence around post-split elections, which occur at different times in the parent and child (see Section 6). Finally, it provides a natural way to investigate whether the effects of changing ethnic divisions vary with the scale of changes in local government. As documented in Appendix A, children experience larger increases in fiscal transfers and a reduction in distance to the capital. In the framework of Section 3.2, this arguably implies a larger, post-split increase in $\frac{R}{\gamma}$ in children than parents. Consequently, we would expect the effects of $\Delta diversity$ to be amplified in child districts, a result we corroborate in the following section.

Columns 2–4 of Table 3 estimate these relationships within the given child and parent boundaries. Together, these more granular results reveal similar effects as those at the aggregate original district level, but also point to potential changes in the geography of violence. Pooling parent and child districts in column 2 yields estimated effects that are statistically indistinguishable from those in column 1. Turning to columns 3 and 4, we see that ΔP has similar effects when splitting the sample into parent and child districts, respectively. The effect size is slightly larger for child districts, which also have relatively lower mean conflict before redistricting. Although this difference is imprecise (p-value=0.23), it is nevertheless consistent with the larger changes in $\frac{R}{\gamma}$ for child districts. Looking at ΔF, we see similarly weak effects as in the original district specification. However, the positive albeit noisy estimate in column 3 suggests that some of the conflict-inducing changes in ethnic divisions may differentially load onto fractionalization in parent districts, a conjecture we further substantiate in Appendix D.7.

Discussion. While recent models clarify how conflict responds to diversity in long-run equilibrium, our results identify how political boundaries can shock that equilibrium by changing the salience of different group cleavages in society. The point estimates in Table 3 identify the magnitude of this shift over a 5–10 year period. That redistricting can alter the effects of diversity so quickly is perhaps surprising. In Section 6, we link the resulting conflict dynamics to the nature of politics and majoritarian elections in new democracies. While these effects may yet die out over time, the new ethnic divisions may also deepen, bringing us closer to the long-run correlation between diversity and conflict (within stable boundaries).

Our findings offer two policy-relevant, methodological innovations. First, prior work shows how the colonial partitioning of ethnic groups across international borders contributes to modern conflict (e.g., Michalopoulos and Papaioannou, 2016). Our strategy moves beyond static differences to show how changes in political boundaries reshape the ethnic divisions underlying conflict. While infeasible to study these dynamic changes in national boundaries, within-country boundary changes are pervasive and informative about general mechanisms linking diversity to conflict. Second, by isolating the contribution of political boundaries, we rule out a host of other confounding changes in local ethnic diversity often associated with migration flows, which are of independent interest in the study of conflict.

Our focus on boundary-induced changes in ethnic divisions further contributes to an ongoing debate over which type of diversity matters for conflict. To the extent that redistricting changes the incidence of local public goods, one expects greater heterogeneity in preferences among the governed population to lead to greater conflict. Moreover, if private resources are changing more slowly than public ones, one would expect changes in fractionalization to be less important than changes in polarization (Esteban and Ray, 2011a).[38]

5.4 Identification Checks: Isolating Policy-Induced Changes in Ethnic Divisions

This section addresses three key threats to our interpretation thus far: (i) that $\Delta diversity$ is a proxy for other features of Indonesian districts correlated with future conflict, (ii) that changes in contestable public resources confound the effects of $\Delta diversity$, and (iii) that the variation in $\Delta diversity$ captures endogenous boundary choices.

Accounting for Confounders. We begin by ruling out omitted factors correlated with $\Delta diversity$ and conflict. Specifically, we follow a standard approach in heterogeneous DiD specifications and augment equation (4) with interactions of post-split and an array of confounding variables plausibly correlated with diversity and conflict. Our approach is twofold. First, we separately consider groups of initial predetermined variables chosen based on intuition and prior work (see, e.g., Fearon and Laitin, 2003; Esteban et al., 2012). These include, among others: security presence; public goods access; remoteness, transportation infrastructure and access to markets; population size and age distributions; natural resource intensity; educational and occupational distributions; and topography, soil quality, and water access. Many are indeed highly correlated with diversity.[39] As shown in Appendix Tables D.6–D.9, some of these factors also mediate the effects of redistricting on conflict. However, the key coefficients

[38] This may also explain some of the differential effects of diversity in parent and child districts as noted above. The relative importance of ΔF (albeit noisy) for parent districts could be consistent with a many-group generalization of the conceptual framework that also allows R to reflect the ratio of public to private goods as in the original Esteban and Ray (2011a) model. While both goods may be growing over time with redistricting in parent and child districts, public goods grow more slowly in the former, leaving greater scope for per capita payoffs (to private goods) to shape conflict incentives. This would imply that changes in ethnic divisions reflected in ΔF amplify conflict relatively more than those in ΔP. In Appendix D.7, we further probe the differences between polarization and fractionalization and show that border-induced changes in the deeper ethnolinguistic divisions in society are driving the changes in violence around redistricting. We also show there that the key results on ΔF and ΔP hold up to inclusion of $\Delta G/N$ where G/N is the Greenberg-Gini index scaled by population as in the structural equation of Esteban and Ray (2011a) tested by Esteban et al. (2012).

[39] In a cross-section of 310 Indonesian districts, the full set of 65 covariates used in the Lasso procedure below explain 80 (51) percent of the variance in fractionalization (polarization).

of interest on ΔP and ΔF remain mostly unchanged across these different specifications. There are of course hundreds of potential confounding variables that one could combine in various ways in this type of exercise, and with limited degrees of freedom, this leaves the door open to cherry-picking (Gelman and Loken, 2014).

Therefore, we adopt a second strategy that leverages machine learning to take a more disciplined approach to ruling out omitted variable bias. In particular, we utilize the Belloni et al. (2014) double-selection post-Lasso method to select a parsimonious set of influential controls from the large number of variables potentially confounding the relationship between $\Delta diversity$ and conflict. In practice, we expand upon the broad set of sensible covariates noted above and use this approach to select additional interactions with $post\text{-}split$ while penalizing the tendency towards overfitting through a penalty parameter λ.[40] Acknowledging the limits of our natural policy experiment, we choose λ to ensure that the number of variables selected remain sufficiently smaller than the effective degrees of freedom. We set $\lambda = 3,000$ as a baseline and consider alternative values in Appendix D.2.

Panel A of Table 4 presents results based on this principled approach to variable selection. Although noisier than the baseline findings in Table 3, the main qualitative and quantitative findings remain unchanged. The point estimates on ΔP with this rich set of Lasso-selected controls are statistically indistinguishable from the baseline without controls except in column 3 where the estimates here are larger. Note that the fixed λ selects a different number of highly relevant controls across columns, which is due to variation in both the sample size as well as the relevant confounders of $\Delta diversity$. Overall, the conclusions remain unchanged for other reasonable values of λ.

Changes in the Local Public Resources. While the confounding effects of other initial district characteristics is limited, it is also important to account for other factors associated with conflict that change with redistricting. We consider here two significant changes noted in Section 2.2, namely local government transfer revenue and proximity to government institutions in the newly created child district capital. Drawing upon the measures developed in Appendix A, Appendix Table D.10 adds changes in transfers and distance to our baseline specification in Table 3.

We draw a few important takeaways from this exercise. First, these additional controls leave the effects of $\Delta diversity$ unchanged with polarization continuing to amplify conflict. Second, both $\Delta transfers$ and $\Delta distance$ enter as expected based on the conceptual framework in Section 3.2. Greater transfers (higher R) and greater proximity to the district capital (lower γ) are associated with more conflict after redistricting, particularly in child districts where these changes are much more pronounced. Together, these results suggest that border-induced changes in ethnic divisions matter per se. When redistricting also changes contestable public resources, ethnic divisions may be even more important, a conjecture borne out in additional results in Appendix Table D.11 interacting $\Delta diversity$ with $\Delta transfers$ and $\Delta distance$. Overall, these findings are suggestive, but we do not push the interpretation too far given concerns about endogeneity and limited degrees of freedom.[41]

[40] Appendix G details the full set of 65 potential confounding variables, and Appendix D.2 details our application of this method, which is particularly effective at dealing with the problem of overfitting in a setting where one aims to learn about a particular causal effect of interest rather than simply develop a good prediction of the outcome. We discipline variable selection around ΔP and ΔF but find similar results when also disciplining on $\Delta Relig$. Interestingly, when disciplining on ΔP alone, ΔF is selected among the small number of included confounders.

[41] Further exogeneity may be possible using rules on transfers (Cassidy, 2017) and geographic determinants of capital locations

Feasible Redistricting. Although initial diversity in 2000 is predetermined, the particular way in which the borders are drawn, and hence $\Delta diversity$, may be endogenous. One concern is that districts that chose particularly unfavorable borders with high ΔP were the ones where future conflict would have risen anyway, say because of bad governance. We show here that the effects of $\Delta diversity$ on conflict are not explained by the particular way that districts chose to draw new borders but rather by institutional constraints on redistricting and ethnic geography that did not allow for more homogenous new districts.

To do so, we consider all the possible ways an original district could split along subdistrict lines into k new districts, given that regulations require each new district has at least three contiguous subdistricts. This provides us with a distribution of feasible partitions, and associated $\Delta diversity$, for each district. Appendix E provides full details on this NP-hard combinatorial problem.

We use this set of feasible partitions to clarify that our identifying variation in $\Delta diversity$ comes from cross-district variation in the set of feasible partitions, as opposed to similar districts choosing very different ways of redrawing their borders. First, we re-estimate our baseline specifications from Table 3, replacing the realized changes in diversity with the mean, feasible ΔP and ΔF for each district. Panel B of Table 4 shows that this produces very similar results to our baseline, providing initial evidence that strategic redistricting is unlikely to explain our core effects.

To further clarify this point, we look not at the average but rather at random combinations of extreme feasible $\Delta diversity$. Specifically, we re-estimate our baseline specification randomly assigning ΔP (and associated ΔF) for each district to be either the maximum or minimum from the feasible set.[42] We repeat this randomized procedure 50,000 times at the original district level and plot the resulting estimates in Appendix Figure E.2. Reassuringly, all the estimated effects of min or max feasible ΔP are greater than zero and smoothly distributed around the baseline estimated effect size. This is consistent with the fact that within-district variation in feasible splits is small relative to the between-district variation.[43]

Together, these results suggest that unobserved heterogeneity in boundary choice does not explain the effects of $\Delta diversity$ on conflict. This further highlights the importance of the preceding exercise ruling out confounding interactions with *post-split*. More substantively, these results demonstrate the importance of designing redistricting schemes that account for constraints on strategic border formation.

5.5 Additional Robustness Checks

This section describes a battery of robustness checks fully detailed in the Appendix. Overall, this series of tests further bolsters our causal interpretation of the main findings.

We first address concerns about the effective sample size in Appendix D.1. Most importantly, we take the disciplined approach of Belsley et al. (1980) to rule out the influence of outliers in the baseline panel regressions in Table 3. Doing so systematically increases the overall effects of ΔP. Moreover, new conservative refinements to inference due to Young (2016) suggest that outliers are not driving our

(Campante et al., 2016). However, our main goal here is to rule out confounders of $\Delta diversity$, and the OLS results should help assuage first-order concerns.

[42] That is, on any given draw, one district would receive its minimum ΔP while another district would receive its maximum ΔP , thereby shuffling randomly across all districts.

[43] Appendix Figure E.1 further illustrates this point by showing examples of how there is relatively little overlap in the distributions of feasible ΔP across original districts. Indeed, original district fixed effects account for over 88 percent of the variation in feasible ΔP.

qualitative takeaways.

Second, in Appendix D.4, we address the concern that SNPK coverage might be changing systematically with redistricting. The main concern is that newspapers differentially report on events in locations with greater changes in ethnic divisions, leading to overestimates of the actual effects. The comprehensive coverage of SNPK from many different outlets provides some reassurance. We provide further supportive evidence using auxiliary Google Trends data capturing the relative monthly frequency of search for the original, parent and child district names. While imperfect, this proxy reflects the frequency of general interest in the given location, some of which may be orthogonal to media reporting incentives. To the extent that Google trends are less prone to differential underreporting than the SNPK data, controlling for such trends should dampen the overall effects we estimate. Nevertheless, doing so leaves our key results unchanged.

Third, we rule out several additional concerns about the baseline generalized DiD specification in Appendix D.8. First, we separately exclude the regions of Aceh and Maluku, which experienced intense conflict in the late 1990s and early 2000s at the onset of decentralization. Second, we omit the years 2011 to 2014 to ensure results are not driven by periods well beyond the unexpected moratorium. Third, we omit districts that enter the data in 2005, which is important given that these later entrants were selected on account of policy concerns about recent violence. Fourth, we consider the number of conflict events rather than a binary indicator, leaving the key takeaways mostly unchanged, though introducing more noise. Fifth, we consider alternative parametrizations of the time and location fixed effects and trends as well as an alternative identification strategy that includes as additional control areas those nearby districts that have not undergone redistricting. Sixth, we consider alternative measures of $\Delta diversity$ that scale the changes by initial levels. Finally, Appendix D.6 shows that results are robust across alternative groupings of violence categories and hence are not an artifact of our definition of social conflict.

Beyond these robustness checks, we also offer evidence in Appendix D.8 on the external validity of our findings across Indonesia. Recall that our baseline sample of 52 original districts is based on two restrictions: (i) inclusion in the SNPK conflict data and (ii) redistricting between 2000 and 2010. While the internal validity of our estimates is high, these restrictions might raise questions about generalizability. Nevertheless, key results in Tables 2 and 3 remain unchanged when reweighting by the inverse probability of selection on (i) and (ii), estimated using a Lasso-based propensity score model with the full array of covariates discussed in Section 5.4. This standard reweighting approach of Horvitz and Thompson (1952) suggests that our results are not driven by (observable) peculiarities of these 52 districts.

6 Ethnic Reconfiguration and Political Cycles of Violence

Our core results show that changes in ethnic divisions—arising purely from a reshuffling of *political* boundaries—can affect conflict within a matter of years. This suggests that the boundaries of political contests fundamentally shape the way that diverse groups interact and compete with one another. This section bolsters this interpretation by linking changes in violence to district politics and local elections. As noted in Section 2.1, district governments play a large role in the local polity with mayors in control of vast public resources. Given the salience of ethnicity during mayoral elections, we investigate how border-induced changes in ethnic divisions affect violence around these political contests. We show that violence surges around new, closely contested, mayoral elections, and that these political conflict cycles are amplified in high $\Delta diversity$ areas. Further, we provide evidence of ethnic favoritism in the allocation of public resources as a potential mechanism for generating grievances and amplifying incentives for ethnic mobilization around these majoritarian contests. We conclude by discussing a case of redistricting that nicely captures our broad empirical findings and clarifies the way that political boundaries can reshape ethnic divisions.

6.1 Electoral Violence

The empirical evidence thus far suggests redistricting may create strong incentives for group mobilization and violence. In settings with weak institutions, such violence may help shape the degree of control that one's group exerts over new institutions responsible for public goods or help influence resource allocation after another group assumes control. Here, we provide empirical evidence of these mechanisms in the context of mayoral elections.

In Table 5, we augment the parent/child specifications in Table 3 with indicators for direct mayoral election periods. These quinquennial elections, which began in 2005, vary in their timing (i) in parent districts, due to predetermined path dependence from Suharto-era election schedules (see Martinez-Bravo et al., 2016; Skoufias et al., 2014), and (ii) in child districts, due to the timing of redistricting (with elections typically occurring 1.5–2.5 years after the split).[44] Following Harish and Toha (2017) and others cited therein, we define the election period as a six month window centered on the month of the election, but results are similar for other bandwidths. The coefficient on *post-split×first (second) election* identifies whether the incidence of conflict during the first (second) election deviates from the average incidence after redistricting. To see whether electoral violence cycles are more likely in newly polarized areas, we further interact post-redistricting election periods with $\Delta diversity$.

Looking across columns of Table 5, the likelihood of social conflict after redistricting is generally higher around the initial mayoral elections, particularly where redistricting sharply changed ethnic divisions. Column 1 shows this result pooling parent and child districts. Columns 2 and 3 show results separately for parent and child districts, pointing to important differences between pre-existing and new seats of government.

Child districts with ΔP one standard deviation above the mean are nearly 70 percent more likely to exhibit differentially more violence around the first election (comparing 0.027 to 0.041). This result lines up with the fact that polarization is associated with closer elections (see Appendix Table F.1), and violence is significantly more pronounced during those close elections (see Appendix Table F.3). Moreover, the amplifying effect of ΔP on political violence persists and may even be larger during the second election period 5–8 years after redistricting.

Meanwhile, in parent districts, initial elections are generally less violent. Border-induced changes in ethnic polarization seem less important than changes in fractionalization, which exerts a large albeit noisy positive amplification effect.[45] Second election periods appear differentially less violent in high

[44] All direct elections in child districts follow splitting. Some original district have first direct elections that precede splitting, and hence we include a term for first direct elections in addition to the term *post-split×first election*. We observe a second quinquennial election for the three-quarters of new districts in existence long enough to hold a second round by 2014.

[45] This may be consistent with the stronger correlation of F than P with victory margins in parent districts (see Appendix Table F.1), and, like child districts, more closely contested elections are associated with greater violence (along the intensive margin,

ΔP areas, which is unexpected and helps explain the null ΔP in that bottom section of column 1.

The differential effects of changing ethnic divisions on electoral violence in parent and child districts admit several possible interpretations. The relatively stronger effects of changes in ethnic polarization in child districts might be explained by the greater stakes of winning initial elections to control a completely new local government as opposed to winning control of an existing one. Another explanation for these diverging results could be differential institutional capacity. Parent districts may not only run more effective and safer initial elections than child districts but also learn more quickly how to manage the changing ethnopolitical divisions.

Overall, the results in Table 5 suggest that ethnic mobilization around mayoral elections are an important feature of conflict dynamics after redistricting.[46] Additional results in Appendix F.2 further corroborate these new and distinct political cycles of conflict around mayoral elections. First, we rule out confounding media attention using Google trends data and show similar intensive margin effects using the number of conflict events. Furthermore, we show that the amplifying effects of $\Delta diversity$ on conflict around mayoral elections are a distinctive feature of the high contestability of political resources in this setting. In particular, the effects of $\Delta diversity$ on conflict do not systematically differ during the province-specific rice harvest period, the (lunar) holy month of Ramadan, or the quinquennial parliamentary (and presidential) elections. In each case, $\Delta diversity$ exhibit small, insignificant heterogeneous effects that are statistically different from the amplifying effects of $\Delta diversity$ around mayoral elections. The lack of a similar amplifying effect around parliamentary elections is particularly interesting. It is also consistent with the fact that proportional representation legislative elections impart very different group-based incentives than the majoritarian mayoral elections (see Fjelde and Höglund, 2016, for similar evidence in sub-Saharan Africa).

Furthermore, the changes in violence due to changing ethnic divisions are not merely a transitory phenomenon around elections. Across all three columns, the coefficient on $post\text{-}split \times \Delta P$ is statistically indistinguishable from that in Table 3, meaning that the post-split differences in the incidence of social conflict extend beyond election periods. This is what one would expect if grievances among losing group continued to manifest in violent acts protesting governance- and resource distribution-related issues in the future. Further evidence can be found in the fact that second elections continue to be violent. Next, we provide evidence for one potential reason for such grievances, namely ethnic favoritism in the allocation of public resources.

6.2 Ethnic Favoritism

Given hotly contested mayoral elections and their interplay with ethnic divisions, one would expect political favoritism towards co-ethnics. Recent studies document favoritism in resource allocation towards newly elected leaders' ethnic homelands in sub-Saharan Africa (see, e.g., Burgess et al., 2015; Hodler and Raschky, 2014). While a full accounting of this phenomenon in Indonesia is beyond the scope of

see Appendix Table F.3).

[46]This is consistent with Tanasaldy (2012, p. 263) who notes that in several areas of West Kalimantan (in our study), "Due to ethnic polarization introduced in previous elections, masses from each ethnic group tended to rally for candidates from their own ethnic group." Indeed, we bear this out more generally using individual-level data from a 2014 survey, which shows that $\Delta diversity$, and, in particular, $\Delta polarization$ is strongly correlated with the reported importance to voters of mayoral ethnicity and patronage (see Appendix F.1 for details.).

this study, we present here evidence consistent with ethnic favoritism as a potential factor contributing to the patterns of discontent underlying the link between changes in ethnic divisions and conflict.

Following prior literature, we use nighttime light intensity as a proxy for local economic development and targeted public resources.[47] Importantly, electricity cannot be provided solely by villages and often requires support from higher levels of government. Mayors have been responsible for setting electricity policy within their districts since 2005 (Jayawardena, 2005).[48] Moreover, as noted by Pal and Wahhaj (2016), mayors generally have significant discretionary power in their choice of how to allocate resources across villages. Altogether, this suggests scope for rivalry across villages in access to this public resource, and indeed, publicly-provided electricity is a factor underlying some of the violent incidents reported in the SNPK data.[49]

We investigate ethnic favoritism by exploiting the fact that redistricting often changes either the identity or strength of the dominant group in the district. In particular, we examine changes in resources flowing to village v after redistricting as a function of that village's initial ethnic composition. Specifically, we ask whether the new boundaries imply that the village's initial population (N) share of ethnics from the new districts' largest group is (i) larger, (ii) smaller, or (iii) the same as the village's initial share of ethnics from the original districts largest ethnic group. Formally, we compare $\frac{N_{e_{\mathcal{O}}v}}{N_v}$ to $\frac{N_{e_i v}}{N_v}$ where $e_{\mathcal{O}}$ is the largest ethnic group in original district $\mathcal{O}$, and e_i is the largest group in child or parent district i.[50]

For example, appealing to Figure 4, those Gayo majority villages in the new parent district will fall under (ii) since the Gayo are no longer the largest group. Meanwhile, the Gayo majority villages in the new child district of Gayo Lues will fall under (iii) as the largest group has not changed with redistricting. Nevertheless, note that, like most villages in category (iii), the size of their majority has increased, consistent with the general reduction in fractionalization that comes with redistricting.

In Table 6, we show how nighttime light intensity evolves across these three different types of villages after redistricting. In particular, we examine interactions of post-split with indicators for the change in alignment status, conditional on year and village fixed effects. Villages that lose their alignment with the largest ethnic group (ii) exhibit differentially lower light intensity after redistricting compared to those that either remain (iii) or become newly (i) aligned with the largest group. The results are consistent at both the parent and child level albeit slightly larger and more precisely estimated for the latter. Column 1 suggests that villages that become newly (remain) aligned with the largest group have 1.1 p.p. (2.8 p.p.) more village area with light coverage post-redistricting relative to those that lose their alignment. These are large differences relative to the mean of 16.3 percent of village area covered with any lights.

[47] Olivia and Gibson (2015) validate a strong correlation of light intensity with district-level output and expenditure data. In the predominantly rural areas of our study, nighttime lights tend to disproportionately capture public street lights. Moreover, not unlike other areas of the developing world, electricity provision in Indonesia is almost exclusively concentrated in a single public utility company, which is often subject to the same sort of political manipulation identified in South Asia (see Baskaran et al., 2015; Min, 2015).

[48] Aspinall and Asad (2015) provide nice examples of other ways in which mayors strategically target resources to villages.

[49] For example, in Aceh Selatan district on 17 August 2007, "Hundreds of residents of Meukek subdistrict damaged PLN (Public Electricity Company) office and head of Subranting PLN's house by throwing stones. Citizens were induced to action by irritation due to irregular schedules of power outages. Other examples are provided in Appendix B.1. More recent examples, not (yet) in SNPK, provide further insight into the politicization of electricity provision with demonstrations against both PLN and the mayor (KabarNias, 2015) or being led by village heads against PLN (ProKal, 2016).

[50] Note that if the largest group does not change with splitting, the village will fall under category (iii). Nearly 70 percent of these villages are in districts where the share of the largest group increased. There are 1,764 villages in 32 districts in category (i), 558 villages in 28 districts in category (ii), 12,182 villages in 119 districts in category (iii).

These results are consistent with ethnic favoritism, which may be one vehicle for generating the sort of grievances that lead to persistently higher violence in areas where new boundaries create fresh ethnic divisions, even outside of election periods. We turn now to a case study highlighting some of the particular mechanisms underlying our empirical results.

6.3 Case Study

We discuss here an illustrative case study in West Kalimantan. This region has a significant history of ethnic strife including Dayak violence against the Chinese, and repeated clashes between Dayak and Madurese as well as Malay and Madurese. As in the rest of Indonesia, these large-scale open conflicts largely subsided in the early 2000s, replaced by more sporadic violence that remains a serious concern to policymakers (see Barron et al., 2016). We briefly present this interesting case below.

We focus on the original district of Sambas, which split into three separate districts: Sambas, Bengkayang (in 1999), and Kota Singkawang (from Bengkayang in 2001). Before splitting, Sambas was comprised of 52 percent Malay ethnics, 15 percent Dayak, and 15 percent Chinese, with other smaller groups including Javanese and Madurese. Redistricting significantly altered these group shares.

After the fall of Suharto, demands for decentralization and local empowerment spread across Indonesia, and West Kalimantan was no exception. As Tanasaldy (2012, p. 269) notes "In West Kalimantan such [native empowerment] movements were initially led by Dayaks who demanded more top jobs in the government and competed zealously against the Malays, for those political positions. Held in check during the authoritarian New Order [Suharto era], political polarization between the two ethnic groups was now unavoidable."

With these mounting tensions came a push for redistricting, motivated in part by a desire to reduce ethnic divisions. Tanasaldy notes that "government officials thought that separating conflict-prone areas and allowing the Dayaks to govern their own areas was a solution to chronic ethnic conflicts there." After the two splits, the now-parent district of Sambas was about 80 percent Malay, with the next largest group being ethnic Chinese at 11 percent. Bengkayang became 52 percent Dayak, 19 percent Malay, and 10 percent Chinese, while Singkawang was 42 percent Chinese, 27 percent Javanese, 8 percent Malay, and 7 percent Dayak. This split is often depicted as having cleanly separate the three groups: "the Malays in Sambas, the Chinese in Singkawang, and the Dayaks in Bengkayang" (Kobayashi, 2011, p. 374). However, as evident from the group shares, Singkawang remains far more polarized than Benkayang.

In Sambas and Bengkayang, the split was successful in reducing violence as the changing ethnic divisions translated into more amicable politics. Kobayashi nicely summarizes, noting that "district head elections became less tense because the Dayaks and Malays understood each others' rights to lead districts where they were dominant," and more generally that "interethnic strife to obtain political positions has declined since 2000." Government officials often argue that redistricting "contributed to prevention of ethnic violence," drawing connections, for example, between increased Dayak representation in the civil service and the end of violent street demonstrations.

Meanwhile, Singkawang presents an interesting contrast. Despite being a significant 40 percent plurality, the Chinese had generally stayed out of politics, with the "sons of the soil" Malay typically dominating. However, in 2007, the first direct mayoral election after redistricting brought their numeric advantage to the fore amidst a growing "desire within the Chinese community to increase the number of Chinese in the government and to elect a Chinese mayor" (Kobayashi, 2011, p. 295). In the 2007 election, much to the surprise of the Malay candidates, Hasan Karman, an ethnic Chinese beat the three Malay candidates (whose votes were split). Once in power, though, Karman "fumbled the delicate issue of ethnicity", as he "irked Malays by building a [Chinese] dragon statue... in the heart of the city" and "disparaged the Malay community... by [publicly] linking them to pirates" (Sukarsono, 2012).[51] In the 2012 election, tensions mounted amid Chinese accusations of intimidation and vote-tampering after the Malay candidate won. Violent clashes erupted between Malay security personnel and Chinese protestors outside the election commission office.[52]

Overall, West Kalimantan highlights both the promise and pitfalls of redistricting as a vehicle for reshaping ethnic divisions in society. Greater homogeneity in Sambas and Bengkayang may have helped to resolve some of the longstanding interethnic grievances. However, the new district of Singkawang gave rise to fresh grievances and cycles of violence by invigorating hitherto less salient ethnic divisions. These cases highlight the tradeoffs of redistricting in diverse societies where creating purely homogenous political units is not feasible everywhere.

7 Discussion

This paper identified the casual effect of political boundaries on ethnic divisions. We showed how redrawing subnational boundaries can alter the salience of different ethnic cleavages in society, and, in turn, affect conflict. By bringing the government closer to the governed, redistricting holds promise for increasing social stability. However, this common policy reform is not without pitfalls. Our natural experiment showed in particular that fresh cycles of violence may erupt when new borders increase ethnic polarization. We argued further that electoral democracy may amplify the underlying incentives for group mobilization that often lead to violence. Overall, our findings provide novel evidence on the interlinkages between ethnic and political divisions. These results help inform ongoing debates on the causes of violence as well as policy efforts aimed at curbing it.

Some of our findings suggest that border-induced changes in ethnic divisions may have persistent effects on conflict. This persistence can be interpreted through the lens of models like Rohner et al. (2013b), which feature vicious cycles of inter-group violence and erosion of trust. Political violence in newly created districts may be particularly prone to such dynamics as seen, for example, in the case of Singkawang. While over the long-run redistricting may foster new interethnic interactions, learning and cooperation, it is important to understand and prepare for the scope for violence during the transition.

Local government proliferation is a pervasive feature of decentralization today. Although our findings may not fully generalize to other settings, the widespread prevalence of ethnic mobilization (Fearon, 2006) and favoritism (De Luca et al., 2016) suggest that similar conflict dynamics could play out in other diverse countries. For example, Green (2010) discusses some of the same unintended consequences of

[51] These violent incidents are reported in the SNPK data with event details such as "series of arson cases by unknown perpetrators believed to be related to ethnical issues" in May 2010, and "there was a clash in the parade of Singkawang Parliament, the village of Pasiran, the city of Singkawang. Clash involving two groups of the pro and contra period of the construction of a dragon statue that will be built at the crossroads (2 injured)" in July 2010.

[52] This event is reported in the SNPK data on October 1st, 2012 as "a clash between the masses and the police when the Mayoral Candidate campaign handed over evidence of more than 3,000 people being denied the vote. [2 injured]"

redistricting in Uganda that we identify empirically in Indonesia. Nevertheless, we acknowledge that ours is only a partial analysis of the vast political and economic implications of redistricting.

We see four important directions for future research on redistricting in Indonesia and elsewhere. First, a small but growing literature highlights the importance of *within*-ethnolinguistic or -religious group heterogeneity in culture (Desmet et al., 2017), genes (Arbatli et al., 2015), or income (Esteban and Ray, 2008; Mitra and Ray, 2014) in shaping conflict. This is an interesting question in the context of decentralization and one that can be explored using heterogeneity in responses to household survey questions on preferences, variation in vote shares for different parties of the same religion, and within-group educational or occupational inequality.

A second question is whether redistricting can be a vehicle for a central government to constrain secessionist tendencies. Coming on the heels of East Timor's independence and concerns about break-away regions in Aceh and Papua, Indonesian policymakers in the late 1990s strategically chose districts rather than provinces as the primary administrative units allowed to proliferate. According to observers like Booth (2011), their goal, among others, was to fracture the strength of broader regional identities. It would be interesting to explore whether this policy of "breaking up to stay together" stifles secessionist sentiments and ultimately shifts violence from higher to lower levels.

Third and relatedly, redistricting has the potential to activate more granular cultural distinctions. Although many areas created ethnically homogenous districts, sub-ethnic distinctions may have emerged over time as groups sought new vehicles for political mobilization. Redistricting may have contributed to the dramatic growth in the number of self-reported ethnic identities from 1,087 in the 2000 Census round to 1,331 in the 2010 round. As recounted in Fearon (2006), Horowitz (1985, p. 66) provides a telling example of this burgeoning of local identity in the Indian context of state proliferation in the 1950s: In Madras state, ". . . with large Tamil and Telugu populations, cleavages within the Telugu group were not very important. As soon as a separate Telugu-speaking state was carved out of Madras, however, Telugu subgroups—caste, regional, and religious—quickly formed the bases of political action." In the Indonesian context, one could explore empirically how political boundaries lead to new forms of identity related not only to sub-ethnic distinctions but also to shared national identity (Bazzi et al., 2017).

Finally, there are several open questions about the public goods and welfare consequences of redistricting. Recent studies identify environmental externalities (Burgess et al., 2012; Lipscomb and Mobarak, forthcoming). There are other interesting implications of reduced government scale and changes in the network of administrative responsibilities; not to mention increased proximity to service providers in the new district capitals. A full account of the welfare implications of redistricting clearly extends beyond the effects of changing ethnic divisions.

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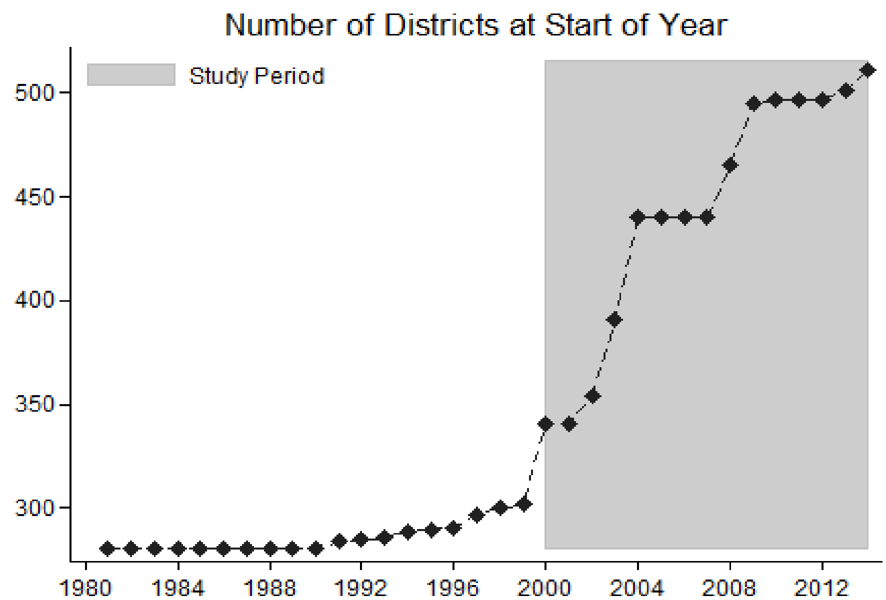
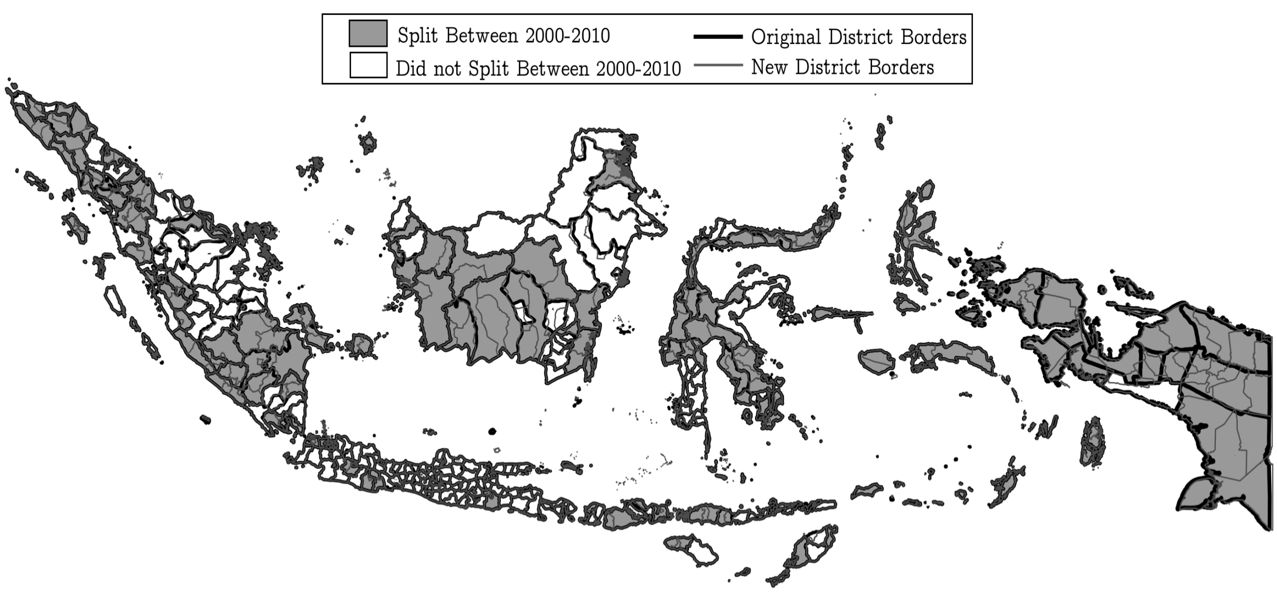
Figures

Figure 1: Indonesia's Remarkable Wave of Redistricting



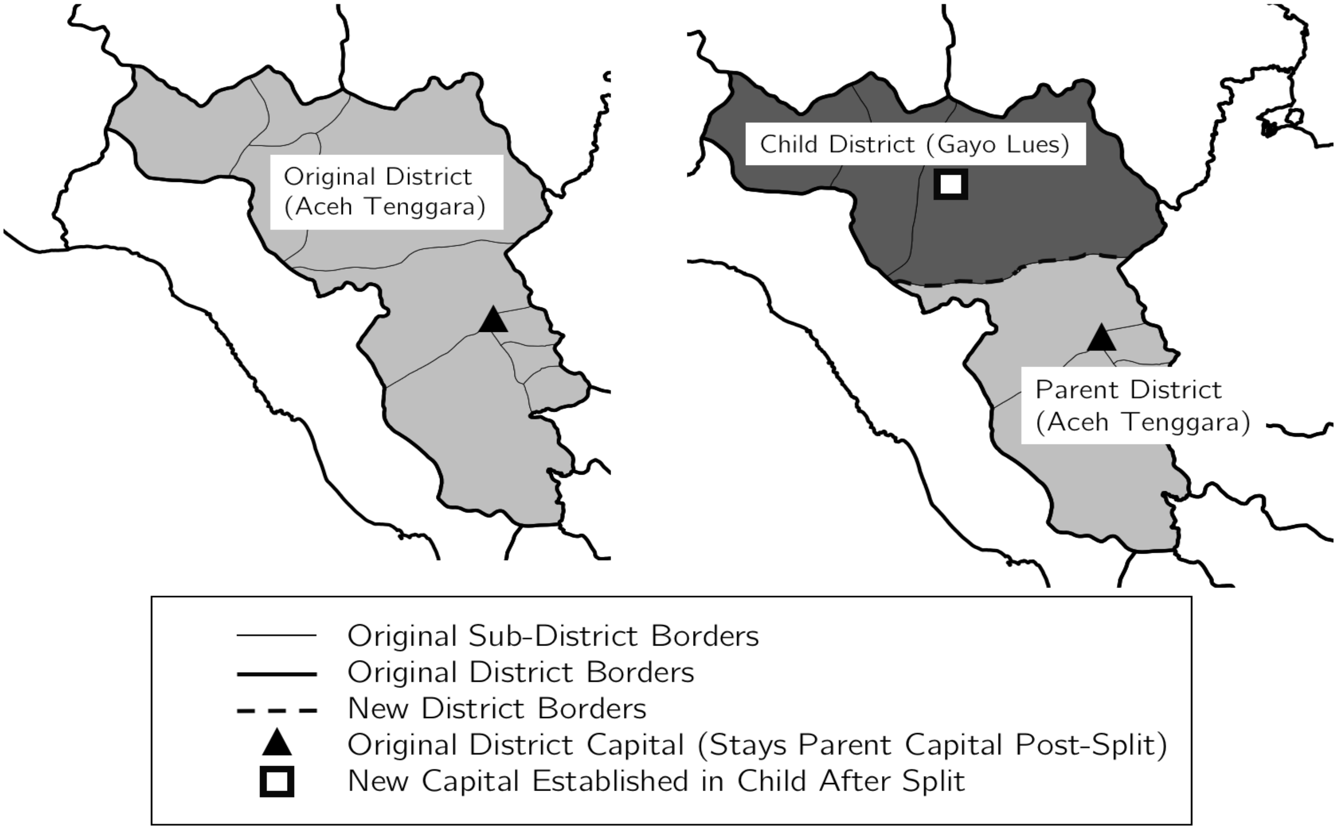
Notes: This figure captures the evolution of new districts across Indonesia from 1980–2014 based on the month each district was passed into law.

Figure 2: Redistricting across the Country



Notes: This map plots the original and new district borders based on district-level shapefiles for 2000 and 2010.

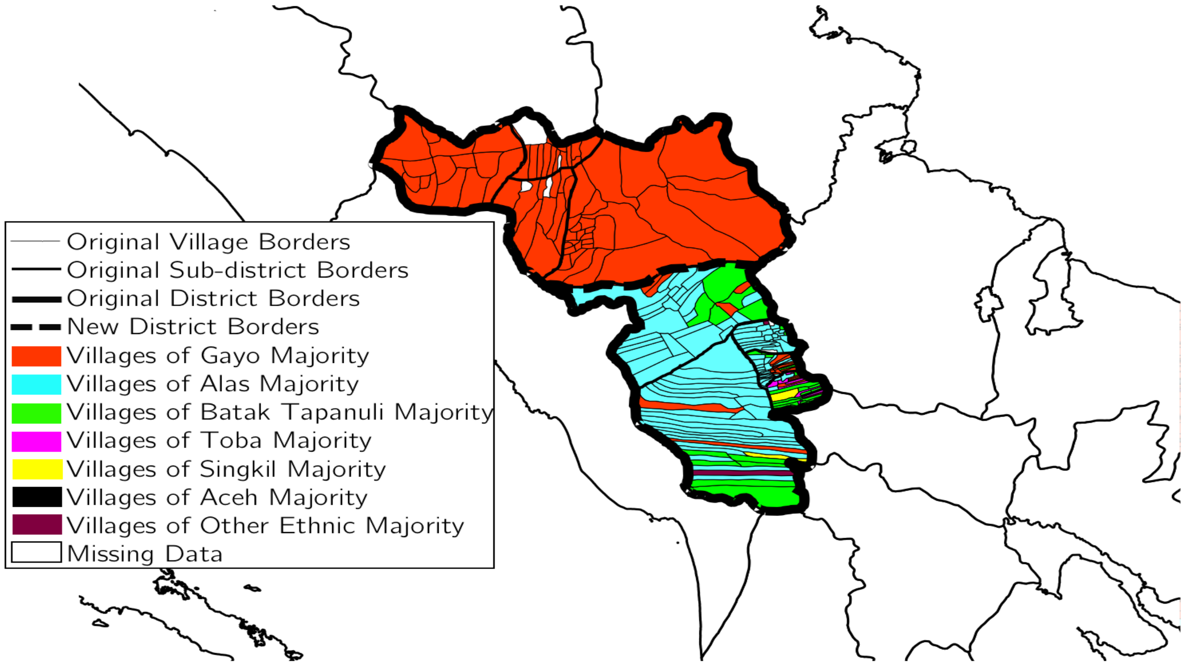
Figure 3: Example of Redistricting into Parent and Child Districts



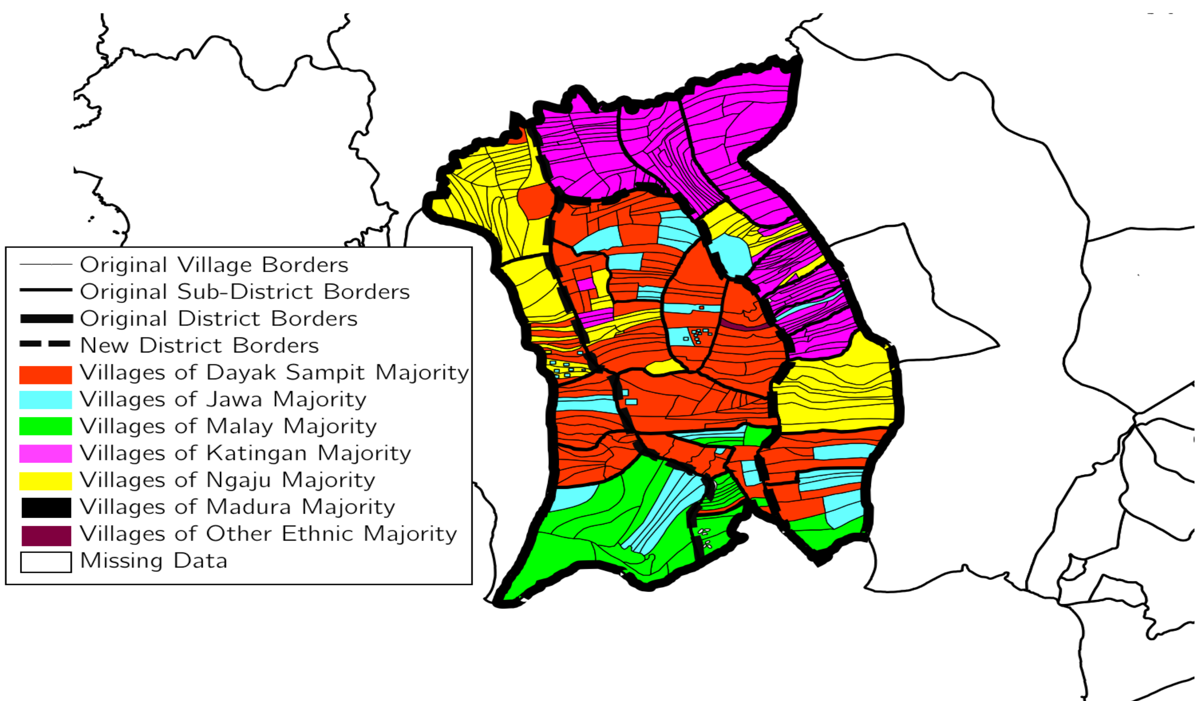
Notes: This figure provides an example of the redistricting process and our nomenclature for the different administrative divisions.

Figure 4: Examples of Border-Induced Δ Diversity

(a) *Homogenizing Case*: Aceh Tenggara District

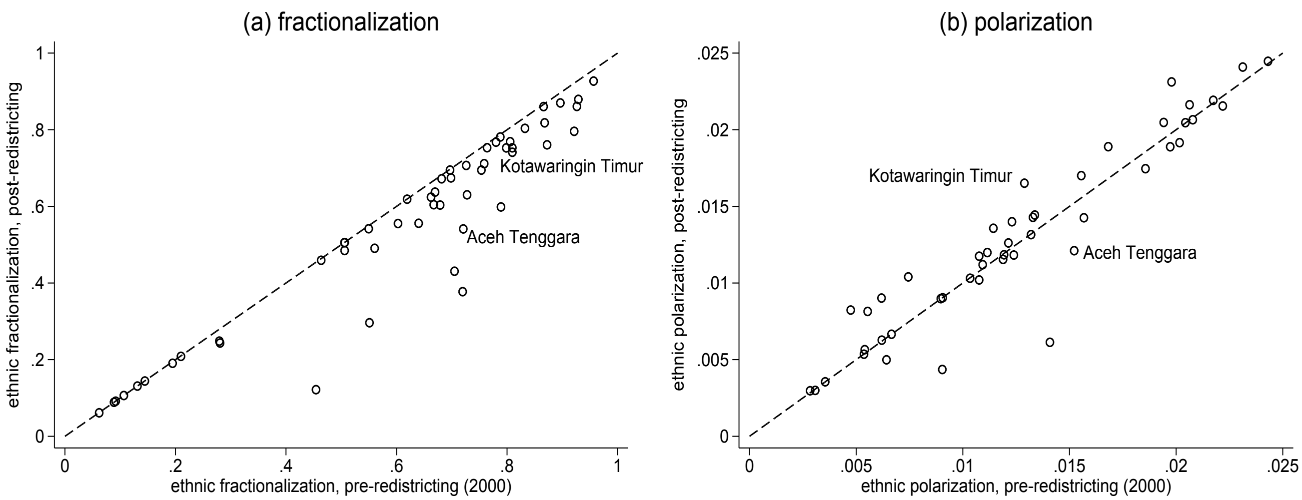


(b) *Newly Salient Divisions*: Kotawaringin Timur District



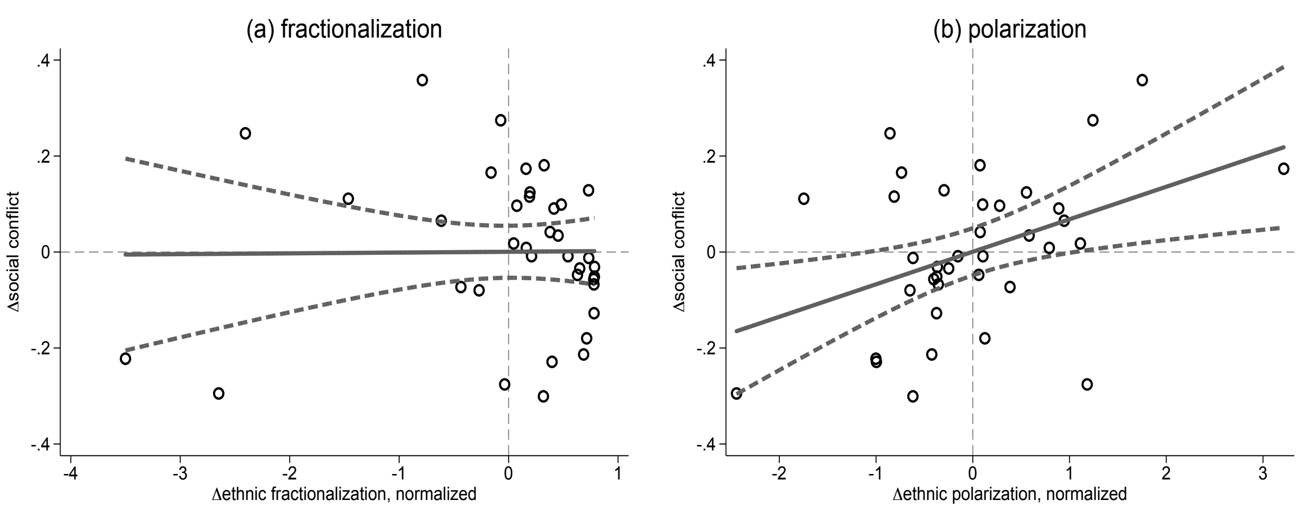
Notes: This figure provides two examples of the types of redistricting patterns that we see in our data in terms of changes in policy-relevant ethnic diversity. Figure (a) shows the original district of Aceh Tenggara as in Figure 3, and Figure (b) shows the original district of Kotawaringin Timur, which splits into two child districts, Seruyan on the left and Katingan on the right with the parent district in the middle. In both figures, we color code the villages based on the majority ethnic group in the village in the 2000 Population Census with red indicating the largest group in the original district as a whole, aqua the second largest, and so on, with a few villages in white with missing data or inability to match with shapefiles.

Figure 5: Diversity Before and After Redistricting



Notes: These figures plot diversity at the original district level baseline boundaries in 2000 (x-axis) against the 2010 boundaries after redistricting (y-axis). The latter measure is the population-weighted average of diversity in the new parent and child districts, but again based on the population residing in those areas at baseline in 2000. The dashed 45 degree line indicates the locus of points along which the new borders imply no change in diversity, and the vertical distance between each point and the line captures our $\Delta diversity$ measure. For presentational purposes, we omit the top 4 districts with baseline polarization >0.025, though they are of course included in all regression analysis. In both graphs, we identify the two example districts seen in Figure 4.

Figure 6: Simple Difference-in-Difference: Δ Conflict against Δ Diversity



Notes: This figure presents a simple difference-in-difference regression relating $\Delta diversity$ to changes in social conflict captured by the difference in the mean monthly likelihood of any violence before versus after redistricting. The results are restricted to those 38 original districts with conflict data pre- and post-redistricting. Graph (a) shows results for fractionalization and (b) for polarization. The thick dashed lines are robust 95 percent confidence intervals. The point estimate in (a) is 0.002 (0.050) and in (b) is 0.068 (0.029)** with robust standard and the HC3 degrees-of-freedom adjustment. We omit one extreme outlier (with ΔP six standard deviations below the mean) based on the outlier detection methods discussed in Appendix D.1, which presents further small-sample robustness and alternative approaches to inference.

Tables

Table 1: Plausibly Exogenous Timing of Redistricting

	Dependent Variable:	
	no. months until split mean: 53	1(post-moratorium split) mean: 0.31
Panel A: Diversity	Standardized Coefficient	
original district ethnic fractionalization	2.183	0.011
	(4.267)	(0.071)
original district Δ ethnic fractionalization	2.328	0.033
	(3.417)	(0.061)
child district ethnic fractionalization	2.641	0.009
	(3.984)	(0.069)
parent district ethnic fractionalization	4.416	0.051
	(3.962)	(0.066)
original district ethnic polarization	-1.829	-0.006
	(2.882)	(0.048)
original district Δ ethnic polarization	2.168	0.039
	(1.880)	(0.026)
child district ethnic polarization	-1.545	-0.002
	(3.122)	(0.045)
parent district ethnic polarization	1.412	0.045
	(4.002)	(0.071)
original district religious polarization	1.530	-0.024
	(3.343)	(0.060)
original district Δ religious polarization	-1.461	0.022
	(2.276)	(0.033)
child district religious polarization	-1.107	-0.063
	(3.821)	(0.060)
parent district religious polarization	2.653	0.013
	(3.749)	(0.063)
Panel B: 65 Potential Confounders (see Appendix D.2)		
mean standardized coefficient	0.096	-0.005
actual number of significant effects at 5% level	4	3
expected number of significant effects at 5% level by chance	3.3	3.3

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 redistricting. 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.2 for discussion and Appendix G for details on the variables. The mean effect size is the average standardized coefficient. The sample size is the 52 original districts in our main analysis, and all regressions include an indicator if the district entered the SNPK data in 2005. Robust standard errors are in parentheses. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 2: Average Effects of Redistricting on Social Conflict

Administrative Unit	Original District	Parent and Child	Parent	Child
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.008	0.001	0.002	0.001
	(0.026)	(0.022)	(0.028)	(0.025)
Number of District-Months	7,956	20,220	7,956	12,264
Number of Districts	52	133	52	81
Dep. Var. Mean, Pre-Split	0.57	0.33	0.47	0.25

Notes: The dependent variable in all columns is an indicator equal to one if there is any social conflict in that district–month. *post-split* is an indicator equal to one for all months after which the original or parent district experiences its first redistricting and a child district is officially passed into law. Columns 1–4 are estimated at the respective administrative unit level listed at the top of the column. There are 52 original districts in column 1, 133 parent/child districts in column 2, 52 parent districts in column 3, and 81 child districts in column 4. 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. Standard errors are clustered by original district. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 3: Redistricting, Changing Ethnic Divisions, and Conflict

Administrative Unit	Original District	Parent and Child	Parent	Child
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.012	-0.003	0.001	-0.005
	(0.025)	(0.021)	(0.026)	(0.025)
post-split $\times$ Δ ethnic polarization	0.036**	0.032	0.027**	0.043*
	(0.018)	(0.019)	(0.013)	(0.025)
post-split $\times$ Δ ethnic fractionalization	-0.003	0.000	0.035	-0.011
	(0.019)	(0.012)	(0.026)	(0.019)
post-split $\times$ Δ religious diversity	0.014	-0.009	-0.031	-0.005
	(0.013)	(0.011)	(0.021)	(0.014)
Number of District-Months	7,956	20,220	7,956	12,264
Number of Districts	52	133	52	81
Dep. Var. Mean, Pre-Split	0.57	0.33	0.47	0.25

Notes: The dependent variable in all columns is an indicator equal to one if there was any social conflict in that district–month. *post-split* is an indicator equal to one for all months after which the original or parent district experiences its first redistricting and the child district is officially passed into law. $\Delta diversity$ measures are normalized to mean zero, standard deviation one. Columns 1–4 are estimated at the respective administrative unit level listed at the top of the column. Δ of the given diversity measure captures the difference in diversity between pre-redistricting (2000) and post-redistricting (2010) boundaries, based on the initial population in 2000. For the original district, this is a weighted average of the parent and child districts. For the parent and child districts, this is a simple difference of their diversity and the original district's diversity. 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. Standard errors are clustered by original district. See the notes to Table 2. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 4: Further Isolating the Effects of Changes in Ethnic Divisions

Administrative Unit	Original District	Parent Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Other Controls×Post-Split Selected via Double Lasso ($\lambda = 3,000$)			
post-split	-0.013	0.001	-0.011	-0.005
	(0.026)	(0.019)	(0.024)	(0.023)
post-split × Δ ethnic polarization	0.025*	0.034**	0.060***	0.048*
	(0.014)	(0.015)	(0.020)	(0.026)
post-split × Δ ethnic fractionalization	-0.024	-0.004	0.036	0.010
	(0.019)	(0.013)	(0.033)	(0.027)
number of post-split × Lasso-selected controls	7	18	15	10
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: Mean Feasible $\Delta diversity$ Based on Potential Redistricting Schemes			
post-split	-0.016	-0.009	-0.005	-0.011
	(0.026)	(0.020)	(0.027)	(0.027)
post-split × mean feasible Δ ethnic polarization	0.053**	0.033***	0.052***	0.030**
	(0.024)	(0.012)	(0.016)	(0.014)
post-split × mean feasible Δ ethnic fractionalization	-0.019	-0.011	0.017	-0.019
	(0.017)	(0.012)	(0.021)	(0.015)
Number of District-Months	7,680	18,540	7,680	10,860
Dep. Var. Mean, Pre-Split	0.57	0.34	0.47	0.25

Notes: This table presents two robustness checks on the main results in Table 3. Panel A introduces additional interactions of $post\text{-}split$ and initial district characteristics. We rely on the Belloni et al. (2014) double-selection post-Lasso approach to select a parsimonious set of influential confounders from the large set of potential covariates we marshal from various data (see Appendix D.2 for details). Subject to a penalty parameter, λ, that helps control overfitting, each column includes a given set of additional $post\text{-}split$ interactions with the number varying with the specification. Alternative values of λ are explored in Appendix D.2. The p-values for a test of coefficient equality with the baseline results for ΔPolarization in Table 3 are as follows across columns: 0.17, 0.79, 0.03, 0.43, and for ΔFractionalization, 0.25, 0.79, 0.99, and 0.16. Instead of actual $\Delta diversity$, Panel B uses the mean of feasible $\Delta diversity$ based on the simulation of potential legal redistricting schemes (see Section 5.5 and Appendix E, which also considers other moments besides the mean). $\Delta diversity$ measures are normalized to mean zero, standard deviation one. These regressions omit two original districts for which a large number of feasible partitions (over which to compute reliable moments) was computationally intractable. The dependent variable in all columns is an indicator equal to one if there was any social conflict in that district–month. 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. Standard errors are clustered by original district. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 5: Changes in Ethnic Divisions, Mayoral Elections and Conflict

Administrative Unit	Parent Child	Parent	Child
	(1)	**(2)**	**(3)**
post-split	-0.003	-0.003	-0.008
	(0.022)	(0.028)	(0.025)
post-split × Δ ethnic polarization	0.030	0.026	0.042*
	(0.019)	(0.016)	(0.025)
post-split × Δ ethnic fractionalization	-0.001	0.033	-0.011
	(0.012)	(0.028)	(0.019)
post-split × 1st election period	0.044	-0.009	0.041*
	(0.044)	(0.051)	(0.021)
post-split × 1st election period × Δ ethnic polarization	0.026**	0.012	0.027***
	(0.010)	(0.022)	(0.010)
post-split × 1st election period × Δ ethnic fractionalization	-0.005	0.041	-0.012
	(0.018)	(0.034)	(0.020)
post-split × 2nd election period	0.049**	0.044	0.053
	(0.023)	(0.028)	(0.032)
post-split × 2nd election period × Δ ethnic polarization	0.008	-0.042***	0.057**
	(0.011)	(0.012)	(0.023)
post-split × 2nd election period × Δ ethnic fractionalization	0.007	0.021	-0.008
	(0.019)	(0.027)	(0.019)
Number of District-Months	19,980	7,836	12,144
Number of Districts	133	52	81
Dep. Var. Mean, Pre-Split	0.33	0.47	0.25

Notes: The dependent variable in all columns is an indicator equal to one if there was any social conflict in that parent or child district–month (see the notes to Table 2). *post-split* is an indicator equal to one for all months after which the child district is passed into law. $\Delta diversity$ measures are normalized to mean zero, standard deviation one. The first election period is an indicator capturing the 6 month window around the district-specific date of the first direct election for the district head after splitting into child and parent districts. The parent district elections occur based on the predetermined schedule inherited from the Suharto era while the child district elections typically occur around 1.5–2 years after redistricting. Hence, parent and child district elections occur at different times. The second election period is defined similarly and occurs five years after the initial election. These second election coefficients are only identified for the three-quarters of districts observed for long enough to hold that second round during our study period. We also include controls for the pre-split election periods, which take place in 10 of the original districts. Hence, the reference period in all columns is the pre-redistricting, non-election period. See Appendix G for details. 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. Standard errors are clustered by original district. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 6: Light Intensity and Changes in Village-Level Alignment with the Largest Ethnic Group in the New Versus Original District

	Parent Child **(1)**	Parent **(2)**	Child **(3)**
post-split	-0.020	-0.006	-0.033**
	(0.012)	(0.022)	(0.013)
post-split $\times$ Δ share of village in largest ethnic group in district > 0	0.011*	0.012	0.021*
	(0.006)	(0.009)	(0.011)
post-split $\times$ Δ share of village in largest ethnic group in district $= 0$	0.028**	0.017	0.040**
	(0.013)	(0.017)	(0.018)
Number of Village–Years	164,594	85,401	79,193
Dep. Var. Mean, Pre-Split	0.163	0.229	0.114

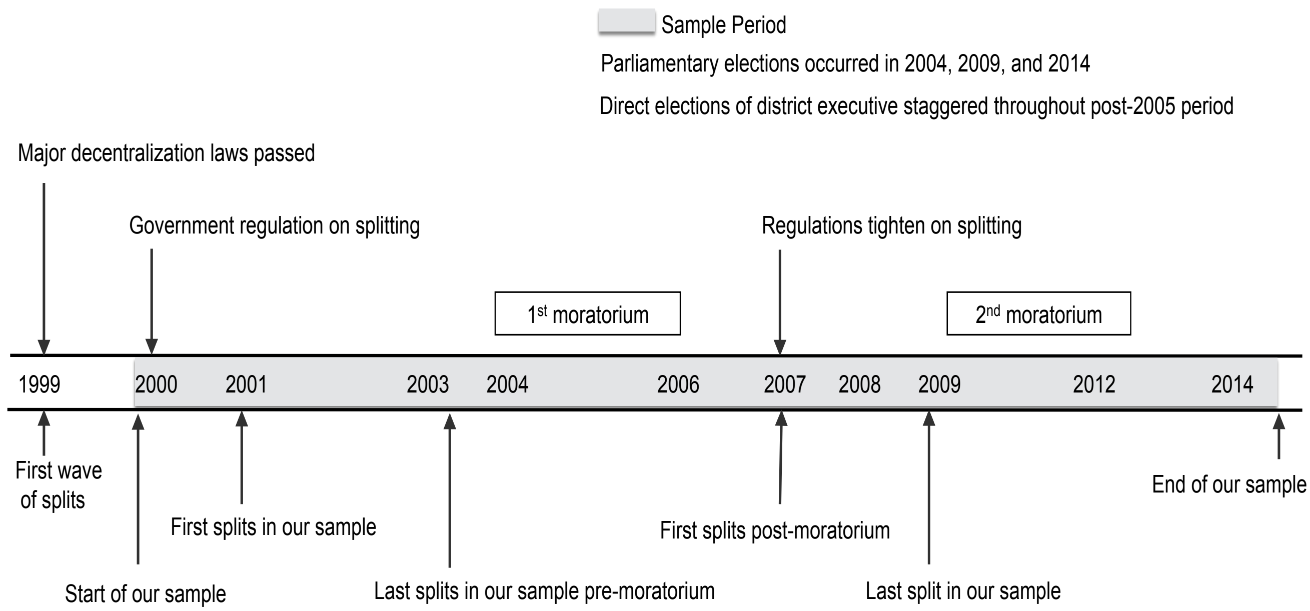
Notes: The dependent variable is share of village area covered with any nighttime lights. The village-level panel spans 2000–2013. The regressions also control for village and year fixed effects. The regressor in row 2 (3) equals one if the share of the given village belonging to the largest ethnic group in the district increased (remained the same) as a result of redistricting. The ethnic shares are, as throughout the paper, defined based on the population in 2000. Standard errors are clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Online Appendix

A Further Background on District Proliferation

Figure A.1 provides a timeline of events over our study period, including major decentralization, redistricting, and electoral reforms. Below, we provide further details on the implications of redistricting discussed in Section 2.2.

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 redistricting due to the step function rule used to determine the seat-to-population ratio. Seats in local parliament always weakly increase with redistricting. 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. Redistricting also leads to an increase in transfers from the central government. We estimate the effects of splitting on total per capita transfers in our sample using the within-district identification strategy detailed in Section 4.[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 cannot observe how transfers were divided between child and parent areas before redistricting. However, one natural benchmark is to assume that pre-split transfers (T) were allocated according to population with the parent receiving $\left(\frac{N_{parent}}{N}\right) T$ 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 redistricting and the differential

[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.

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. We plot the distribution of these differences between actual and expected transfers (based on population shares of the realized original district transfers) in Figure A.2. 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 redistricting 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.

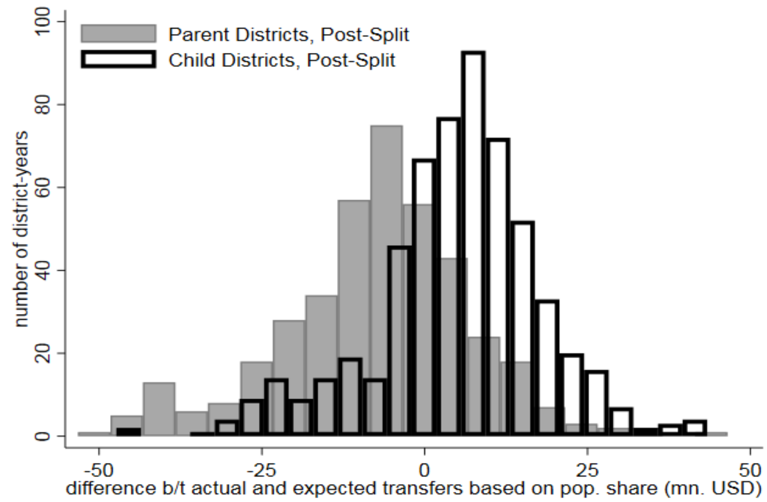
Note that while children gain disproportionately from splitting, parents nevertheless tend to see an increase in transfers as well. To see this, suppose that parents received their population share of original district transfers pre-split. Parents receive a lower share of a larger total transfer 'pie'.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

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 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.

Finally, note that these changes imply a significant reduction in the size of the population governed by any given district. According to Census data from 2000, districts based on 2000 boundaries have a median population of 400,000 whereas the 2010 district boundaries imply a median of 250,000.

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)
No. of District–Years	765	1,965	765	1,200
Dep. Var. Mean	26.6	25.6	26.0	25.3

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 per capita transfer revenue in real 2010 USD (see Appendix G) 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* 2000 and 2011 administrative censuses, for parent (and child districts separately. We are missing data for a small number of the districts in Aceh in 2003. Standard deviations in brackets.

B Further Background on the Conflict Data

B.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 B.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.[2]

Table B.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 4.2, 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.[3] Nevertheless, in a robustness check in Appendix D.6, we effectively show that

[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] Some incidents have no injuries, deaths, or property damage reported in the data due, among others, to missing information in newspaper reports. However, nearly 85 percent have such information, and our results are robust to restricting to those. Nevertheless, like the other information on events, these details are measured with error even if available. Hence, we view the actual reporting of any event as the most accurate measure of conflict incidence.

[3] 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."

our core results are not driven by the particular measure of social conflict. Moreover, as proof of concept, it is reassuring that the differential social conflict around mayoral elections in Table 5 is indeed driven in large part by violence categorized as "elections and appointments conflict."

Event Descriptions. The following Appendix B.2 provides 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", which, like elections/appointments, is plausibly responsive to a similar sort of sociopolitical changes associated with redistricting.

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. As noted in Section 6.2, there are also numerous governance incidents involving violence directed at the public electricity monopoly (PLN) centered on frustration with electricity allocation. A few examples follow:

1. Tapanuli Selatan District, 23 November 2011: *In the office of PLN . . . , about 200 people demonstrated and damaged the office. The action was triggered by anger over electricity being out for three months.*
2. Sumbawa District, 14 December 2014: *In the office of PLN . . . , there was an attack perpetrated by local residents on the head of Human Resources. The incident started when hundreds of residents went to the PLN office to protest the frequent power outages in the last 4 months and the recent total power outage for two days without notice. Angry demonstrators hit the HR's head, leaving him injured. Fortunately, the action did not escalate further because the military, police and village heads intervened to quell emotions.*

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 et al. (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.

B.2 Electoral Violence in the SNPK

As discussed in Sections 2 and 3.2, 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.

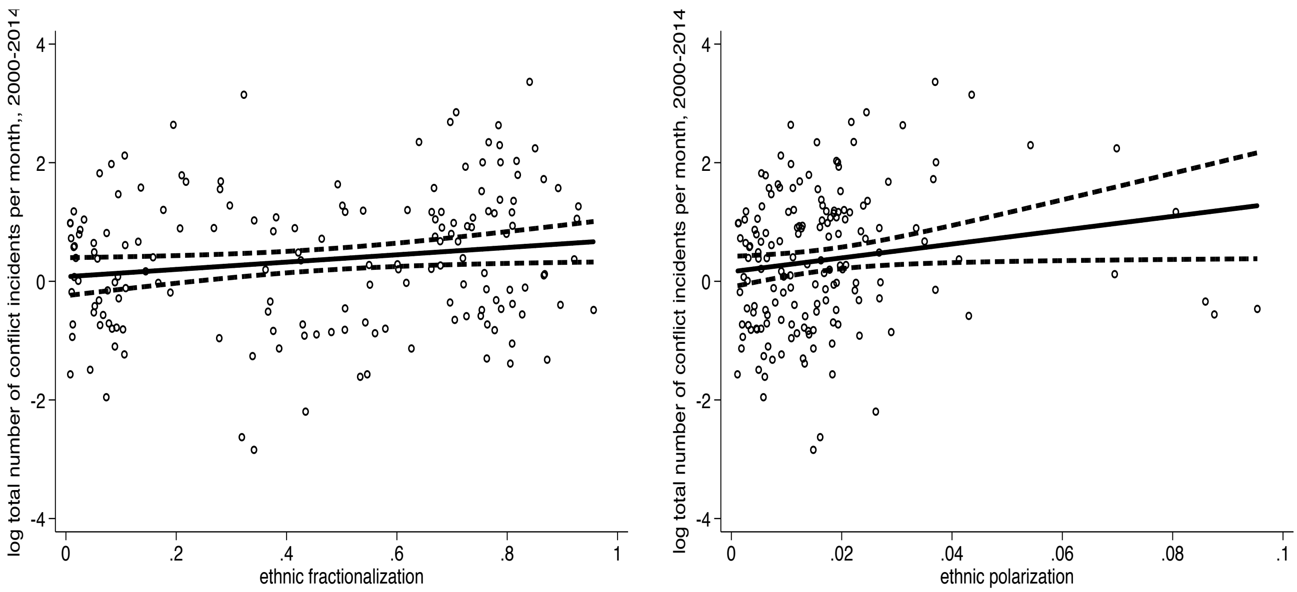
6. Kotawaringin Timur, 6 June 2005: *Incident between supporters of mayoral candidates Wahyu-Amrullah and Thamrina-Mullan Safri because one of them established billboard in the other candidates' area (Seruyan) K Timur: On Jalan Mayjen Suprapto, Seruyan Hilir subdistrict, billboard of mayoral candidate 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 Cross-District Correlations between Diversity and Conflict

We document here the strong positive correlation between ethnic diversity and conflict for Indonesian districts as noted in Section 3.1. Figure C.1 below presents the raw correlations between ethnic diversity and the log of total social conflict incidents per month from 2000 to 2014 for 164 original districts (outside Papua). Note that some of these districts enter the SNPK data in 2005, and hence we scale by total months. These include the 52 original districts in our analysis of redistricting as well as 112 other districts that did not split between 2000 and 2010. The strong positive correlations of conflict with Fractionalization and Polarization are consistent with previous cross-sectional work. In terms of normalized magnitudes, the correlations are very similar for F and P—a one standard deviation increase implies an 18 log point increase in conflict incidence—and significant at the 5 and 10 percent levels, respectively. The graphs also look similar when using the average of binary monthly indicators of any social conflict.

Figure C.1: Ethnic Diversity and Social Conflict in Indonesian Districts



Notes: These figures plot the log incidence of social conflict per month from 2000 to 2014 against initial diversity levels based on 2000 district boundaries. The observations are scaled by population size of those districts.

In Section 3.1, we report effect sizes of 8 (15) percent for P (F), which are based on an analogous pooled monthly panel specification using an indicator for any social conflict as in our main regressions. We include month and province fixed effects to sweep out broad regional and temporal differences in the diversity–conflict relationship. Formally, the estimates are given by:

$$Pr(social\ conflict_{dt}) = \alpha + \underset{(0.027)***}{0.096}\ fractionalization_d + \underset{(0.020)***}{0.051}\ polarization_d + \theta_t + \theta_{p(d)} + \varepsilon_{dt} \quad \text{(C.1)}$$

where standard errors are clustered by district, and the mean outcome is 0.63. The results are unchanged when including religious polarization, which has null effects of 0.012 (0.027).

D Robustness Checks on the Main Results in Section 5

This Appendix discusses the main robustness checks discussed throughout the paper.

D.1 Outliers and Influential Observations: Robust Estimation and Inference

This section shows that our simple and generalized difference-in-difference are robust to and, in fact, strengthened by a principled removal of outliers. Moreover, despite the relatively small effective sample sizes, our qualitative takeaways remain unchanged across a battery of alternative approaches to inference.

D.1.1 Small-Sample Robustness in Simple DiD

Figure 6 presented the raw difference-in-difference estimates relating $\Delta diversity$ to changes in the likelihood of social conflict after redistricting. These graphs are restricted to the 38 original districts that split after entering the SNPK data. We further omit one extreme outlier with ΔP greater than six standard deviations below the mean and identified as extremely high-leverage using any approach to outlier detection (including the Belsley et al. (1980) method used in the generalized DiD results below). Leaving this outlier in the analysis renders the ΔP effect null, which is precisely why it is singled out in any outlier detection method aimed at honing in regressions around central tendencies. The figures showed a strong positive correlation between ΔP and conflict but a null correlation with ΔF. We show here that the estimated results are robust to alternative treatment of outliers, small-sample inference, and simultaneous regression with both ΔP and ΔF.

Table D.1 presents estimates underlying the regression lines in Figure D.1. These are in columns 3 and 6. Columns 1, 4, and 7 are estimates based on the full sample including the extreme outlier. Columns 2, 5, and 8 implement the Huber (1973) method of robust regression that removes extreme outlier observations (the same one identified using the Belsley et al. (1980) method) and further down-weights large residual observations through an iterative process. Columns 3, 6 and 9 report OLS regressions omitting this objectively identified outlier. The standard errors in the OLS columns are robust to heteroskedasticity. Together, these results clarify the main findings from the simple difference-in-difference showing that changes in ethnic polarization are are significantly associated with changes in violence on average. Table D.2 shows that a range of alternative approaches to inference—dealing with clustering and the small (effective) sample size—leave these baseline qualitative findings unchanged.

Table D.1: Simple Difference-in-Difference Estimates

Estimator	OLS	RReg	OLS	OLS	RReg	OLS	OLS	RReg	OLS
Outlier Excluded	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Δ ethnic fractionalization	-0.014	0.001	0.002				-0.003	-0.017	-0.021
	(0.043)	(0.029)	(0.038)				(0.043)	(0.028)	(0.035)
Δ ethnic polarization				-0.034	0.077***	0.068**	-0.033	0.082***	0.074**
				(0.032)	(0.026)	(0.027)	(0.035)	(0.028)	(0.028)
Number of Original Districts	38	37	37	38	37	37	38	37	37
R^2	0.01	0.00	0.00	0.04	0.21	0.18	0.04	0.20	0.19

Notes: This table reports the regression coefficients in columns 3 and 6 corresponding to the simple difference-in-difference estimates in Figure 6 in the paper. The RReg columns are based on the robust regression method of Huber (1973), which removes extreme outliers and down-weights influential observations. Standard errors are robust to heteroskedasticity in the OLS columns. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table D.2: Simple DiD Estimates: Alternative Inference

	ΔF	ΔP
DiD Estimate	-0.021	0.074
Standard Errors		
Robust	(0.035)	(0.028)**
HC2	(0.039)	(0.029)**
HC3	(0.046)	(0.031)**
Wild Bootstrap [p-value]	[0.545]	[0.052]*
HC2 + Imbens and Kolesar (2016) DoF Adjustment	(0.049)	(0.035)**
Young (2016) Effective DoF Adjustment	(0.037)	(0.029)**
Clustering by Province (13)	(0.042)	(0.025)**
Wild Bootstrap [p-value]	[0.665]	[0.067]*
HC2 + Imbens and Kolesar (2016) DoF Adjustment	(0.090)	(0.038)**
Young (2016) Effective DoF Adjustment	(0.048)	(0.027)**

Notes: This table demonstrates the robustness of the inference in the column 9 specification in Table D.1, using alternative clustering and degrees of freedom adjustment procedures.

D.1.2 Small-Sample Robustness in Generalized DiD

As with the simple DiD estimates above, one also worries about outliers in our main generalized DiD specification based on the monthly district-level panel. However, the use of district fixed effects and time trends can help rule out some of the high leverage observations that might otherwise drive the results as they do in simpler DiD specifications. Indeed, our baseline results include all observations, and while outliers can still matter, we show here that a principled approach to their removal does not change our findings and, if anything, strengthens them.

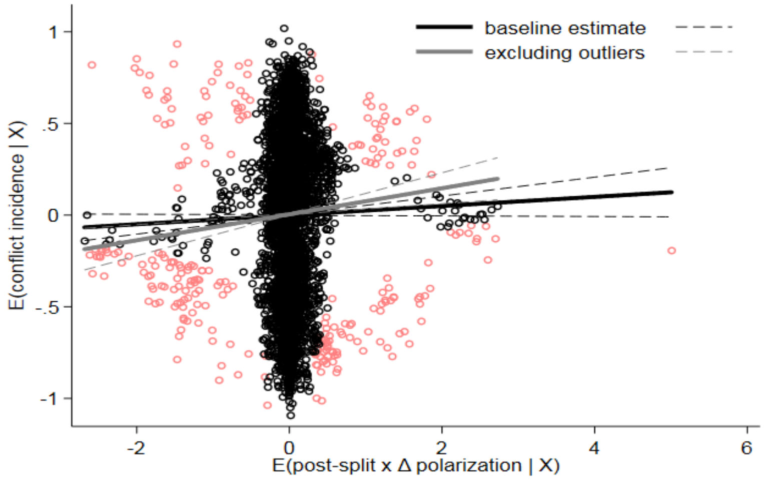
Point Estimates. We begin by demonstrating graphically how outliers affect the main results in Table 3. We adopt the widely used approach of Belsley et al. (1980) to identify observations with high influence as captured by a $dfbeta_i^k$ measure, which captures the difference between the regression coefficient θ 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, θ_k. Belsley et al. (1980, 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.1 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 3. 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.3 presents the corresponding regression results alongside our baseline estimates for reference in Panel A.[1]

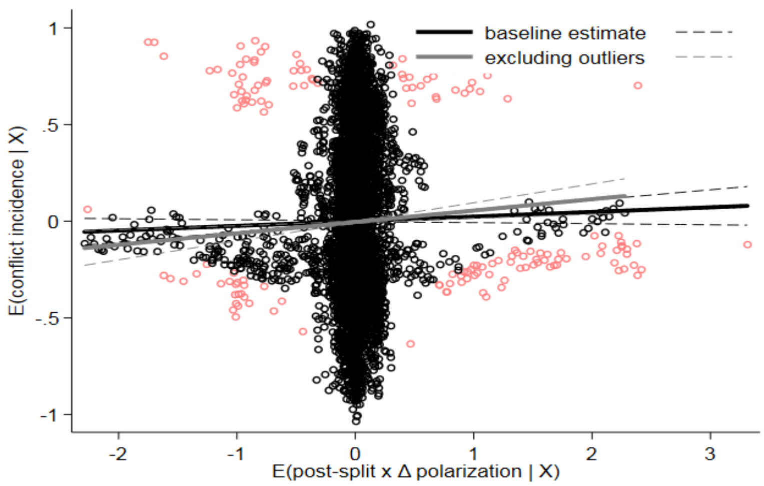
[1]We focus here on outliers in ΔP, but a similar exercise for ΔF suggests that it is also fairly insensitive to outliers.

Figure D.1: Principled Removal of Outliers from Baseline Estimates of Table 3

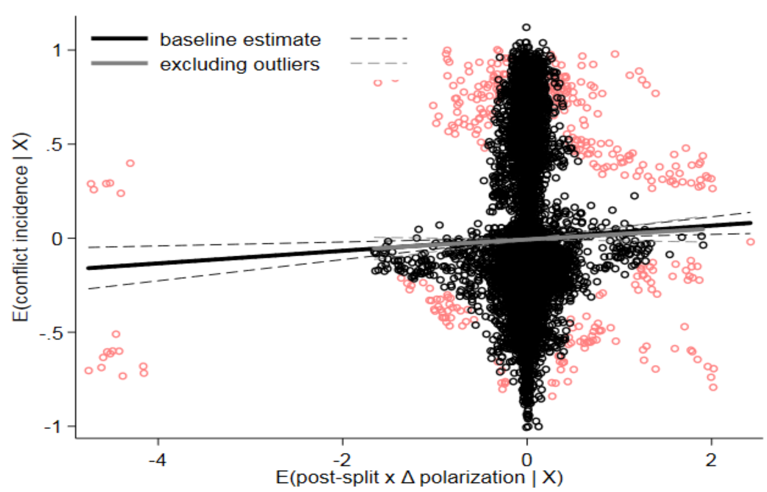
(a) Original Districts



(b) Parent Districts



(c) Child Districts



Notes: These figures present the partial regression plots for *post-split* $\times$ ΔP 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 3. The red observations are district-months identified by the Belsley et al. (1980) method for removing outliers described earlier. The gray regression line and 95 percent confidence interval are based on removing those observations and re-running the baseline regressions.

Table D.3: Robustness to Dropping Outliers

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Baseline			
post-split	-0.012	-0.003	-0.010	-0.010
	(0.025)	(0.021)	(0.032)	(0.026)
post-split × Δ ethnic polarization	0.036**	0.032	0.026**	0.045*
	(0.018)	(0.019)	(0.013)	(0.026)
post-split × Δ ethnic fractionalization	-0.003	0.000	0.062	-0.010
	(0.019)	(0.012)	(0.046)	(0.017)
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: Belsley et al. (1980) Removal of $post\text{-}split \times \Delta P$ Residual Outliers			
post-split	-0.005	-0.009	-0.010	-0.011
	(0.025)	(0.022)	(0.027)	(0.025)
post-split × Δ ethnic polarization	0.082***	0.024***	0.040***	0.029**
	(0.016)	(0.007)	(0.014)	(0.013)
post-split × Δ ethnic fractionalization	-0.027	0.008	0.045*	-0.007
	(0.018)	(0.013)	(0.025)	(0.018)
Number of District-Months	7,700	19,761	7,789	11,927

Notes: This table compares our baseline results in Panel A to results in Panel B that exclude outliers using the procedure from Figure D.1. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Inference. Besides influencing point estimates and implied effect sizes, outliers and small sample sizes more generally can also affect inference. For similar reasons noted above in the simple DiD, we consider in Table D.4 several alternative approaches to inference in the generalized DiD panel setup. We reproduce the baseline point estimates and standard errors clustered at the original district level as would be suggested by the usual Bertrand et al. (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 bandwidth. Second, we two-way cluster on both original district and month using the method of Cameron et al. (2011). This is roughly equivalent to a spatial HAC with an infinite bandwidth. Third, we implement a cluster wild bootstrap procedure to deal with the relatively small number of clusters (Cameron et al., 2008). Fourth, we take seriously the quasi-random timing of redistricting seen in Table 1 and implement a randomization inference procedure that randomly reassigns $\Delta diversity$ across each of the districts in the given regression before estimation. We repeat this 50,000 times and recover the implied nearly exact p-values.[2] Finally, 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.[3] Overall, the main qualitative takeaway of significant effects of ΔP

[2]These are *nearly* exact as they do not recover the entire distribution of possible estimates as there 2^D possible ways to reassign $\Delta diversity$ 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.

[3]This novel approach to inference delivers coefficient-specific degrees-of-freedom (DoF). For example, for ΔP, the DoF across

remain largely unchanged.

Interestingly, the main exception lies in the "effective degrees of freedom adjustment" approach, which leads to significant increases in the standard errors (though all t-statistics remain over one). Given that this method leans heavily on the role of outliers, it is not surprising that the upward adjustment in standard errors is much smaller when first removing outliers using the Belsley et al. (1980) approach. Table D.5 implements this simultaneous removal of outliers and adjustment of inference to account for remaining high influence observations. Together, this delivers the most consistent evidence that ΔP exerts a significant positive effect on social conflict.

Table D.4: Robustness to Alternative Inference Procedures

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.012	-0.003	0.001	-0.005
baseline: clustering on original district (OD)	(0.025)	(0.021)	(0.032)	(0.026)
spatial HAC, 500 km uniform bandwidth	(0.024)	(0.013)	(0.024)	(0.014)
two-way clustering on OD and month	(0.027)	(0.022)	(0.029)	(0.025)
effective degrees of freedom adjustment	(0.026)	(0.022)	(0.034)	(0.026)
wild bootstrap, clustering on OD [p-value]	[0.648]	[0.911]	[0.970]	[0.838]
randomization inference [p-value]	[0.879]	[0.994]	[0.654]	[0.991]
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)**	(0.026)*
spatial HAC, 500 km uniform bandwidth	(0.016)**	(0.005)***	(0.014)*	(0.008)***
two-way clustering on OD and month	(0.017)**	(0.019)*	(0.013)**	(0.024)*
effective degrees of freedom adjustment	(0.029)	(0.023)	(0.019)	(0.030)
wild bootstrap, clustering on OD [p-value]	[0.114]	[0.174]	[0.173]	[0.474]
randomization inference [p-value]	[0.103]	[0.022]**	[0.145]	[0.019]**
post-split × Δ ethnic fractionalization	-0.003	0.000	0.035	-0.011
baseline: clustering on original district	(0.019)	(0.012)	(0.046)	(0.017)
spatial HAC, 500 km uniform bandwidth	(0.021)	(0.011)	(0.012)***	(0.014)
two-way clustering on OD and month	(0.015)	(0.012)	(0.026)	(0.020)
effective degrees of freedom adjustment	(0.022)	(0.013)	(0.030)	(0.021)
wild bootstrap, clustering on OD [p-value]	[0.873]	[0.980]	[0.222]	[0.591]
randomization inference [p-value]	[0.557]	[0.489]	[0.074]*	[0.708]
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

Notes: This table presents the suite of alternative inference procedures for our baseline specification as detailed above. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

columns 1–4 are 11.3, 4.7, 6.2, and 5.6.

Table D.5: Robustness to Outliers and Effective Sample Size Inference

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.005	-0.009	-0.010	-0.011
baseline: clustering on original district (OD)	(0.025)	(0.022)	(0.027)	(0.025)
effective degrees of freedom adjustment	(0.026)	(0.022)	(0.028)	(0.026)
post-split $\times$ Δ ethnic polarization	0.082	0.024	0.040	0.029
baseline: clustering on original district (OD)	(0.016)***	(0.007)***	(0.014)***	(0.013)**
effective degrees of freedom adjustment	(0.023)***	(0.009)**	(0.021)*	(0.016)
post-split $\times$ Δ ethnic fractionalization	-0.027	0.008	0.045	-0.007
baseline: clustering on original district (OD)	(0.018)	(0.013)	(0.025)*	(0.018)
effective degrees of freedom adjustment	(0.020)	(0.013)	(0.028)	(0.020)
Number of District-Months	7,700	19,761	7,789	11,927

Notes: This table demonstrates robustness to both outlier removal and the effective degrees of freedom adjustment developed by Young (2016).

D.2 Ruling Out Confounding Effects of Other Initial District Characteristics

As discussed in Section 5.4, we take several steps to address the concern that the effects of $\Delta diversity$ on conflict are confounded by omitted district-specific characteristics that also differentially matter after redistricting. 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.6–D.9 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.

Therefore, we address such concerns by taking a second, more agnostic approach to variable selection based on the double-selection post-Lasso method of Belloni et al. (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. 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 G), drawn from key Indonesian data sources that cover 1999/2000 and are granular enough to construct controls at the eventual 2010 boundaries. Selection is accomplished using Lasso. The Lasso penalty parameter 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 intensity, 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.

Table 4 showed that our main results are unchanged when including these machine-selected covariate interactions with $post\text{-}split$. The fact that these machine-chosen 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.2 below shows further that these results are robust to varying the penalty parameter, λ, allowing for the inclusion of more or fewer additional covariates.[4] We see that the estimated effects of $\Delta diversity$ 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.

[4]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.6: 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 revenue 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 3 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.7: Robustness to Additional Controls × 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)
× 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)
× 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)
× 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)
× log distance to security post		-0.031*								
		(0.016)								
× log distance to police station		0.030*								
		(0.017)								
× nighttime light intensity			0.003							
			(0.015)							
× share with > primary education			-0.011							
			(0.017)							
× distance to public market				-0.004						
				(0.014)						
× share villages with electricity				-0.017						
				(0.015)						
× share villages with safe water				0.023						
				(0.016)						
× share villages with street light				0.001						
				(0.018)						
× share villages with transport center				0.053***						
				(0.014)						
× health centers per capita				0.007						
				(0.015)						
× high schools per capita				-0.018						
				(0.016)						
× log initial population					0.003					
					(0.015)					
× population share, 5–14					-0.001					
					(0.016)					
× population share, 15-49					-0.005					
					(0.020)					
× nat. resource revenue per capita						-0.016				
						(0.011)				
× cash crop share of total ag. output						0.011				
						(0.016)				
× share of land area with forest						0.006				
						(0.012)				
× parliamentary vote polarization							0.002			
							(0.013)			
× fiscal transfers per capita							-0.007			
							(0.010)			
× share in agriculture								-0.008		
								(0.022)		
× share in forestry/fishing								0.013		
								(0.023)		
× share in other								-0.011		
								(0.024)		
× land area									0.008	
									(0.024)	
× share villages on coast									0.021	
									(0.076)	
× share villages in valley									0.019	
									(0.046)	
× share villages on hill									-0.038	
									(0.072)	
× share villages on flatland									0.009	
									(0.070)	
× shares villages in highlands									0.036	
									(0.031)	
× log elevation									0.005	
									(0.016)	
× log distance to coast									0.006	
									(0.030)	
× log distance to river									-0.013	
									(0.019)	
× log distance to subdistrict capital										0.018
										(0.020)
× log distance to district capital										0.030
										(0.024)
× 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 3 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.8: Robustness to Additional Controls $\times$ 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)
$\times$ 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)
$\times$ 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)
$\times$ 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)
$\times$ log distance to security post		-0.028								
		(0.021)								
$\times$ log distance to police station		0.053**								
		(0.023)								
$\times$ nighttime light intensity			-0.020							
			(0.021)							
$\times$ share with > primary education			-0.024							
			(0.030)							
$\times$ distance to public market				-0.060**						
				(0.028)						
$\times$ share villages with electricity				-0.067**						
				(0.025)						
$\times$ share villages with safe water				-0.010						
				(0.027)						
$\times$ share villages with street light				-0.012						
				(0.022)						
$\times$ share villages with transport center				0.076***						
				(0.017)						
$\times$ health centers per capita				0.049***						
				(0.017)						
$\times$ high schools per capita				0.019						
				(0.017)						
$\times$ log initial population					0.017					
					(0.026)					
$\times$ population share, 5–14					0.058**					
					(0.027)					
$\times$ population share, 15-49					0.011					
					(0.033)					
$\times$ nat. resource revenue per capita						0.010				
						(0.009)				
$\times$ cash crop share of total ag. output						-0.005				
						(0.027)				
$\times$ share of land area with forest						-0.022				
						(0.024)				
$\times$ parliamentary vote polarization							-0.027			
							(0.019)			
$\times$ fiscal transfers per capita							0.017			
							(0.022)			
$\times$ share in agriculture								-0.019		
								(0.036)		
$\times$ share in forestry/fishing								0.008		
								(0.041)		
$\times$ share in other								-0.036		
								(0.038)		
$\times$ land area									-0.018	
									(0.025)	
$\times$ share villages on coast									0.006	
									(0.124)	
$\times$ share villages in valley									0.041	
									(0.083)	
$\times$ share villages on hill									-0.024	
									(0.128)	
$\times$ share villages on flatland									0.003	
									(0.105)	
$\times$ shares villages in highlands									0.032	
									(0.047)	
$\times$ log elevation									-0.029	
									(0.024)	
$\times$ log distance to coast									0.013	
									(0.033)	
$\times$ log distance to river									0.041	
									(0.039)	
$\times$ log distance to subdistrict capital										0.027
										(0.033)
$\times$ log distance to district capital										-0.012
										(0.039)
$\times$ 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

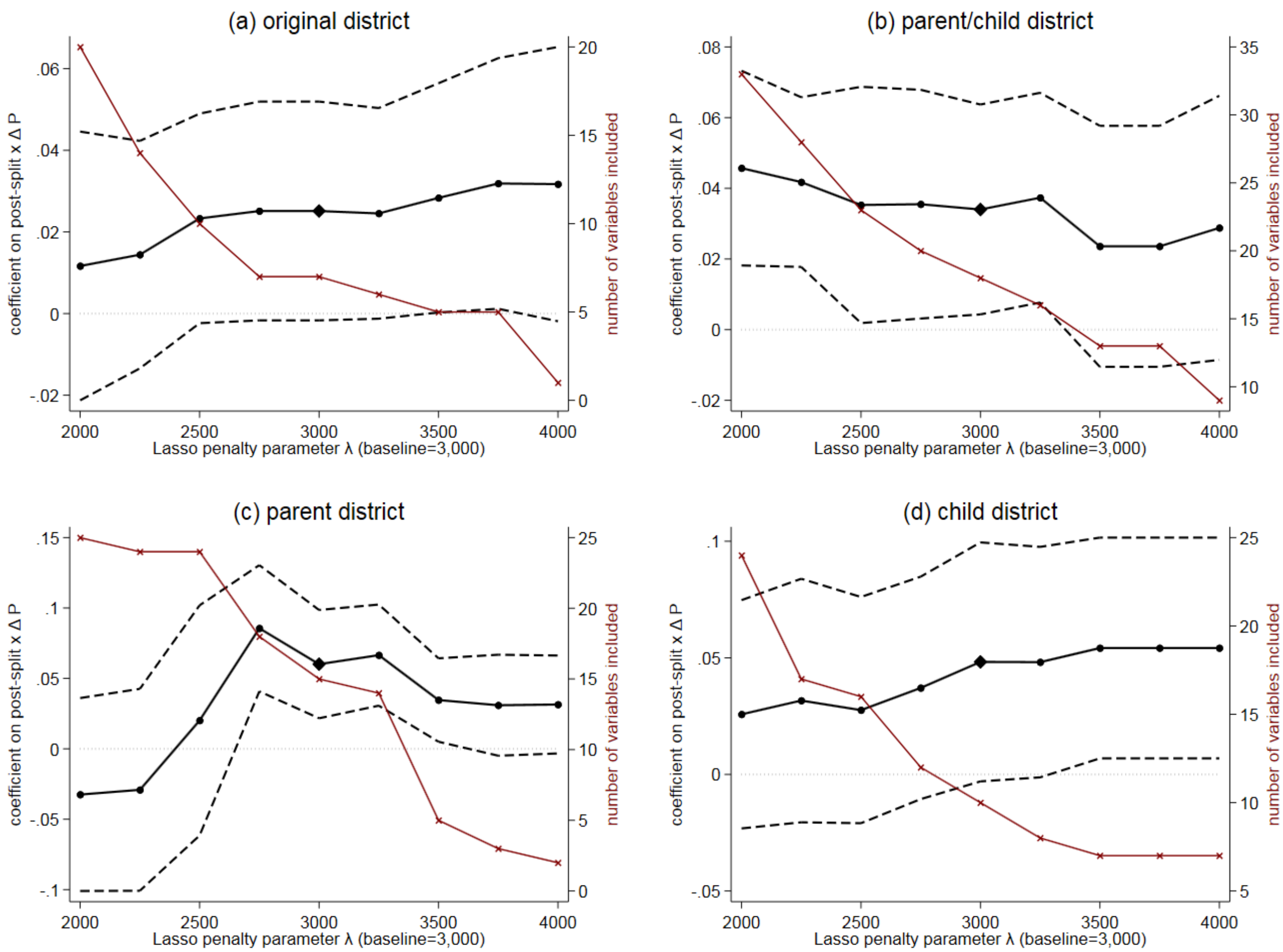
Notes: This table augments our baseline specification from column 3 of Table 3 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Table D.9: 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 revenue 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 3 with additional interactions of *post-split* and potentially confounding initial district characteristics.

Figure D.2: 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. Table 4 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.3 Incorporating Changes in Public Resources and Proximity to Government

As discussed in Section 5.4, we address other confounding effects of redistricting on the size and location of contestable public resources. Appendix Tables D.10 and D.11 incorporate measures of changes in transfer revenue and distance to the district capital as motivated in Appendix A with further details on variable construction on page 98 of Appendix G. Appendix Table D.11 augments the specification in Table D.10 with additional interactions of $\Delta diversity$ and the changes in transfers and distance. Although noisy, these results generally point towards an amplification effect of changing ethnic divisions alongside changes in contestable public resources. In some cases, the effects load onto the interaction while in others they load onto the own terms. It is reassuring that changes in distance to the district capital have null own and interaction effects for parent districts given that this is not changing due to redistricting (but may change due to potentially endogenous road improvements). Consistent with cross-national results in Campante et al. (2016), violence is more pronounced in child districts where redistricting leads to larger changes in proximity to the district capital. The fact that the original district results in both tables are more muted is likely due to the weaker effects at the parent versus child district level. Overall, though, the results in these tables are in line with the predictions from the simple conceptual framework in Section 3.2.

Table D.10: Accounting for Changes in Local Public Resources After Redistricting

Administrative Unit	Original District	Parent Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.006	-0.001	0.002	-0.002
	(0.027)	(0.021)	(0.027)	(0.024)
post-split × Δ ethnic polarization	0.038**	0.032*	0.023	0.034*
	(0.014)	(0.017)	(0.015)	(0.020)
post-split × Δ ethnic fractionalization	-0.006	0.006	0.035	0.005
	(0.022)	(0.012)	(0.027)	(0.017)
post-split × Δ transfer revenue	0.037	0.027**	-0.004	0.038***
	(0.028)	(0.012)	(0.021)	(0.012)
post-split × Δ distance to district capital	-0.002	-0.012	0.010	-0.033
	(0.019)	(0.013)	(0.016)	(0.020)
Number of District-Months	7,836	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.57	0.33	0.47	0.25

Notes: This table augments the baseline specification in Table 3 with two measures capturing changes in public resources and proximity to government institutions due to redistricting. Δ transfer revenue is the difference in log average annual transfer revenue post-split and average annual transfer revenue pre-split under the assumptions of allocations proportional to population pre-split in the parent and child district specifications. Δ distance to district capital is the population-weighted average village-level difference in log reported travel distance to the district capital in 2011 (post-split) and 2000 (pre-split) as reported by village officials. All variables are normalized to mean zero and standard deviation one. These regressions omit one original district in Jakarta on account of it being in the national capital and not receiving the same stream of general district transfer revenue. The dependent variable in all columns is an indicator equal to one if there was any social conflict in that district–month. 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. Standard errors are clustered by original district. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table D.11: Changes in Local Public Resources Amplify the Effects of Changes in Ethnic Divisions

Administrative Unit	Original District	Parent Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.014	-0.003	-0.013	-0.002
	(0.027)	(0.021)	(0.029)	(0.024)
post-split × Δ ethnic polarization (P)	0.122	0.002	0.099	0.012
	(0.080)	(0.024)	(0.066)	(0.013)
post-split × Δ ethnic fractionalization (F)	-0.025	0.015	0.036	0.016
	(0.053)	(0.013)	(0.028)	(0.014)
post-split × Δ transfer revenue	0.041	0.029**	0.004	0.049***
	(0.030)	(0.013)	(0.020)	(0.011)
post-split × ΔF × Δ transfer revenue	-0.011	-0.006	0.020	-0.016
	(0.059)	(0.013)	(0.026)	(0.015)
post-split × ΔP × Δ transfer revenue	-0.036	0.007	-0.029	0.059**
	(0.046)	(0.010)	(0.029)	(0.022)
post-split × Δ distance to district capital	0.004	-0.008	0.012	-0.035*
	(0.033)	(0.013)	(0.015)	(0.018)
post-split × ΔF × Δ distance to district capital	0.008	0.007	-0.007	0.000
	(0.031)	(0.012)	(0.023)	(0.018)
post-split × ΔP × Δ distance to district capital	0.009	-0.024**	-0.006	-0.008
	(0.074)	(0.010)	(0.017)	(0.014)
Number of District-Months	7,836	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.57	0.33	0.47	0.25

Notes: This table augments the specification in Table 3 with additional interactions of $\Delta diversity$ with $\Delta transfers$ and $\Delta distance$. The specification is otherwise unchanged. Standard errors are clustered by original district. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.4 Validating the Conflict Measures and Ruling Out Systematic Reporting Bias

Recall that the SNPK data is based on an exhaustive and carefully vetted set of local media sources across Indonesia. The comprehensiveness of SNPK offers significant advantages relative to other event-based conflict data sources (see Appendix B.1). However, like those sources, 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 redistricting 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.[5] We offer here one important robustness check on our own results and that might also be fruitfully applied to others using similar data.

In particular, 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.[6]

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. Table D.12 below shows this for our baseline results from Table 3. Results look similar for the intensive margin specifications in Table D.19. Table D.13 shows this for the the political cycles of conflict results in Table 5. Note that the Google Trends themselves are positively correlated with conflict, which is consistent with the points above. That the effects of $\Delta diversity$ remain unchanged after removing this media-driven correlation is all the more reassuring. In fact, across several specifications, we find slight improvements in precision, which could be due to the Google trends soaking up some of the residual reporting variation.

[5]Indeed, the same concern would 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).

[6]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.

Table D.12: Table 3 Robust to Controlling for Google Trends

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.011	-0.004	0.003	-0.007
	(0.025)	(0.021)	(0.026)	(0.025)
post-split × Δ ethnic polarization	0.040**	0.033*	0.032**	0.043*
	(0.018)	(0.019)	(0.013)	(0.025)
post-split × Δ ethnic fractionalization	-0.005	0.001	0.035	-0.011
	(0.019)	(0.012)	(0.026)	(0.019)
Google trends	0.125*	0.071*	0.145*	0.042
	(0.067)	(0.041)	(0.073)	(0.039)
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

Notes: This table re-estimates the baseline specification controlling for monthly Google Trends in searches for each district's name. This measure takes on a value ranging from 0 to 1 indicating for each district–month the relative frequency of searches for its name when compared to other benchmark searches. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table D.13: Table 5 Robust to Controlling for Google Trends

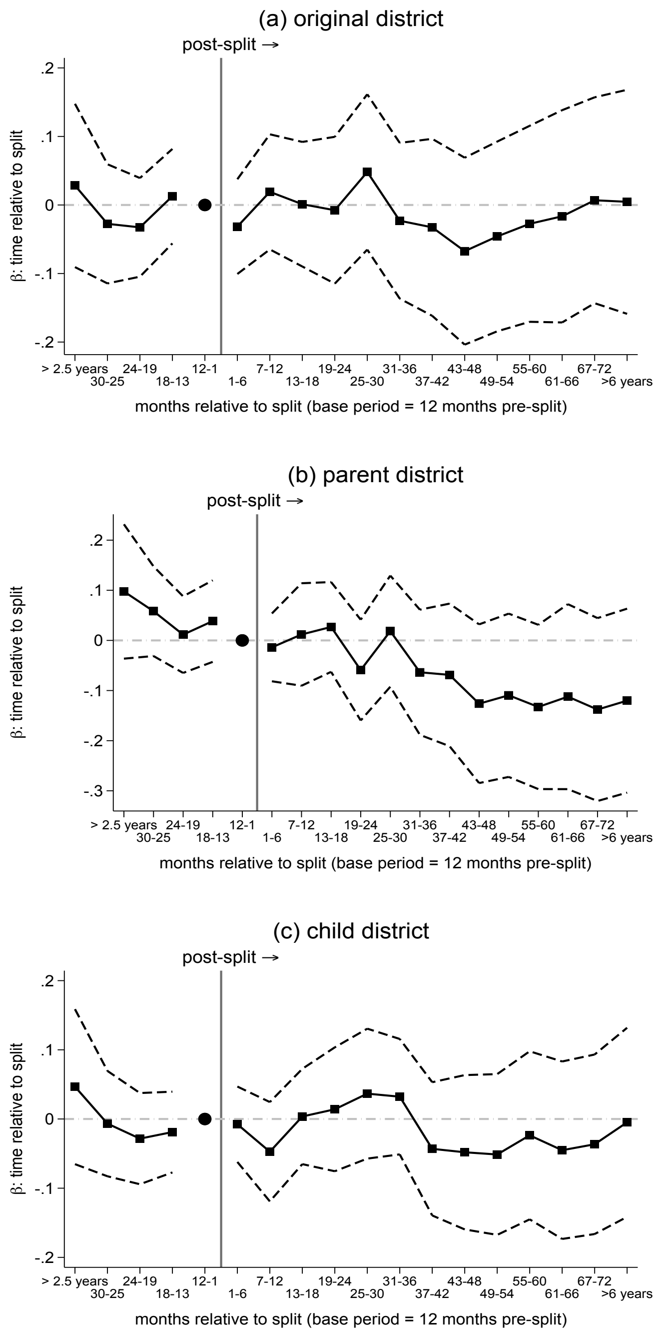
Administrative Unit	Parent and Child	Parent	Child
	(1)	**(2)**	**(3)**
post-split	-0.004	-0.001	-0.009
	(0.022)	(0.027)	(0.024)
post-split × Δ ethnic polarization	0.031	0.031*	0.043*
	(0.019)	(0.016)	(0.025)
post-split × Δ ethnic fractionalization	-0.001	0.033	-0.011
	(0.012)	(0.027)	(0.019)
post-split × 1st election period	0.046	-0.004	0.040*
	(0.044)	(0.050)	(0.021)
post-split × 1st election period × Δ ethnic polarization	0.026**	0.013	0.027***
	(0.011)	(0.022)	(0.010)
post-split × 1st election period × Δ ethnic fractionalization	-0.005	0.041	-0.012
	(0.018)	(0.034)	(0.020)
post-split × 2nd election period	0.045*	0.035	0.051
	(0.022)	(0.027)	(0.032)
post-split × 2nd election period × Δ ethnic polarization	0.008	-0.042***	0.057**
	(0.011)	(0.013)	(0.023)
post-split × 2nd election period × Δ ethnic fractionalization	0.008	0.021	-0.008
	(0.019)	(0.028)	(0.019)
Google trends	0.062	0.139*	0.027
	(0.041)	(0.071)	(0.040)
Number of District-Months	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.33	0.47	0.25

Notes: This table re-estimates the Table 5 specification controlling for monthly Google Trends in searches for each district's name. This measure takes on a value ranging from 0 to 1 indicating for each district–month the relative frequency of searches for its name when compared to other benchmark searches. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.5 Event Study Specifications

We present here the event study generalization of the main equations (3) and (4) as discussed in the paper. These figures highlight both the lack of worrying pre-trends before redistricting as well as provide some insight into the post-redistricting conflict dynamics.

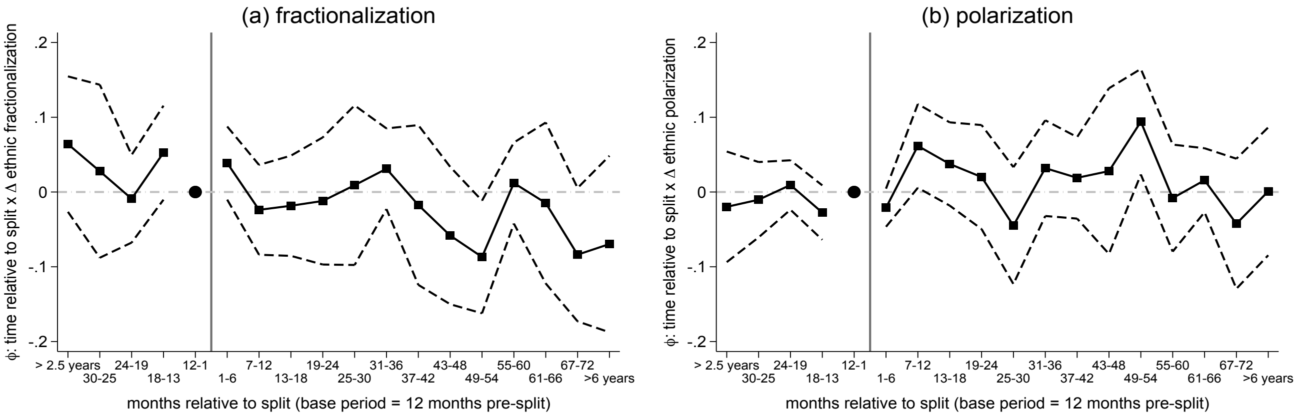
Figure D.3: Event Study: Average Effects of Redistricting on Social Conflict (Table 2)



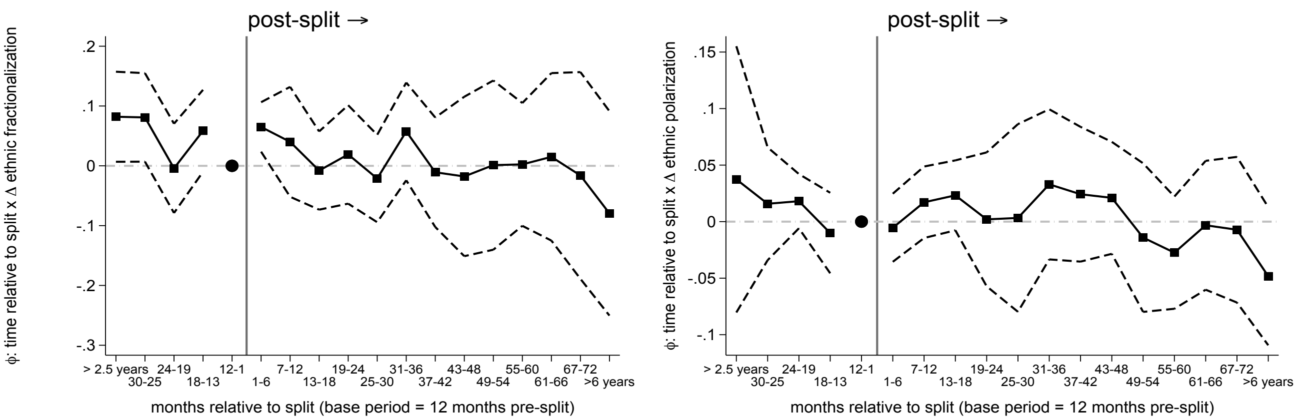
Notes: These figures report coefficient estimates and 95% confidence intervals from event study versions of the regression specification in equation (3) and given by: $conflict_{dt} = \nu + \sum_{j=-5}^{13} \beta_j post\text{-}split_{d,t-j} + \theta_t + \theta_d + \theta_d \times t + \varepsilon_{dt}$, where j denotes 6 month bins beginning 30 months prior to splitting (i.e., $j = -4$ for months 30–24 before splitting) and ending 72 months after (i.e., $j = 12$ for months 67–72 after splitting) with an additional $j = -5$ for greater than 30 months before splitting (where defined) and $j = 13$ for all months after 72. The reference period is the 12 months just prior to splitting. The graph shows the β_j coefficients.

Figure D.4: Event Study: Redistricting, Polarization, and Social Conflict (Table 3)

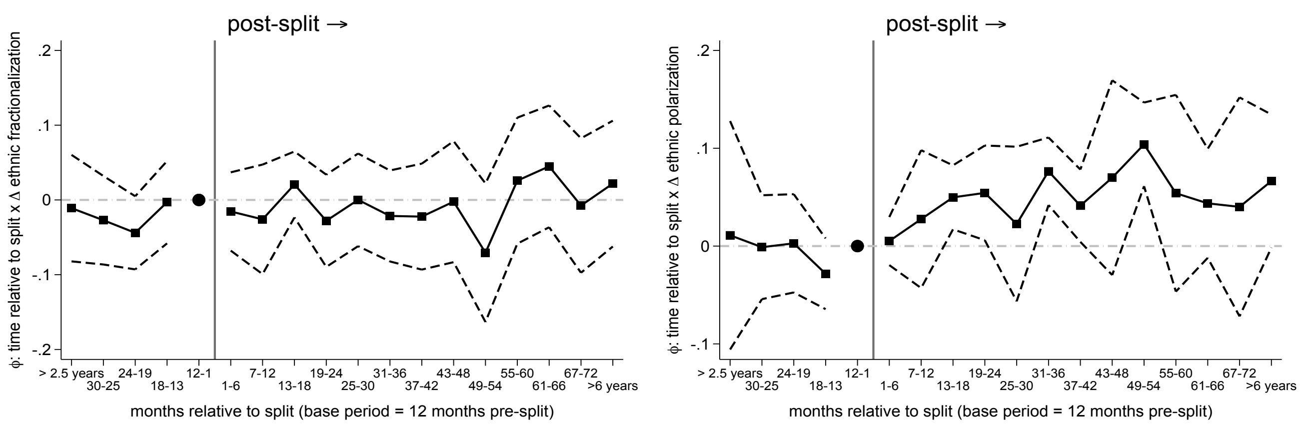
(a) Original District



(b) Parent District



(c) Child District



Notes: These figures report coefficient estimates and 95% confidence intervals from event study versions of the regression specification in equation (4) and given by: $conflict_{dt} = \nu + \sum_{j=-5}^{13} \left[\beta_j post\text{-}split_{d,t-j} + \sum_{k\in\{F,P\}} \phi_j^k \left(post\text{-}split_{d,t-j} \times \Delta k_d\right)\right] + \theta_t + \theta_d + \theta_d \times t + \varepsilon_{dt}$, where j denotes 6 month bins beginning 30 months prior to splitting (i.e., $j = -4$ for months 30–24 before splitting) and ending 72 months after (i.e., $j = 12$ for months 67–72 after splitting) with an additional $j = -5$ for greater than 30 months before splitting (where defined) and $j = 13$ for all months after 72. The reference period is the 12 months just prior to splitting. The graph shows the ϕ_j coefficients for ethnic fractionalization on the left and polarization on the right.

D.6 Alternative Categorizations of Violence

Our main analysis considered a set of violence categories in the SNPK that aimed to capture group-based conflict (see Appendix B.1). This appendix rules out 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.[7] Hence, their omission may be deemed arbitrary at best and biasing at worst. Table D.14 shows that the main results in Table 3 are robust to using 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 the background on the SNPK data in Appendix B.1.

Table D.14: Effects are Similar When Not Restricting to Social Conflict

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Dep. Var.: Any Violence			
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)
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. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

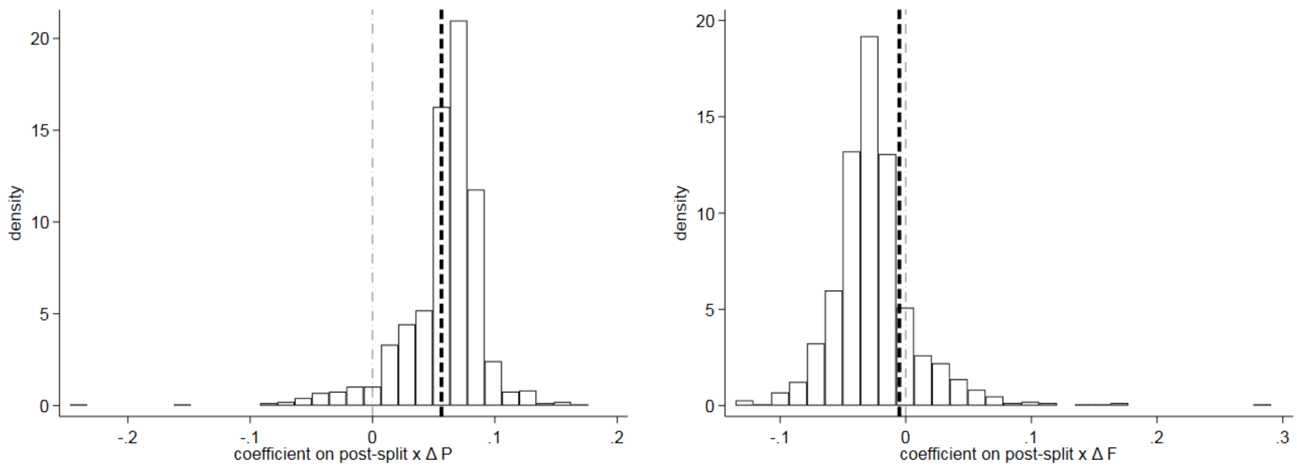
Second, we further gauge robustness to event misclassification by re-estimating our regressions for all possible combinations of the ten main categories of violence in the SNPK. Figure D.5 presents the distribution of the estimated coefficients on $post\text{-}split \times \Delta P$ and $post\text{-}split \times \Delta F$ 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 D.5 helps to dispel such concerns and shows that our core estimated effect of ΔP on social conflict appears

[7] 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 et al., 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.

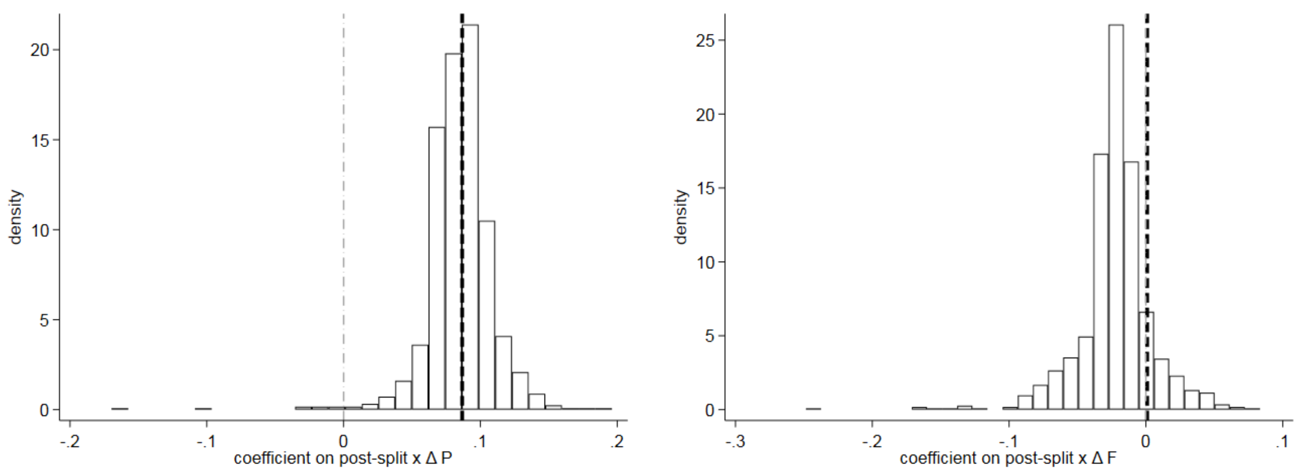
to be around the middle of the distribution of effect sizes across all possible combinations of violence categories. Moreover, the distribution of these coefficients seems to lie mostly above zero, which again points to the fact that changing ethnic divisions shifts most types of violence in the same direction. The takeaways are similar for ΔF.

Figure D.5: 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 3.

D.7 Alternative Measures of Diversity

Following Fearon (2003), we use linguistic differences to proxy for cultural distance between groups. We map each of the over 1,000 ethnic groups in the 2000 Census to a language in *Ethnologue*, which provides a full classification of the linguistic origins of each language (see Bazzi et al., 2016, for details). Recall that we measure polarization as $P = \sum_{j=1}^{\mathcal{N}_e} \sum_{k=1}^{\mathcal{N}_e} g_j^2 g_k \eta_{jk}$. The widely used Fearon (2003) metric sets $\eta_{jk} = 1 - s_{jk}^{\delta}$, where s_{jk} measures the similarity between the languages spoken by j and k as given by the share of common branches on the language classification tree. See Appendix G for further details. Low δ stresses differences between languages with the fewest branches in common; as δ increases, smaller differences become relatively more important until in the limit all differences are equal to 1 unless groups share a common language. Following Desmet et al. (2009) and Esteban et al. (2012), we set $\delta = 0.05$ as our baseline. This low δ emphasizes deeper ethnolinguistic cleavages and hence puts more weight on polarized districts with the most culturally dissimilar groups.

Dissecting Ethnolinguistic Cleavages. In Table D.15 below, we show that increasing δ leads to weaker estimated effects of ΔP, which suggests that border-induced changes in ethnic divisions have more significant effects on conflict where those divisions are among the deeper ones in society.[8] This is consistent with findings in Esteban et al. (2012) and Desmet et al. (2012) who argue that the positive cross-country relationship between diversity and conflict is driven by countries with deeper linguistic cleavages. Indeed, Esteban et al. (2012) similarly find a smaller and less significant effect of ethnic polarization on conflict when using $\delta = \infty$ (with *Ethnologue* data) as we do in Panel C. Nevertheless, we do not push this argument too far given that few of the coefficients across Panels B and C are statistically different from the baseline in Panel A. Nor for that matter are the differences between ΔP and ΔF (as we discuss in the paper).

In defining F, we allow each self-reported ethnicity in the Population Census to be its own group. This permits rich sub-ethnic breakdowns within broader ethnic categories. This data-driven approach is consistent with political science research, which suggests that ethnic distinctions became increasingly granular in the era of decentralization as groups looked for ways to mobilize around actionable identities at the local level (e.g., Mietzner, 2014). This is different from Fearon (2003), which is based on defining groups according to subjective assessments of ethnic boundaries relevant to social conflict. Our approach is more akin to defining groups based on all of those reported in the *Ethnologue* data. Interestingly, when using the Fearon (2003) groupings, Esteban et al. (2012) find that F has a significant positive correlation with conflict, but this becomes smaller and even null when using the full *Ethnologue* elaboration.

We further clarify the remaining distinction between P and F by considering the Gini-Greenberg index, $G = \sum_{j=1}^{\mathcal{N}_e} \sum_{k=1}^{\mathcal{N}_e} g_j g_k \eta_{jk}$. Alongside ΔF, the ΔG then clarifies what role the squaring of the own-group term plays in the polarization index. Panel D of Table D.15 shows the results based on this measure, which makes clear that the squaring of the own-group term matters above and beyond simply accounting for linguistic distances between groups in the definition of P. Together, the results in Panels C and D suggest that the combination of deep linguistic divisions and polarizing effects of having a few large, similarly sized groups contribute to our core findings on the importance of ΔP in driving changes in violence around redistricting.

[8]The case study in Section 6.3 provided examples of this in comparing distances between Malay and Dayak versus Malay and Chinese. Similar examples abound across Indonesia's diverse ethnolinguistic landscape.

Table D.15: Alternative Parametrization of Ethnolinguistic Divisions
Increasing δ Emphasizes Shallower Ethnic Divisions

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: P with $\delta = 0.05$, baseline			
post-split	-0.012	-0.003	0.001	-0.005
	(0.025)	(0.021)	(0.026)	(0.025)
post-split × Δ ethnic polarization	0.036**	0.032	0.027**	0.043*
	(0.018)	(0.019)	(0.013)	(0.025)
post-split × Δ ethnic fractionalization	-0.003	0.000	0.035	-0.011
	(0.019)	(0.012)	(0.026)	(0.019)
	Panel B: P with $\delta = 0.5$			
post-split	-0.009	0.000	0.003	-0.000
	(0.025)	(0.021)	(0.026)	(0.025)
post-split × Δ ethnic polarization	0.049	0.014	0.013	0.015
	(0.034)	(0.016)	(0.017)	(0.024)
post-split × Δ ethnic fractionalization	-0.022	-0.003	0.029	-0.010
	(0.024)	(0.015)	(0.025)	(0.022)
	Panel C: P with $\delta = \infty$ (every group equally distant)			
post-split	-0.008	0.000	0.004	-0.001
	(0.026)	(0.021)	(0.027)	(0.025)
post-split × Δ ethnic polarization	0.022	0.012	-0.013	0.023
	(0.038)	(0.017)	(0.023)	(0.022)
post-split × Δ ethnic fractionalization	-0.005	-0.004	0.037*	-0.016
	(0.029)	(0.017)	(0.021)	(0.022)
	Panel D: G with $\delta = 0.05$			
post-split	-0.010	0.001	-0.002	0.001
	(0.026)	(0.022)	(0.027)	(0.025)
post-split × Δ Gini-Greenberg (G)	0.022	0.003	0.039**	-0.010
	(0.028)	(0.022)	(0.015)	(0.019)
post-split × Δ ethnic fractionalization	0.003	0.003	0.030	0.001
	(0.021)	(0.013)	(0.025)	(0.017)
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

Notes: Panels B and C in this table compare the baseline estimates in Panel A to alternative parametrizations of linguistic distance in the definition of polarization where increasing values of δ emphasize shallower linguistic cleavages. Panel D replaces polarization with the Gini-Greenberg index, which removes the squaring of the own-group term in polarization. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Esteban and Ray (2011a) Structural Model. To streamline the presentation of our reduced form natural experiment, we focus in the paper on specifications with F and P. However, as seen in Appendix Table D.16 below, the main takeaways—positive and significant effects of ΔP and null effects of ΔF—remain unchanged when also including $\Delta G/population$ as in the structural equation of Esteban and Ray (2011a) tested in Esteban et al. (2012). While reassuring, we do not push this result too far given that correlations between the three measures make it difficult to interpret the findings, particularly on G/N. Indeed, in looking at both Esteban et al. (2012) and the application in Amodio and Chiovelli (forthcoming), one finds results on G/N that are positive, negative, and null. Again, though, the key findings continue to suggest that the political boundaries of ethnic divisions matter for conflict.

Table D.16: Applying the Structural Esteban and Ray (2011a) Specification

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.017	-0.002	-0.001	-0.004
	(0.025)	(0.020)	(0.027)	(0.023)
post-split × Δ ethnic polarization (P)	0.034**	0.057***	0.015	0.067***
	(0.014)	(0.018)	(0.044)	(0.020)
post-split × Δ ethnic fractionalization (F)	-0.011	0.007	0.033	0.000
	(0.018)	(0.012)	(0.028)	(0.017)
post-split × Δ Greenberg-Gini / population (G/N)	0.058***	-0.042***	0.017	-0.049***
	(0.012)	(0.014)	(0.046)	(0.013)
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

Notes: This table re-estimates the baseline specification in Table 3 augmented with the Δ Greenberg-Gini index scaled by population as in Esteban et al. (2012).

D.8 Alternative Econometric Specifications

As discussed in Section 5.5, we present here nine sets of robustness checks on the econometric specifications in Table 3.

D.8.1 Excluding Historic Conflict Zones

Table D.17 below excludes the two regions of Indonesia with the most intense civil conflict in the late 1990s and early 2000s at the onset of democratization. Panel A excludes districts in the Maluku islands, which saw fierce interreligious warfare from early 1999 through early 2002. Panel B excludes the entire province of Aceh, which was home to a longstanding guerilla movement to secede from Indonesia. The violent campaigned ended with a peace agreement in mid-2005. Omitting either of these two regions leaves the main takeaways intact, which is reassuring from the standpoint of generalization outside historic conflict zones per se.

Table D.17: Excluding Civil War Regions

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Excluding Maluku			
post-split	-0.025	-0.020	-0.014	-0.026
	(0.029)	(0.023)	(0.028)	(0.029)
post-split × Δ ethnic polarization	0.067***	0.044***	0.043***	0.051***
	(0.021)	(0.008)	(0.012)	(0.014)
post-split × Δ ethnic fractionalization	-0.016	0.009	0.071**	-0.002
	(0.021)	(0.012)	(0.035)	(0.017)
Number of District-Months	6,900	17,100	6,900	10,200
Dep. Var. Mean, Pre-Split	0.64	0.38	0.53	0.29
	Panel B: Excluding Aceh			
post-split	0.027	0.019	0.035	0.009
	(0.023)	(0.020)	(0.029)	(0.024)
post-split × Δ ethnic polarization	0.026*	0.032	0.024	0.048*
	(0.014)	(0.022)	(0.015)	(0.026)
post-split × Δ ethnic fractionalization	0.009	0.009	0.037	0.001
	(0.021)	(0.013)	(0.030)	(0.019)
Number of District-Months	6,696	17,340	6,696	10,644
Dep. Var. Mean, Pre-Split	0.55	0.30	0.45	0.21

Notes: Panel A excludes the districts in the Maluku islands, and B excludes districts in Aceh. The specification in both panels is otherwise the same as in the baseline Table 3 with time and district FE, district-specific time trends, and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.8.2 Omitting Later Time Periods

Panel A of Table D.18 omits the years 2011 to 2014 from the panel. The results are statistically indistinguishable from the baseline. This suggests that the results are not driven by periods well beyond the unexpected moratorium on redistricting from 2004–6, which was already evident to some extent from event study estimates in Figure D.4.

D.8.3 Omitting Later Entrants to SNPK Data

Panel B of Table D.18 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.18: Alternative Time Restrictions

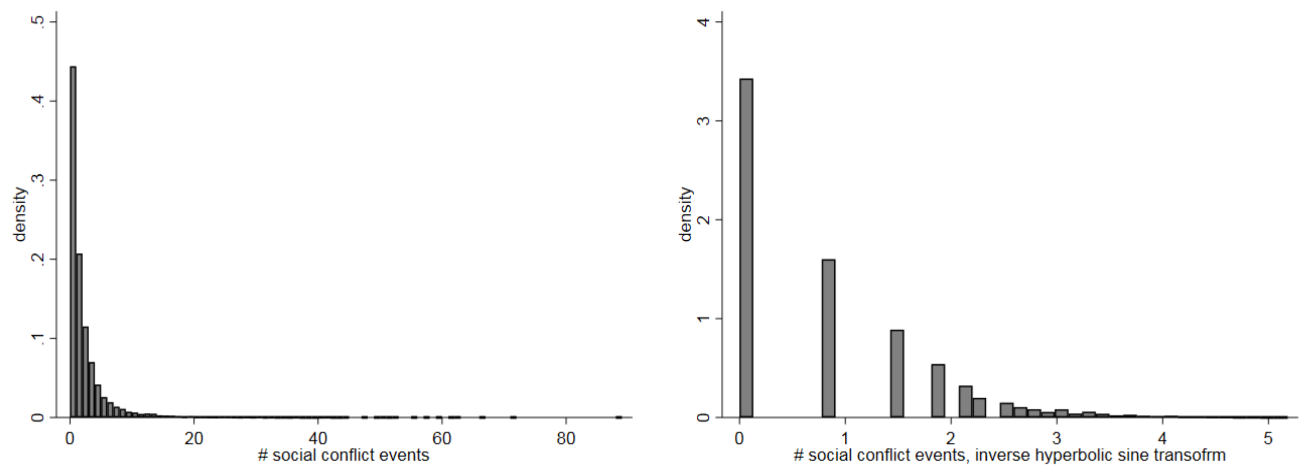
Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Excluding 2011–14			
post-split	-0.015	-0.008	0.007	-0.020
	(0.026)	(0.021)	(0.024)	(0.026)
post-split $\times$ Δ ethnic polarization	0.034	0.040**	0.040***	0.053**
	(0.022)	(0.017)	(0.010)	(0.022)
post-split $\times$ Δ ethnic fractionalization	0.027	0.005	0.055***	-0.018
	(0.020)	(0.013)	(0.017)	(0.019)
Number of District-Months	5,484	13,956	5,484	8,472
Dep. Var. Mean, Pre-Split	0.57	0.33	0.47	0.25
	Panel B: Excluding 2005 Entrants to SNPK			
post-split	-0.015	-0.018	-0.013	-0.022
	(0.032)	(0.027)	(0.031)	(0.031)
post-split $\times$ Δ ethnic polarization	0.046*	0.041*	0.034**	0.060*
	(0.023)	(0.024)	(0.016)	(0.031)
post-split $\times$ Δ ethnic fractionalization	-0.006	-0.008	0.025	-0.024
	(0.022)	(0.015)	(0.026)	(0.025)
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: Panel A drops all months after 2010m12, and B drops all districts that entered the SNPK conflict data starting in 2005, thereby imposing a balanced panel. The specification in both panels is otherwise the same as in the baseline Table 3 with time and district FE, district-specific time trends, and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.8.4 Intensive Margin of Violence

Our baseline specification focuses 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 graphs in Figure D.6 below). Even at the aggregate original district level—where 63 percent of district–months have any social conflict in column 1 of Table 3—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, it is of course possible that they are part of the same underlying conflict, which means that the intensive margin specification might simply introduce noise. Nevertheless, there may be substantive empirical content in the intensive margin variation of incidents.

Figure D.6: 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.19 presents intensive margin specifications based on the widely used hyperbolic inverse sine transformation, $\log\left(\#events_{dt} + (\#events_{dt}^2 + 1)^{1/2}\right)$, due to Burbidge et al. (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,[9] the main takeaway from Table D.19 is that the results look very similar to the baseline extensive margin specification albeit slightly less precise. This lack of precision is due in part to the continued importance of the long tail (see the right graphs in Figure D.6. We can increase precision by winsorizing the top 5th percentile of $\#events$ to further deal with the extreme skew, as seen in Panel B of Table D.19.

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

Table D.19: Intensive Margin Specifications

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Hyperbolic Inverse Sine			
post-split	0.005	-0.000	-0.012	0.002
	(0.067)	(0.039)	(0.070)	(0.033)
post-split × Δ ethnic polarization	0.016	0.036	0.034	0.057
	(0.030)	(0.026)	(0.025)	(0.036)
post-split × Δ ethnic fractionalization	0.013	-0.016	0.064	-0.039
	(0.050)	(0.021)	(0.057)	(0.034)
Number of District-Months	7,956	20,220	7,956	12,264
Dep. Var. Mean, Pre-Split	1.00	0.48	0.76	0.32
	Panel B: H. Inv. Sine, Winsorizing			
post-split	-0.038	-0.021	-0.045	-0.008
	(0.060)	(0.033)	(0.051)	(0.032)
post-split × Δ ethnic polarization	0.021	0.041	0.030*	0.060*
	(0.031)	(0.025)	(0.018)	(0.036)
post-split × Δ ethnic fractionalization	0.010	-0.018	0.046	-0.037
	(0.046)	(0.019)	(0.049)	(0.030)
Number of District-Months	7,956	20,220	7,956	12,264
Dep. Var. Mean, Pre-Split	0.96	0.44	0.68	0.31

Notes: The dependent variable is the hyperbolic sine transformation of the number of social conflict incidents in the given month. Panel B additionally winsorizes at the 95th percentile of the outcome distribution. Otherwise, the specification is the same as in the baseline Table 3 with time and district FE, district-specific time trends, and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.8.5 Alternative Identification Strategies

Our baseline generalized DiD strategy achieves identification by comparing districts that split early to districts that split late, while allowing each district to have its own time trend in social conflict. Here, we consider refinements and alternatives to this baseline strategy with the goal of clarifying the key sources of identification.

First, we introduce province$\times$month fixed effects which further restricts comparisons to districts within the same province (of which there are 16). The estimates in Table D.20 are somewhat imprecise, which is not surprising given the relatively small number of within-province comparisons in any given month. However, some of the ΔP effects are significant at the 10 percent level and all are statistically indistinguishable from the baseline estimates. This provides some reassurance that the comparison between early and late splits is not based on far-removed districts operating in very distinct regional settings.

Table D.20: Including Region$\times$Time Fixed Effects

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
post-split	-0.040	-0.020	-0.044	-0.005
	(0.032)	(0.023)	(0.036)	(0.029)
post-split $\times$ Δ ethnic polarization	0.026*	0.023	0.032*	0.017
	(0.015)	(0.022)	(0.018)	(0.031)
post-split $\times$ Δ ethnic fractionalization	-0.017	-0.005	0.039	-0.013
	(0.021)	(0.013)	(0.028)	(0.022)
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

Notes: This table adds province$\times$month fixed effects to the baseline specification in Table 3 with district FE, district-specific time trends, and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Second, Table D.21 considers an alternative strategy that removes the district fixed effects altogether and incorporates an additional control group in those districts that never split from 2000 to 2010. In this case, the coefficients identify a mixture of differential effects of redistricting (i) among early versus late splitters and never-splitters, and (ii) late-splitters versus never-splitters. However, we also include province×month fixed effects to ensure that each of these comparisons takes place between nearby districts. Note that the removal of district fixed effects means that we not longer identify within-district changes in conflict but rather cross-sectional differences (i) and (ii) within a given province akin to a nearest (geographic) neighbor matching-type design. In other words, all estimates below are with reference to the mean social conflict among never-splitters within the same province in a given month. Interestingly, as seen in Table D.21, this alternative identification strategy delivers estimated effects of changes in ethnic divisions among those that undergo redistricting that looks very similar to the baseline. The same holds in Panel B if we remove district-specific time trends, which is consistent with the fact that once we hone in on nearby districts, the role of differential trends becomes less important for the overall identifying variation in post-split and $\Delta diversity$.

Table D.21: Expanding the Counterfactual to Include Nearby Never-Splitters

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Province×Month FE District-Specific Trends			
post-split	0.053	0.028	-0.004	0.019
	(0.043)	(0.035)	(0.049)	(0.038)
post-split × Δ ethnic polarization	0.040***	0.038**	0.067**	0.056**
	(0.013)	(0.015)	(0.027)	(0.025)
post-split × Δ ethnic fractionalization	0.006	0.004	0.025	-0.004
	(0.029)	(0.013)	(0.040)	(0.021)
Number of District-Months	22,896	35,160	22,896	27,204
Dep. Var. Mean, Pre-Split	0.62	0.55	0.61	0.56
	Panel B: Province×Month FE No District-Specific Trends			
post-split	0.067	-0.146***	-0.102*	-0.249***
	(0.051)	(0.044)	(0.052)	(0.050)
post-split × Δ ethnic polarization	0.038***	0.030**	0.057**	0.047*
	(0.011)	(0.012)	(0.023)	(0.024)
post-split × Δ ethnic fractionalization	0.012	0.031**	-0.006	0.028
	(0.029)	(0.015)	(0.037)	(0.023)
Number of District-Months	22,896	35,160	22,896	27,204
Dep. Var. Mean, Pre-Split	0.62	0.55	0.61	0.56

Notes: This table adds districts in the SNPK data that never split over the sample period. Relative to the baseline Table 3, the specification therefore omits district FE but does include province× month FE. We include district-specific time trends in Panel A but not Panel B. Standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Third, in Table D.22, we consider alternative approaches to specifying location-specific time trends in conflict. Panel A removes the district-specific time trends from the baseline specification. Panel B instead uses province-specific trends. Together, these results clarify the importance of accounting for differential regional trends in conflict. The absence of such trends renders the differential effects of ΔP much weaker, which suggests that some of what we are identifying in the baseline specifications in Table 3 are deviations from trend over the sample period. The importance of trends is consistent with the history and time path of violence being very different across regions of the country. Failing to account for these differences makes it difficult to identify the contribution of political boundaries to the diversity–conflict relationship over time.

Table D.22: Alternative Identification Strategies: Location-Specific Specific Trends

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Dropping District-Specific Trends			
post-split	-0.035	-0.006	-0.027	0.005
	(0.030)	(0.022)	(0.029)	(0.023)
post-split × Δ ethnic polarization	0.015	0.009	-0.002	0.015
	(0.016)	(0.012)	(0.014)	(0.016)
post-split × Δ ethnic fractionalization	0.008	-0.004	0.006	-0.001
	(0.037)	(0.010)	(0.025)	(0.014)
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: Adding Province-Specific Trends			
post-split	-0.019	0.003	-0.007	0.002
	(0.028)	(0.022)	(0.030)	(0.024)
post-split × Δ ethnic polarization	0.029**	0.008	0.004	0.016
	(0.012)	(0.011)	(0.014)	(0.017)
post-split × Δ ethnic fractionalization	-0.007	-0.007	0.009	-0.005
	(0.027)	(0.009)	(0.024)	(0.014)
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

Notes: The table omits district-specific time trends in Panel A and adds province-specific (instead of district-specific) trends in Panel B. Otherwise, the specifications are the same as in Table 3 with district FE and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.8.6 Alternative Inclusion of $\Delta diversity$

The baseline specification includes ΔP, ΔF and $\Delta Relig$ simultaneously. Table D.23 below shows that results for P and F are nearly identical when omitting religion or entering each term on its own. This rules out concerns about collinearity between the two measures that might arise in settings with more limited diversity.

Table D.23: Alternative Specifications of $\Delta diversity$ Vector

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Omitting $\Delta Relig$			
post-split	-0.012	-0.002	-0.001	-0.005
	(0.025)	(0.021)	(0.027)	(0.024)
post-split $\times$ Δ ethnic polarization	0.033*	0.031	0.029*	0.043*
	(0.017)	(0.019)	(0.016)	(0.025)
post-split $\times$ Δ ethnic fractionalization	-0.001	-0.001	0.035	-0.012
	(0.020)	(0.012)	(0.027)	(0.019)
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: ΔF Alone			
post-split	-0.007	0.001	0.002	0.000
	(0.025)	(0.021)	(0.027)	(0.025)
post-split $\times$ Δ ethnic fractionalization	0.009	0.002	0.031	-0.003
	(0.020)	(0.012)	(0.026)	(0.017)
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 C: ΔP Alone			
post-split	-0.012	-0.002	-0.000	-0.004
	(0.025)	(0.021)	(0.028)	(0.024)
post-split $\times$ Δ ethnic polarization	0.032*	0.031	0.025	0.040
	(0.017)	(0.019)	(0.015)	(0.026)
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

Notes: This table removes Δreligious polarization in Panel A, includes only ΔF in Panel B and only ΔP in Panel C. Otherwise, the specifications are the same as in Table 3 with district FE and standard errors clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

D.8.7 Reweighting for External Validity (within Indonesia)

As discussed in Section 5.5, we consider a reweighting approach to account for the two dimensions of selection in our generalized DiD sample of districts. First, Table D.21 above notwithstanding, our results are based solely on districts that split between 2000 and 2010. We know from prior work and our analysis that this sample of districts look different along a number of observable dimensions. One way to assess whether these differences are important for our results is to reweight the estimates by the inverse probability of redistricting, assigning greater weight to those original districts that look more like the ones that never split. We do this using a standard inverse probability weighting (IPW) approach in which we first predict the cross-sectional probability of redistricting and then apply IPW to our main estimates from Table 3. We estimate that probability based on a logit specification, using Lasso to select relevant variables from a set of 67 baseline district characteristics used for other exercises in Section 5.4. Applying the IPW in Panel A of Table D.24 leaves our key results unchanged.

Second, our results are restricted to those districts in provinces covered by the SNPK data. We adopt an analogous IPW strategy to rebalance the baseline sample for these differential inclusion probabilities. Doing so in Panel B leaves the results similarly unchanged albeit less precise. Finally, Panel C estimates the joint probability redistricting and being in the SNPK, using these to construct the IPWs. Again, the results look similar to the baseline if a bit noisier.

Table D.24: Inverse Probability Weighting (IPW) for External Validity

Administrative Unit	Original District	Parent and Child	Parent	Child
Boundaries	2000	2010	2010	2010
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: IPW: Redistricting			
post-split	-0.019	-0.016	-0.001	-0.028
	(0.027)	(0.019)	(0.026)	(0.024)
post-split × Δ ethnic polarization	0.036	0.037*	0.030*	0.057**
	(0.026)	(0.021)	(0.015)	(0.027)
post-split × Δ ethnic fractionalization	-0.021	0.003	0.053**	-0.019
	(0.037)	(0.014)	(0.024)	(0.023)
	Panel B: IPW: in SNPK			
post-split	-0.016	-0.001	0.010	-0.006
	(0.027)	(0.020)	(0.026)	(0.022)
post-split × Δ ethnic polarization	0.026	0.024	0.021	0.038
	(0.018)	(0.022)	(0.014)	(0.028)
post-split × Δ ethnic fractionalization	-0.014	0.002	0.038	-0.007
	(0.024)	(0.013)	(0.028)	(0.020)
	Panel C: IPW: Redistricting + in SNPK			
post-split	-0.027	-0.018	-0.013	-0.021
	(0.027)	(0.025)	(0.026)	(0.029)
post-split × Δ ethnic polarization	0.029	0.029	0.028*	0.043
	(0.020)	(0.020)	(0.015)	(0.027)
post-split × Δ ethnic fractionalization	-0.007	0.003	0.064**	-0.017
	(0.026)	(0.014)	(0.027)	(0.021)
Number of District-Months	7,956	20,220	7,956	12,264

Notes: This reweights each observation in the baseline specification in Table 3 by its inverse probability of redistricting in Panel A, of being in the SNPK data in Panel B, and of both in Panel C. The IPW are estimated in an initial step based on a logit specification with a battery of Lasso-selected control. The IPW reduce precision, which is a common finding in these approaches. Standard errors are clustered at the original district level Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.

E Further Details on Redistricting Constraints

Section 5.4 presented a policy exercise aimed at clarifying the sources of identifying variation in $\Delta diversity$. This appendix provides further background on that exercise and also demonstrates further results consistent with the takeaway in the paper: The redistricting policy itself constrained the possible changes in ethnic divisions, and the associated effects on conflict can be explained by these policy constraints and the underlying ethnic geography rather than the particular way in which the boundaries were drawn. The concern is that better or worse borders were chosen by districts in manner correlated with latent conflict. We argue here that this is not consistent with the data.

We construct the distribution of feasible $\Delta diversity$ based on redistricting 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. Table 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 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 E.1, 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 3 should look very different for at least some of these permutations.

Figure E.2 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 redistricting and underlying geography limited the extent to which redistricting could reshape ethnic divisions.[5]

[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).

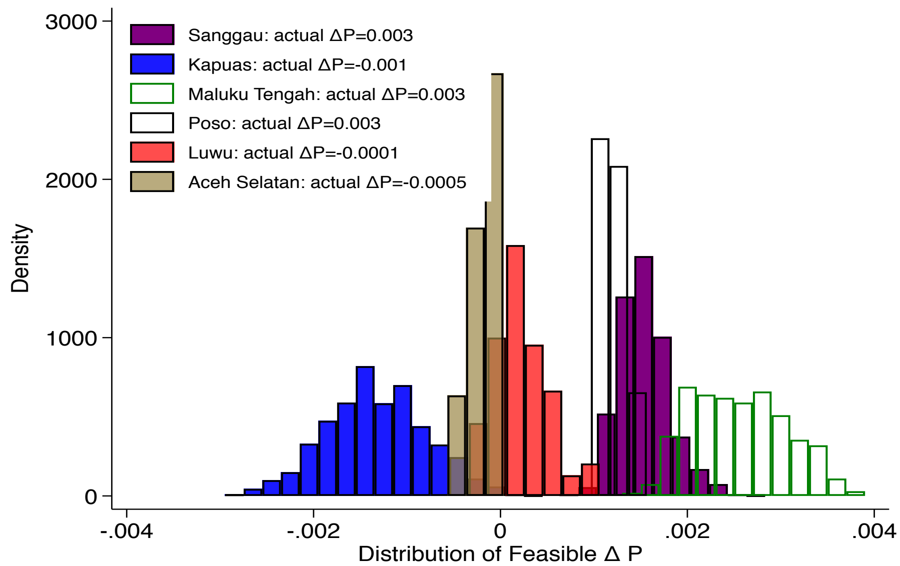
[2] Contiguity matrices are computed from shapefiles. We connect islands to the closest non-island.

[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.

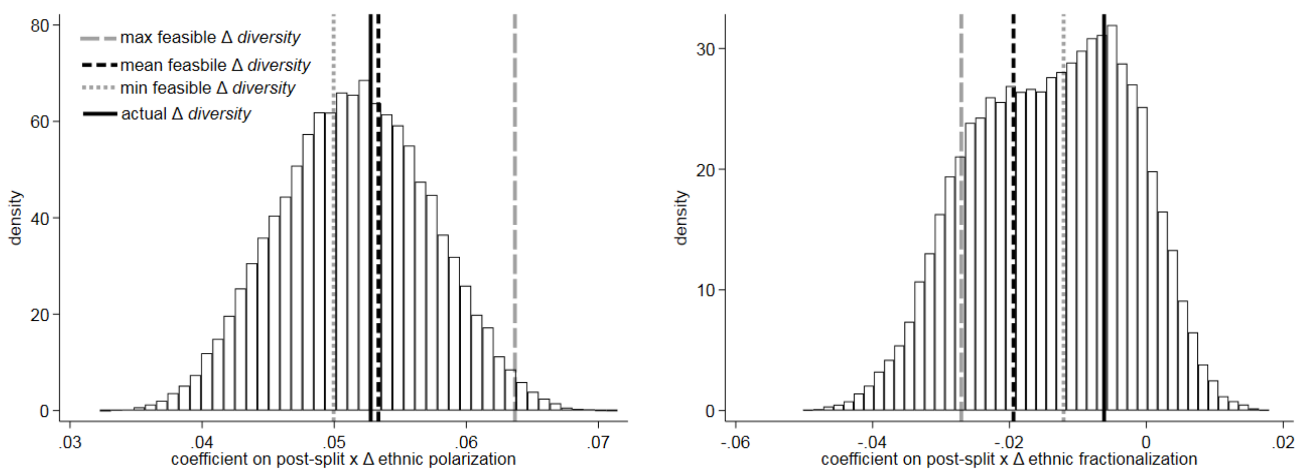
[5] These graphs look similar when including the Lasso-selected control variables used in the other robustness checks.

Figure E.1: 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 E.2: 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 Table 4, and the dashed lines are based on the observed min and max $\Delta diversity$.

F Additional Evidence Supporting Political Violence Results in Section 6

F.1 Further Background on Ethnicity in Indonesian Politics

Section 3.1 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) redistricting 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 redistricting: *"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)."*

In the context of our case study in Section 6.3, 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 *[redistricting]. 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 F.1 demonstrates that ethnic diversity is associated with significantly closer mayoral elections. In particular, we regress the victory margin for the winning candidate on ethnic polarization (P) and fractionalization (F) within the newly created parent and child districts. We consider both the first and second (when possible) quinquennial direct election after redistricting.[1]

The main takeaway is that greater diversity is associated with closer elections, 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 P and 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 the (districts that have) second elections.

Looking separately at parent and child contests, however, reveals a difference between P and F. In parent districts, fractionalization matters much more than polarization whereas the opposite holds for child districts. These patterns line up nicely with the results in Table 5 where P does more than F to exacerbate violence around elections in child districts whereas the opposite holds for parent districts. Though perhaps consistent with differences in the stakes of political control (as noted in Section 6), these differences between P and F in Table F.1 are not statistically significant.[2]

[1] As discussed in Appendix G, 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 redistricting. 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 F.1.

Table F.1: Diversity and Close Elections After Redistricting

	Dependent Variable: Victory Margin for Winning Mayoral Candidate in								
Administrative Unit	Parent/Child			Parent			Child		
Which Election?	All	1st	2nd	All	1st	2nd	All	1st	2nd
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
ethnic polarization	-0.014***	-0.013**	-0.028***	-0.012	-0.002	-0.021	-0.015***	-0.017**	-0.029**
	(0.004)	(0.006)	(0.010)	(0.018)	(0.017)	(0.022)	(0.005)	(0.007)	(0.013)
ethnic fractionalization	-0.011	-0.013	-0.018	-0.027	-0.040	-0.056**	0.000	0.000	0.026
	(0.010)	(0.012)	(0.018)	(0.019)	(0.025)	(0.027)	(0.013)	(0.015)	(0.018)
Number of Districts	113	103	68	44	34	32	69	69	36
Mean Victory Margin	0.14	0.14	0.13	0.14	0.14	0.14	0.14	0.14	0.12

Notes: This table presents simple regressions relating ethnic diversity in the newly created parent/child districts to the victory margin in the first and second direct mayoral elections post-redistricting. Columns 1–3 pool parent/child districts, and columns 4–9 examine each separately. The $\Delta diversity$ measures are normalized, and standard errors are clustered at the original district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

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 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 F.2 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 redistricting are strongly associated with preferences for mayor's ethnicity as well as their provision of patronage (formally, "gifts"). 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 6 of the paper and described further below.

Table F.2: Changes in Ethnic Divisions and Preferences for Mayoral Candidates

	Dep. Var. (binary): Respondent in 2014 Believes that the Mayor's . . . Is Important							
	Appearance	Popularity	Program Quality	Political Affiliation	Religion	Ethnicity	Experience	Patronage
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Δ ethnic polarization	0.020	-0.014	-0.011	0.020	0.067	0.097***	-0.000	0.034**
	(0.017)	(0.018)	(0.009)	(0.016)	(0.044)	(0.026)	(0.011)	(0.016)
Δ ethnic fractionalization	-0.011	-0.036**	0.010*	0.008	0.047	0.037**	-0.003	0.020
	(0.013)	(0.014)	(0.005)	(0.010)	(0.039)	(0.018)	(0.009)	(0.012)
Number of Individuals	2,343	2,343	2,343	2,343	2,343	2,343	2,343	2,343
Number of Districts	40	40	40	40	40	40	40	40
Dep. Var. Mean	0.74	0.75	0.93	0.70	0.76	0.59	0.92	0.45

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 normalized, and standard errors are clustered at the district level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

F.2 Additional Results on Electoral Violence

This section presents additional results and robustness checks on the patterns of violence around mayoral elections identified in Section 6.1.

Close Elections and Conflict. The first set of results in Table F.3 demonstrates that violence is more likely around new elections after redistricting when those contests are closely contested. In particular, we interact the post-split×election period indicator with the victory margin (ranging from 0.004 to 0.55).[3] Panel A examines the baseline outcome of any social conflict, and Panel B examine the intensive margin number of conflict incidents transformed via the inverse hyperbolic sine used in baseline robustness checks in Appendix D.8.4. This latter specification allows for the possibility that the intensive margin 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 (see Appendix Table F.1).

Table F.3: Differential Conflict Around Close New Elections After Redistricting

Administrative Unit	Parent Child	Parent	Child
	(1)	**(2)**	**(3)**
	Panel A: Any Social Conflict		
post-split	0.020	-0.002	0.025
	(0.029)	(0.038)	(0.036)
post-split × 1st election period	0.069	-0.030	0.091**
	(0.049)	(0.063)	(0.035)
post-split × 1st election period × victory margin	-0.259	0.077	-0.427**
	(0.155)	(0.201)	(0.206)
Number of District-Months	18,120	7,176	10,944
Dep. Var. Mean	0.35	0.51	0.26
	Panel B: # Social Conflict Events Hyperbolic Inverse Sine		
post-split	0.016	-0.050	0.053
	(0.059)	(0.105)	(0.050)
post-split × 1st election period	0.204**	0.236*	0.106*
	(0.097)	(0.126)	(0.053)
post-split × 1st election period × victory margin	-0.652*	-1.465***	-0.306
	(0.341)	(0.515)	(0.355)
Number of District-Months	18,120	7,176	10,944
Dep. Var. Mean	0.52	0.84	0.34

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 5. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

[3] The takeaways are similar when looking at binary indicators for close elections below the median of 0.095 or 25th percentile of 0.06. See Appendix G for details on the vote margin data, which is non-missing for 47 (out of 51) parent districts and 72 (out of 81) child districts. In the few cases where there is a runoff, second round vote, we take second round as the observation for the given district.

Looking across specifications, the evidence in Table F.3 suggests that after redistricting, 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 B.2, and (ii) the conflict-amplifying effects of $\Delta diversity$ around elections seen in Table 5. 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 (see Appendix F.1), these findings paint a rich picture of how (changes in) ethnic divisions reshape conflict dynamics in settings with high returns to local political control.

Intensive Margin Results for Table 5. Table F.4 below re-estimates the election period heterogeneity specification in the paper using the intensive margin of conflict measure in the prior table. As noted in the paper, results look very similar to those in the extensive margin specification.

Table F.4: Changes in Ethnolinguistic Alignment, Elections and the Intensive Margin of Conflict

Administrative Unit	Parent Child	Parent	Child
	(1)	**(2)**	**(3)**
post-split	-0.003	-0.021	-0.004
	(0.040)	(0.070)	(0.033)
post-split × Δ ethnic polarization	0.032	0.025	0.057
	(0.027)	(0.026)	(0.037)
post-split × Δ ethnic fractionalization	-0.019	0.056	-0.041
	(0.021)	(0.059)	(0.033)
post-split × 1st election period	0.117	0.053	0.070**
	(0.083)	(0.102)	(0.027)
post-split × 1st election period × Δ ethnic polarization	0.039**	0.053	0.021*
	(0.018)	(0.054)	(0.012)
post-split × 1st election period × Δ ethnic fractionalization	0.006	0.111	-0.003
	(0.025)	(0.077)	(0.023)
post-split × 2nd election period	0.111***	0.155***	0.083**
	(0.030)	(0.048)	(0.039)
post-split × 2nd election period × Δ ethnic polarization	-0.026	-0.100***	0.054*
	(0.021)	(0.023)	(0.030)
post-split × 2nd election period × Δ ethnic fractionalization	0.013	0.009	-0.010
	(0.028)	(0.051)	(0.026)
Number of District-Months	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.48	0.76	0.32

Notes: This table re-estimates Table F.4 using the intensive margin specification. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Ethnic Divisions Are Less Important for Legislative Elections. Legislative elections are another potentially important local political contest around which ethnic mobilization and grievances may matter. However, unlike mayoral elections, the proportional representation system for Indonesia's parliamentary means that the stakes are very different than the majoritarian system governing mayoral elections. Gaining representation for one's ethnic group in parliament can be achieved even for small groups under this system. Hence, the stakes and incentives for violence around such elections are arguably much weaker than for mayoral contests. This comparison is one that has been borne out in a range of other settings including many (newly democratic) countries in sub-Saharan Africa (see Fjelde and Höglund, 2016). Consistent with this evidence, Table F.5 below shows that changes in ethnic polarization amplify conflict around local mayoral but not local parliamentary elections. The differential effects of ΔP around mayoral elections are significantly larger than the effects around parliamentary elections.

Table F.5: Ethnic Divisions and Legislative Elections with Proportional Representation

Administrative Unit	Parent and Child **(1)**	Parent **(2)**	Child **(3)**
post-split	-0.006	-0.008	-0.011
	(0.022)	(0.028)	(0.024)
post-split × Δ ethnic polarization	0.030	0.028*	0.042
	(0.019)	(0.016)	(0.025)
post-split × Δ ethnic fractionalization	-0.001	0.032	-0.011
	(0.013)	(0.029)	(0.019)
post-split × parliamentary election period	0.152**	0.251***	0.091
	(0.066)	(0.079)	(0.085)
post-split × parliamentary election period × Δ ethnic polarization	-0.014	-0.004	-0.022
	(0.010)	(0.030)	(0.016)
post-split × parliamentary election period × Δ ethnic fractionalization	0.011	0.020	0.014
	(0.016)	(0.043)	(0.018)
post-split × mayoral election period	0.046	-0.005	0.040*
	(0.044)	(0.051)	(0.021)
post-split × mayoral election period × Δ ethnic polarization	0.025**	0.013	0.025**
	(0.011)	(0.023)	(0.010)
post-split × mayoral election period × Δ ethnic fractionalization	-0.005	0.041	-0.012
	(0.018)	(0.034)	(0.020)
Number of District-Months	19,980	7,836	12,144
Dep. Var. Mean	0.33	0.47	0.25
ΔP mayor = ΔP parliament [p-value]	0.000	0.510	0.022
ΔF mayor = ΔF parliament [p-value]	0.395	0.637	0.307

Notes: This table re-estimates Table F.4 augmented with analogous interactions for parliamentary election period as well. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Additional Placebo Checks. Tables F.6 and F.7 present two additional placebo checks that validate the importance of political resources in shaping the relationship between ethnic divisions and conflict. Table F.6 shows that $\Delta diversity$ has null effects on violence around the local rice harvest period whereas the ΔP continues to exacerbate violence around mayoral elections.[4] Similar null results arise during the holy month of Ramadan, which varies across years with the lunar cycle. Like mayoral elections, these are significant local events during which group mobilization may be important. Nevertheless, we do not find that border-induced changes in ethnic divisions fundamentally change violence during these periods. This contrast with mayoral elections is intuitive insomuch as the zero-sum nature of resource contestation (or cooperation) is most pronounced during majoritarian elections.

Table F.6: Placebo Check: District-Specific Rice Harvest Season

Administrative Unit	Parent and Child **(1)**	Parent **(2)**	Child **(3)**
post-split	0.001	0.001	-0.005
	(0.022)	(0.028)	(0.026)
post-split × Δ ethnic polarization	0.029	0.027	0.041*
	(0.018)	(0.016)	(0.024)
post-split × Δ ethnic fractionalization	-0.004	0.029	-0.015
	(0.012)	(0.028)	(0.018)
post-split × mayoral election period	0.044	-0.008	0.040*
	(0.044)	(0.051)	(0.021)
post-split × mayoral election period × Δ ethnic polarization	0.025**	0.011	0.026**
	(0.011)	(0.021)	(0.010)
post-split × mayoral election period × Δ ethnic fractionalization	-0.004	0.040	-0.011
	(0.018)	(0.034)	(0.020)
post-split × harvest season	-0.011	-0.011	-0.010
	(0.010)	(0.015)	(0.015)
post-split × harvest season × Δ ethnic polarization	0.003	0.007	0.001
	(0.007)	(0.012)	(0.006)
post-split × harvest season Δ ethnic fractionalization	0.008	0.012	0.008
	(0.007)	(0.007)	(0.011)
Number of District-Months	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.33	0.47	0.25
ΔP election = ΔP harvest [p-value]	0.003	0.865	0.007
ΔF election = ΔF harvest [p-value]	0.505	0.449	0.296

Notes: This table re-estimates Table F.4 augmented with analogous interactions for the province-specific rice harvest season. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

[4] Rice is the most important crop across Indonesia, and we borrow from Maccini and Yang (2009) who identify province-specific rice harvest periods ranging from 3–7 months.

Table F.7: Placebo Check: Ramadan

Administrative Unit	Parent and Child **(1)**	Parent **(2)**	Child **(3)**
post-split	0.009	0.005	0.005
	(0.022)	(0.030)	(0.026)
post-split × Δ ethnic polarization	0.030	0.030*	0.040*
	(0.018)	(0.017)	(0.024)
post-split × Δ ethnic fractionalization	-0.002	0.033	-0.012
	(0.013)	(0.028)	(0.020)
post-split × mayoral election period	0.039	-0.012	0.038*
	(0.044)	(0.052)	(0.021)
post-split × mayoral election period × Δ ethnic polarization	0.026**	0.013	0.026***
	(0.010)	(0.021)	(0.010)
post-split × mayoral election period × Δ ethnic fractionalization	-0.005	0.041	-0.012
	(0.018)	(0.034)	(0.020)
post-split × Ramadan	-0.069**	-0.041	-0.079*
	(0.029)	(0.039)	(0.041)
post-split × Ramadan × Δ ethnic polarization	-0.000	-0.012	0.006
	(0.006)	(0.010)	(0.009)
post-split × Ramadan × Δ ethnic fractionalization	0.004	-0.003	0.008
	(0.010)	(0.014)	(0.014)
Number of District-Months	19,980	7,836	12,144
Dep. Var. Mean, Pre-Split	0.33	0.47	0.25
ΔP election = ΔP Ramadan [p-value]	0.000	0.192	0.053
ΔF election = ΔF Ramadan [p-value]	0.609	0.231	0.419

Notes: This table re-estimates Table F.4 augmented with analogous interactions for the calendar month(s) during which Ramadan falls in the given year. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

G 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).[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, which is no longer active due to a recent contracting change. However, as of June 2016, the data hosted on and available through the World Bank website. A search in their Central Microdata Catalog for "Sistem Nasional Pemantauan Kekerasan" will yield the data, downloadable year by year, from 1998 to 2014.

Diversity

All measures are computed using the universal 2000 Population Census. 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. We also consider the related Greenberg-Gini version, which allows for non-binary distances between groups: $G = \sum_{j=1}^{\mathcal{N}_e} \sum_{k=1}^{\mathcal{N}_e} g_j g_k \eta_{jk}$, where η_{jk} captures the linguistic distance between groups j and k as detailed below.

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 $\delta = 0.05$ in our baseline, but consider alternate values. 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. As a result religious polarization is effectively identical to religious fractionalization in our data (with a correlation of 0.96).

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 $G_{\mathcal{O}} = G_{\mathcal{P}} + G_{\mathcal{C}_1}(+G_{\mathcal{C}_2})$ the change in ethnic polarization is $\Delta P = \left(\frac{G_{\mathcal{P}}}{G_{\mathcal{O}}} P_{\mathcal{P}} + \frac{G_{\mathcal{C}_1}}{G_{\mathcal{O}}} P_{\mathcal{C}_1} + \frac{G_{\mathcal{C}_2}}{G_{\mathcal{O}}} P_{\mathcal{C}_2}\right) - P_{\mathcal{O}}$. 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 $G_{\mathcal{O}} = G_{\mathcal{P}} + G_{\mathcal{C}_1}(+G_{\mathcal{C}_2})$ the change in ethnic fictionalization is given by $\Delta F = \left(\frac{G_{\mathcal{P}}}{G_{\mathcal{O}}} F_{\mathcal{P}} + \frac{G_{\mathcal{C}_1}}{G_{\mathcal{O}}} F_{\mathcal{C}_1} + \frac{G_{\mathcal{C}_2}}{G_{\mathcal{O}}} F_{\mathcal{C}_2}\right) - F_{\mathcal{O}}$. 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 $G_{\mathcal{O}} = G_{\mathcal{P}} + G_{\mathcal{C}_1}(+G_{\mathcal{C}_2})$ the change in religious polarization is given by $\Delta Relig = \left(\frac{G_{\mathcal{P}}}{G_{\mathcal{O}}} Relig_{\mathcal{P}} + \frac{G_{\mathcal{C}_1}}{G_{\mathcal{O}}} Relig_{\mathcal{C}_1} + \frac{G_{\mathcal{C}_2}}{G_{\mathcal{O}}} Relig_{\mathcal{C}_2}\right) - Relig_{\mathcal{O}}$. 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 G.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 polariation	-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
	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	0.005	-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

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 G for variable definitions.

Voting and Elections

District Head 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 Commissions, many of which were graciously provided by Monica Martinez-Bravo, Andreas Stegmann, and Audrey Sacks. 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 et al., 2016).

1st Direct 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/child's first direct election date. In the case of the latest splits, this can occur pre-split.

2nd Election Period: We construct an indicator that equals one in the 6 month window around the parent/child's second direct election date. There are some children (the latest splits) for which we do not observe a second election post-split.

District Head Election Victory Margins: Using the General Election Commissions records, we compute victory margins in the district head elections conducted after redistricting. This continuous measure is simply equal to the vote share for the winner minus the vote share for the loser (in the second round runoff if it occurs).

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*) 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 micro census 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 (DAPOER), 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 as a proxy for initial GDP (Henderson et al., 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.

Village Level Light Data: For our ethnic favoritism results, we also use the village level light directly. When looking at how nighttime light intensity varies by share of residents in 2000 belonging to the largest ethnic group in the eventual child district, we use the fraction of the village area covered with any lights in each year 2000–2013.

Other Variables

Climate: We compute the population weighted average rainfall and temperature from 1948 to 1978 using village level information from NOAA-GPCP.

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 administrative village census (*Potensi Desa* or *Podes*) 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.

Time Varying Transfers and Distance

For use in Section 5.4, we construct measures of how distance to the capital and fiscal transfers from the center changed with splitting.

Δ Distance: Using PODES 2000 and PODES 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 2000. 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/parents 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.