Roads to Rule, Roads to Rebel: Relational State Capacity and Conflict in Africa*

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Abstract

Weak state capacity is one of the most important explanations of civil conflict. Yet, current conceptualizations of state capacity typically focus only on the state and ignore the relational nature of armed conflict. We argue that conflict arises where relational state capacity is low, that is, where the state has less control over its subjects than local elites. This occurs in ethnic groups that are poorly accessible from the state capital, but internally highly interconnected. To test this argument, we digitize detailed road maps of Africa, and convert them into a road atlas akin to Google Maps. We measure the accessibility and internal connectedness of groups via travel times obtained from this atlas. To address the challenge of endogeneity, we use an instrumental variable design based on simulated road networks. We find that low relational state capacity is a key determinant of armed conflict in Africa.

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Introduction

Weak state capacity is a leading explanation of civil war. Scholars and policy-makers frequently argue that rebels fight where governments are too poor, incompetent, and distant to defend their monopoly of violence. Yet, despite its relevance in the literature, the empirical link between state capacity and conflict remains elusive. For one, existing studies often argue that conflict occurs in areas where states are weak or even absent. This perspective neglects that conflict is inherently relational. Whether the state is sufficiently capable of defending its monopoly of violence depends on whether local conditions are favorable to non-state mobilization. Second, it is challenging to measure subnational state capacity consistently across countries. And finally, investments in state capacity may be endogenous to (anticipated) conflict, thus complicating causal inference.

This paper addresses these points. Building on a relational concept of state capacity, we employ road network data to measure how well states can reach their subjects, and how well subjects are interconnected among themselves. Focusing on ethnic groups in Africa, we show that state access reduces the risk of conflict, while groups' internal connectedness increases it. This result holds when we exploit exogenous variation from simulated road networks.

Our theoretical argument focuses on violent competition between the state and non-state actors over controlling local populations. We argue that opportunities for conflict arise where states are weak compared to potential challengers. Because physical access is a precondition for political control, we operationalize this concept of "relational state capacity" with accessibility metrics computed with road network data. Building on Herbst's (2000) seminal study of road networks, we argue that states can exercise control only in areas that are accessible from their capitals. However, roads can also help armed groups to rebel. Areas that are internally well interconnected will be considerably easier to mobilize and control for local challengers of state rule. Combining these two arguments, we expect relational state capacity to be low in areas that are poorly accessible from the capital, but internally well interconnected. Because state rule in Africa is frequently threatened by violent challengers that mobilize along ethnic lines, we test this argument by assessing the effect of relational state capacity in the settlement areas of ethnic groups.

We compute our road-based proxy of relational state capacity using historical road maps from Michelin, a tire manufacturer. To extract road-network information from these maps in an efficient and replicable manner, we leverage recent innovations in computer vision and develop a deep-learning model that automatically translates scanned maps into digital road network data. Equipped with these data, we create an electronic historical road atlas for Africa akin to Google Maps, complete with information on road quality and driving speeds. This allows measuring ethnic groups' accessibility from the capital and their internal connectedness via traveling times. To test the effect of relational state capacity on conflict, we use data on the number of and battles involving the state, rebels groups, and local militias from the post-1997 period (Raleigh et al. 2010).

As a main challenge to causal identification, road builders may react to threats of violence or secondary factors such as natural resources that affect conflict risks. Road networks are thus likely endogenous to conflict patterns. An instrumental variable strategy based on artificial road networks addresses this caveat. Specifically, we simulate road networks that are designed to maximize the connectivity between any two inhabitants of a country using historical population data. These simulated networks are exogenous to politics by design, and exhibit strong similarities to the observed networks. We recompute our accessibility metrics on these simulated networks, and employ the resulting variables as instruments.

In line with our expectations, we observe more rebel groups and militias, more violence among these armed groups, and more violence between armed groups and the state in ethnic settlement areas with low relational state capacity. The results from our instrumental variable analyses imply that increasing states' access to ethnic groups by a moderate 10 percent or increasing groups' internal connectedness by the same amount leads to a rise in the number of armed groups and battles between them by 2.8 and 3.7 percent, respectively. The same change in relational state capacity is associated with an increase in the number of battles between government forces and armed groups by 1.2 percent, a result that is less robust to some sensitivity checks.

In sum, the data support our claim that challenges to state rule arise not just where states are weak, but where they are at risk of being outgoverned. Our findings also highlight the dual role of road networks as tools for political mobilization and control. For states, building roads is literally a two-way street. It extends their ability to govern, but also provides potential challengers with an infrastructure for mobilization. Still, our theoretical framework also exhibits clear limitations, in that its opportunity-driven reasoning has little to say about motivations for rebellion and conflict. Future research will have to explore how relational state capacity interacts with motives for violence.

Literature

Much of the contemporary discussion on state capacity and conflict is inspired by Fearon and Laitin (2003), who assert that civil wars are a consequence of weak statehood. Following this seminal contribution, more recent studies have refined the concept and measurement of state capacity. A first wave of research argues that conflict erupts where states lack the military and financial resources to uphold their monopoly of violence. While intuitive, country-level studies report mixed evidence for this resource-centric mechanism (Buhaug 2010; Walter 2006; Fjelde and De Soysa 2009; Hendrix 2010). A second argument focuses on institutions and asks whether states with an incoherent set of institutions that feature both autocratic and democratic decision-making elements have an increased risk of conflict (Hegre et al. 2001; Vreeland 2008).

Finally, and at the center of this article, a third approach focuses on the role of *social control*, which refers to the ability of states to control the behavior of their subjects through targeted incentives (Mann 1984; Migdal 1988). Capable states, then, are those that can administer selective incentives through, for example, a professionalized police force, bureaucracy, and a judicial system. Social control is central to the prevention of rebellion because it undermines mobilization. Individuals who believe that the state scrutinizes their behavior will be less likely to join and more likely to denounce organizations planning to challenge the state's monopoly of violence.

Perhaps the most widely used proxy of social control is the fraction of national economic output that states capture through taxation (see Thies 2007; Fjelde and De Soysa 2009; Thies 2010; Hendrix 2010; Buhaug 2010). Because levying taxes requires effective and penetrative institutions high tax ratios should be indicative of high social control. Empirically, however, the relationship between states' tax ratios and the occurrence of rebellion is inconclusive (Thies 2010; Fjelde and De Soysa 2009; Buhaug 2010). One likely reason is endogeneity (Thies 2010). The fear of rebellion may deter states from levying taxes, which would veil any pacifying effect of taxation. Another drawback is that most data on taxation is only available at the country-level, while social control is best conceptualized and measured at a more local level.[1] Because the effectiveness of institutions of social control deteriorates drastically over distance, states may be strong in some parts of their territory, but not in others (Buhaug and Rød 2006; Buhaug 2010; Tollefsen and Buhaug 2015).

Adopting this spatially explicit logic, recent contributions introduce new local measures of state capacity. Lee and Zhang (2017) construct a census-based measure of local 'legibility,' and Wig and Tollefsen (2016) introduce a measure of the quality of local state institutions computed from survey data. These two approaches rely on census or survey data, which are rarely available in countries with low levels of state capacity because their collection requires at least some social control to begin with.[2] Third, Koren and Sarbahi (2018) use nightlight luminosity as a proxy for local state capacity, but this approach makes it difficult to distinguish local state capacity from local development.

Faced with the challenge of measuring social control directly, a number of studies use physical *accessibility* as a proxy for social control. These studies find that areas that are difficult for states to reach – i.e. areas far removed from their country's capital, and covered by mountainous terrain – are particularly prone to civil conflict (Buhaug and Rød 2006; Raleigh and Hegre 2009; Tollefsen and Buhaug 2015). These results coincide with the long-standing argument by Herbst (2000) and Tilly (1992) according to which favourable geography is a key determinant for the emergence of strong social control. However, while very insightful, these geographic findings have an important drawback because they do not take into account that states may overcome geographic impediments to social control by investing in transport infrastructure. As a remedy, some authors have analyzed the role of roads, in particular the density of road networks, as a determinant of social control. In a pioneering effort, Herbst (2000) presents aggregate data on African road network

[1]But see Harbers (2015) who presents subnational tax data to measure local state capacity in Ecuador.

[2]Lee and Zhang (2017) approach of leveraging age-heaping in census data to proxy the legibility comes with the further disadvantage that age-heaping is also caused by low levels of education (A'Hearn, Baten and Crayen 2009), which result from low levels of local state capacity.

densities and finds that weak social control and sparse road networks tend to go hand in hand. Buhaug and Rød (2006) and Raleigh and Hegre (2009) analyze the relationship between local road densities and African conflict at the sub-national level, but obtain mixed results.[3] Most recently and studying one-sided violence, Rogall (2017) finds that rainfall-induced reductions in the accessibility of Rwandan villages curtailed Hutu militia's efforts to mobilize their inhabitants to participate in the genocide of their neighbors.[4]

Despite considerable progress over the past decade, the measurement of social control and its effect on political violence remains elusive for three main reasons. First, with the exception of Rogall (2017), current measurements of accessibility – and, by extension, social control – do not appropriately factor in transport networks. While country-level aggregates obfuscate local variation, local road density metrics disregard that roads form a network. Therefore, they cannot capture the costs associated with actually *reaching* an area. To measure these transaction costs, we approximate accessibility of a given location via realistic travel times on observed road networks.

Second, endogeneity afflicts past uses of road data to estimate the effect of social control on conflict. Low social control and anticipated or actual violence may deter road-building, thus complicating causal inference. Rogall (2017) relies on short-term variation in roads' quality, a strategy that is econometrically sound but cannot capture the long-term effects of accessibility. As a solution, we leverage exogenous variation in the structure of road networks to identify the causal effect of accessibility on conflict.

Finally, with few exceptions, the recent empirical state capacity literature tends to ignore the relational nature of social control and accessibility.[5] Many scholars adopt a state-centric view, argue that rebellion erupts where the state is absent and test whether inaccessibility is associated with conflict. In contrast, we argue that conflict is likely where actors that compete with the state over local power have more social control than the state. As a corollary, we argue that conflict is likely in areas that are more accessible to such challengers than they are to the central government.

[3]While Buhaug and Rød (2006) find local road densities to be associated with less conflict events, Raleigh and Hegre (2009) report a positive association.

[4]In a similar vein, Zhukov (2016) finds that local road networks are positively associated with one-sided violence perpetrated by governments and rebels.

[5]Dargent, Feldmann and Luna (2017) provide a theory of relational state capacity similar to our own, but do not study its relationship with organized violence.

Theoretical Framework

In this section, we advance a theoretical framework of relational state capacity (RSC) and its effects on conflict that motivates an accessibility-based measurement strategy for testing our claims.

Social Control and the State's Monopoly of Violence

According to Mann, social control is the "capacity of the state to actually penetrate civil society, and to implement logistically political decisions throughout the realm" (Mann 1984, p. 189).[6] In this state-centric view, a state's social control denotes its ability to steer individuals' behavior through targeted incentives. To do so, the state needs the capacity to *monitor* the behavior of its subjects. Without information about individual behavior, the state is unable to punish non-compliance or reward cooperation. The state also needs *individual leverage* in order to wield influence over subjects' lives in a targeted manner. Clearly, whether the state exercises social control in a community hinges on both factors. Inducing compliance requires observing behavior and administering punishment and rewards accordingly.[7]

Modern states have amassed impressive amounts of monitoring capacity and individual leverage. In fact, some of them "can enforce [their] will within the day almost everywhere in [their] domains" (Mann 1984, p. 189). States have achieved this level of social control by developing and adopting mechanisms of direct rule that deeply penetrated their societies. These "instruments of surveillance and control" (Tilly 1992, p. 182) include official police forces, professionalized, Weberian bureaucracies, and the monopolization of local public goods provision. By embedding state agents into local communities, these institutional mechanisms allow the state to monitor and steer individual behavior directly. Moreover, such direct control creates dependencies on state services that affect individuals' actions indirectly. In such systems, individuals are hesitant to disobey state rule if they receive government welfare, are employed in the public sector, or rely on public schools.

[6]While Mann prefers the term "infrastructural power" over "social control", the two concepts are equivalent; see Soifer and Vom Hau (2008) for an overview of recent work that discusses Mann's understanding of social control.

[7]Nationalism and other ideologies allow modern states to prevent challenges to their rule by increasing their citizens' loyalty to the organization, but we do not study this important aspect with our opportunity-driven framework.

Direct rule and the resulting social control are key requirements for the state to monopolize violence. Where the state is able to monitor and punish individual behavior, subjects are deterred from joining or financing rebel organizations. In addition, even radical ideologues who are not deterred by the state find it difficult to escape state forces and mobilize support. Few civilians, including those who share the insurgents' grievances, are ready to risk their livelihoods for some greater cause with uncertain outcome (Lichbach 1994). As a result, it is difficult for prospective rebels to challenge state rule where governments wield effective social control. Notably, counterinsurgency strategists have long highlighted this logic (Galula 1967; Kilcullen 2010).

In the African context, scholars have argued at length that African states' lack of direct control constitutes the main reason for their "security predicament" (Ayoob 1995, see also Migdal 1988; Herbst 2000). In contrast to its European counterpart, the African state system emerged from colonial rule rather than from century-long competition over territory (Mann 1984; Tilly 1992). Colonial rule, in turn, hardly ever resulted in administrative structures that yielded high social control. Backed by imperial armies that could be called in on demand, colonial administrations were not designed to maximize control over their subjects, but to operate at minimal cost (Herbst 2000; Mamdani 1996). Consequently, many post-independence leaders inherited states that exercised social control around the capital, but not over their peripheries (Herbst 2000). Since then, few African states have faced strong incentives to overcome these limitations. Thus, these states today exert little social control over remote areas, leaving much room for rebels to mobilize and fight the state.

While the incomplete nature of many African states' social control is well documented in the qualitative literature (Migdal 1988; Ayoob 1995), measuring variation in social control is challenging. In a seminal contribution, Herbst (2000) identifies variation in social control by analyzing at road network data. Because physical accessibility from administrative capitals is a necessary condition for social control, poor transport infrastructure serves as a reliable proxy for weak statehood. Two mechanisms underpin this argument. First, accessibility is a prerequisite for building and maintaining the institutions that exercise social control over distance (Herbst 2000). Political organizations that seek to monitor and steer the behavior of their subjects rely on a dense network of local agents that are embedded in local communities. Controlling these agents is difficult where transport costs prohibit regular interaction with them. Moreover, accessibility facilitates economic integration and the provision of public services, both of which increase individual costs of disobeying political directives. Importantly, this long-term link between accessibility and the effectiveness of direct rule is the main driver behind the historical co-evolution of transport infrastructure and state institutions (Herbst 2000; Mann 1984; Tilly 1992; Weber 1976).

Apart from this institutional mechanism, accessibility also has an immediate impact on social control, in that it is necessary for upholding the government's monopoly of violence in times of crisis. If a political organization's rule in a given area is contested, maintaining social control requires the ability to quickly punish individual violations of central policy. In practice, this means employing coercive resources for repressive and punitive purposes, a response that requires physical accessibility.

Fragmented Social Control and Mobilization

We have so far outlined the state-centric argument that conflict erupts where the state has little control over its subjects. This logic rests on the assumption that rebellions emerge from a vacuum of social control caused by the state's absence. Empirically, however, this view is incomplete, as the absence of the state rarely implies a vacuum of social control. Migdal (1988, p. 28) points out that

> through most of human history, legions of strategies have been at work in areas today claimed by single states. Territories have hosted a diversity of rules of the game – one set for this tribe and another for a neighboring tribe, one for this region and another for that. Social control has not been of a piece, but it has frequently been highly fragmented through a territory.

In contrast to the state-centric perspective, Migdal (1988) thus argues that social control often resides with societal institutions that emerge in communities that speak the same language, trade at the same markets, and follow the same customs. In other words, where states are absent or weak, social control is typically organized along ethnic lines.

An important difference between these ethnic governance institutions and modern state rule lies in the way social control is organized. Ethnic power holders rarely preside over "proto-states" that rule their subjects directly. Rather, non-state governance institutions oftentimes rely on patronage networks. Hence, hierarchical networks of personal allegiance and protection, rather than professionalized bureaucracies, ensure surveillance of, and control over subjects. Acknowledging that ethnic governance structures often compete with, or sometimes even replace, the state has important implications for our understanding of political violence. For one, the emergence of armed groups is much more likely where ethnic governance institutions trump state control and allow prospective rebels to govern their realm (e.g. Weinstein 2007; Mampilly 2011; Arjona 2014). If local ethnic leaders decide to defend or expand their power by force, dense and hierarchical social networks (e.g. Humphreys and Weinstein 2008; Parkinson 2013) will allow them to mobilize more funds and fighters than otherwise possible. Similarly, existing governance structures allow ethnic power holders to secure civilian cooperation, a key requirement for successful insurgencies. Civilians will tend to cooperate with whatever party is able to credibly threaten to punish defection (Kalyvas 2006). Tried and tested patronage networks likely provide higher levels of surveillance, control, and thus threat potential than a weak and distant state bureaucracy (Weinstein 2007).

However, the emergence of such armed organizations does not only raise the prospect of conflict against the state, but also that of conflict among armed groups. Unlike state bureaucracies that rest on centralized and mutually exclusive hierarchies, ethnic governance networks often overlap and are decentralized. Consequently, multiple leaders can mobilize subsets of their co-ethnics. Absent a state capable of enforcing a peaceful resolution of disputes, competition among local power-holders may quickly lead to violence between the armed groups they command. Indeed, violence among armed groups that are fighting the state is a common characteristic of civil wars (Fjelde and Nilsson 2012).

Even a cursory analysis of recent African history confirms that fragmented social control is a more fitting description of the political topography of African states than the state-centric perspective of the previous section. When European colonizers rushed to conquer Africa in the 19th century, they encountered pre-colonial societies featuring a variety of political structures, ranging from complex empires to acephalous groups (Murdock 1959). Through their varying strategies of local rule, colonial rulers invented or co-opted local notables as intermediaries to govern oftentimes ethnically delimited constituencies. Many of these (pre)colonial governance institutions survived well into the postcolonial period (Mamdani 1996; Crowder 1964; Herbst 2000; Reno 1995). Left with weak central administrations and armies, post-colonial governments had to accept that actors outside the state's formal institutional framework ruled over much of their states' territory (Migdal 1988). This configuration of state power has been an important driver of conflict in Africa civil war is often the result of ethnic strongmen defending or expanding their power against local rivals and the state (Reno 1999).

The acknowledgment that social control is often fragmented adds a new dimension to the link between social control and conflict. Beyond the focus on the presence or absence of the state, social control exerted by those who might challenge the state must be accounted for. What determines the feasibility of rebellion is *relational state capacity* (RSC), that is the degree to which the state's control over its subjects outweighs that of non-state ethnic governance institutions. Where RSC is low, local elites can easily mobilize against the state and each other, frequently taking up arms in the process.

This relational perspective has direct implications for the accessibility-based measurement of social control. In particular, the link between accessibility and social control is not limited to the state alone, but extends to any political organization operating within a country's territory. In the context of contemporary Africa, this implies that local ethnic elites will be better able to control their co-ethnics in areas with high levels of internal accessibility. Again, the underlying logic is two-fold. Over the long-term, infrastructure that permits accessing members of an ethnic group at low cost facilitates the maintenance of effective non-state governance structures. In the short-term, accessibility facilitates upholding control over subjects in times of conflict by coercive means, i.e. when competing over civilian cooperation against the state or other challengers (Zhukov 2012). In sum, these arguments suggest a relational measurement strategy: RSC is low in areas that are difficult to access for the state, but easy to access for local power holders, and vice-versa.

Observable Implications

In practice, we approximate RSC with two accessibility-based metrics, both defined on the level of ethnic groups. The first is *state access*, which is the degree to which the state is able to access all members of a given ethnic group. Because in Africa state power and resources are typically concentrated in the capital (Herbst 2000), we define state access as the ease of travel from a country's capital to any given member of an ethnic group.[8] The second metric is ethnic groups' *internal connectedness*, the degree to which transport network interconnect the members of a given group. Because ethnic governance institutions are often internally fragmented and overlapping, we do not define a single geographical ethnic power center, but remain agnostic about the location of political leadership within an ethnic group. We operationalize RSC as the difference between state access and internal connectedness. Hence, groups that are difficult to reach by the state but internally highly interconnected exhibit low RSC. The state's relational capacity is high, in contrast, in groups that are easily accessible from the capital but lack internal connectedness.

Based on our theoretical argument and empirical proxy, we derive three hypotheses on the effects of RSC on armed conflict in African states. Our first hypothesis concerns the emergence and presence of armed non-state actors such as rebel groups and militias, both of which we refer to as *challengers* to local state power, in the settlement areas of ethnic groups. As discussed earlier, where the state exercises little control over an ethnic group that is internally well connected, challengers can mobilize recruits and resources with relative ease. Thus, we expect that:

Hypothesis 1 *More challengers to local state rule are active in ethnic settlement areas with low RSC.*

As outlined above, ethnic groups that are internally well connected rarely feature a single, all-powerful node of social control. Instead, patronage structures will often allow multiple power centers to exert social control in parallel. Aiming to build, defend, and extend their realm, competition between these peripheral actors often takes a violent turn if no superior central power, like the state, is capable of enforcing the peace. Hence, departing from the previous state capacity literature's focus on conflict involving the state, we expect that:

[8]While we acknowledge the existence of less important outposts of the state (such as regional capitals or military bases), we focus on capitals for two reasons. First, we lack systematic data on the location and relative importance of states' outposts outside of capitals. Second, even if such information was available, employing it may not be advisable. Peripheral state agents may become challengers to the state themselves, as exemplified by frequent mutinies.

Hypothesis 2 *Ethnic settlement areas with low RSC are more likely to experience conflict* among *challengers to local state rule.*

Most challengers will thus be found in ethnic groups over which the state has little control to begin with, cannot count on developing it anytime soon, and faces logistical difficulties to fight. Lacking good access to the national capital, such peripheral challengers might not pose a vital risk to governments that are more concerned about rebellions in or near their capital (Roessler 2011; Roessler and Ohls 2018). For these reasons, governments might choose not to intervene, letting rebels and militias fight among themselves. However, in practice, this strategy of non-intervention might prove intolerably risky in the long run. Rulers must fear that if challengers grow too powerful, they threaten the state's authority in other parts of the country and may take over the state as a whole. This fear may motivate governments to eventually intervene and militarily weaken their peripheral challengers in areas with low RSC:

Hypothesis 3 *Ethnic settlement areas with low RSC are more likely to experience conflict between local challengers and the state.*

Data and operationalization

As outlined above, we measure RSC as the difference between ethnic groups' accessibility from the state's capital and their internal connectedness. State access is operationalized as the inverse average travel time from the state capital to any member of a given ethnic group:

$$\textsf{state access}_g = \left(\frac{1}{I_g} \sum_{i=1}^{I_g} time_{C,i} \right)^{-1}, \tag{1}$$

where I_g enumerates the members of group g and $time_{C,i}$ is the shortest-path traveling time from the capital C to the location of individual i.[9] Groups' internal connectedness is computed as the inverse average travel time between any two group members,

$$\textsf{internal connectedness}_g = \left(\frac{1}{I_g^2} \sum_{i=1}^{I_g} \sum_{j=1}^{I_g} time_{i,j} \right)^{-1}. \tag{2}$$

[9] All travel times start at a constant of 1h to avoid division-by-zero errors for groups with small territories.

Finally, we approximate RSC by computing the ratio of state access to internal connectedness,

$$\mathsf{RSC}_g = \frac{\mathsf{state\ access}_g}{\mathsf{internal\ connectedness}_g}. \tag{3}$$

To compute expressions 1 to 3 we require three types of data, namely ethnic settlement patterns, spatial population distributions, and information on road networks, the primary type of transport infrastructure in Africa (Herbst 2000, ch. 5). We obtain data on ethnolinguistic settlement areas from the Ethnologue dataset (Global Mapping International and SIL International 2015). Our analysis uses the Ethnologue data over alternative sources like the Atlas Naradov Mira (Weidmann, Rød and Cederman 2010) and Murdock's (1967) Ethnographic Atlas because of its extensive coverage. Still, we conduct robustness checks based on these alternative datasets in Appendix A4.6. For demographic information we rely on the dataset produced by Goldewijk, Beusen and Janssen (2010), who provide historical and contemporary gridded population data at high spatial resolution.

Finally, while geo-coded road network data is abundant (see e.g. CIESIN and ITOS 2013), existing datasets are ill-suited for our purposes. One concern is reverse causality, since all available cross-national road datasets focus on contemporary data, and are thus inappropriate for analyzing past outcomes. Moreover, non-commercial datasets are frequently inconsistent across countries, and thus inappropriate for cross-country analyses. To circumvent these issues, we compile a new historical African road dataset by digitizing the Michelin map corpus. This collection of maps covers the entire African road network at a resolution of 1:4,000,000 and has been updated repeatedly since 1966. In our baseline analysis, we rely on the 1966 road data to maximize the temporal distance between the road-network "treatments" and conflict outcomes in order to limit the potential for reverse causality bias.[10]

To ensure replicability at low cost, we develop software that extracts road networks from map sheets automatically. More specifically, we refine and implement a deep-learning model originally designed for object detection in photographs (Shelhamer, Long and Darrell 2017) to separate road-related information from other features in scanned map images.

[10]The main danger of using contemporaneous road data is that roads in conflict areas decay. This creates reverse causality bias if conflicts that have begun before 1990 have destroyed the road network and caused conflict after 1990. Note however that the results barely change in a robustness check for which we use the 1990 road network data (Appendix A4.3).

In combination with a set of post-processing algorithms, this approach allows us to extract Michelin's road-network information with human-level accuracy at a fraction of the cost. For details see Appendix A1.

Equipped with these new data, we build a digital road atlas akin to Google Maps that allows us to compute travel times between any two points on the African continent in 1966 and 1990. Underlying this atlas is a gridded, 8-connected network with a resolution of $.1667 \times .1667$ decimal degrees onto which we superimpose the road network data as additional edges. Travel time queries are made possible by assigning each edge a travel speed estimate based on observed road quality. For the 8-connected base network we assign a travel speed corresponding to travel on foot. Accordingly, we call these baseline edges "footpaths." For all details on the construction of the road networks, we refer to Appendix A2.

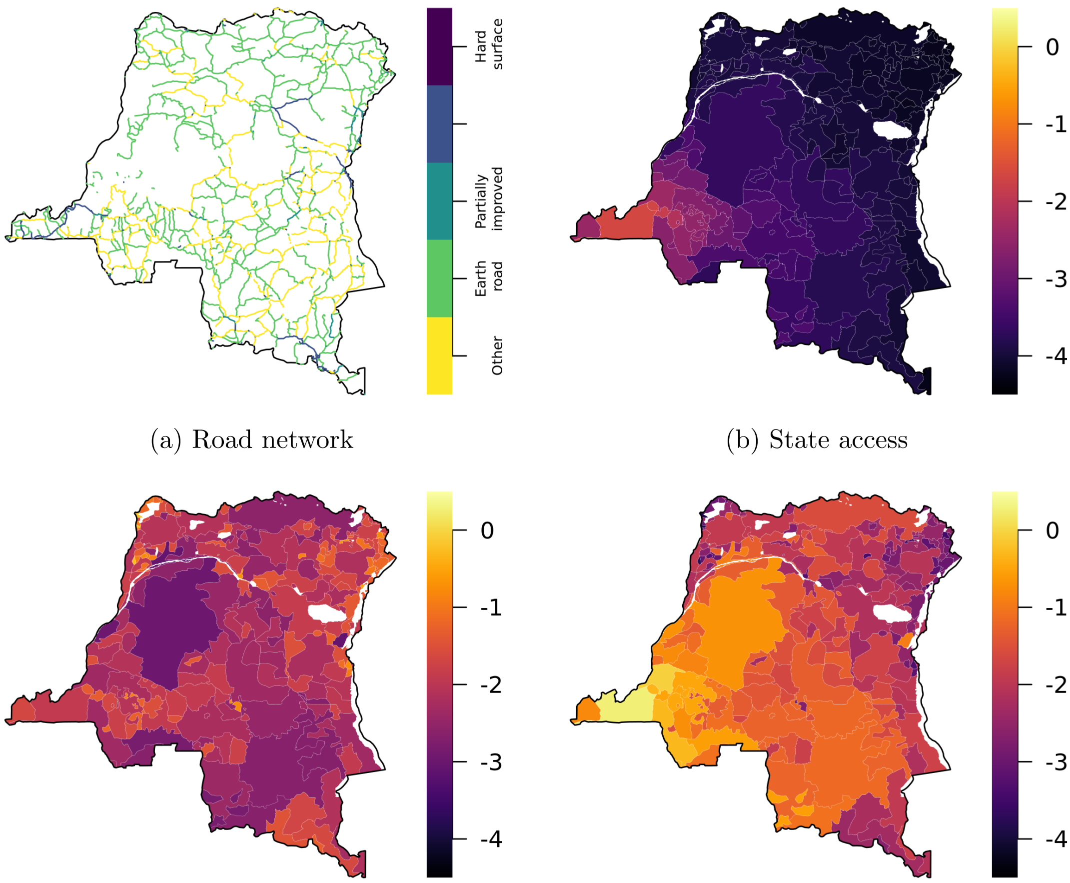
Having collected all necessary data, we can now compute all groups' state access, internal connectivity, and relational state capacity in 1966 and 1990.[11] Figure 1 illustrates the resulting estimates for the Democratic Republic of the Congo in 1966. Map 1a shows that the road network is the densest in the country's eastern and western parts. However, the sparsity of roads in the center curbs state access from the capital Kinshasa towards ethnic groups in the east and the north (see Map 1b). In contrast, the local road networks in the East result in high levels of internal connectedness of the respective ethnic groups (see Map 1c). RSC, in turn, is high in the West, intermediate in the North, and very low in the East (Map 1d). These patterns highlight that, in contrast to local road densities, RSC accounts for the structure of the entire road network.

Throughout our empirical analyses, we employ a panel setup with group-years as units of analysis to account for moving borders and capitals.[12] To measure the three main outcomes of interest we employ the ACLED dataset (1997-2016; Raleigh et al. 2010), which provides the most extensive collection of geo-coded event data for Africa. To reflect Hypotheses 1-3, we encode for each group-year the number of:

1. *challengers*, defined as active rebel groups and ethnic or political militias,

2. *challenger events*, conflict events in which challengers fight against other challengers,

[11] We use population data from either 1960 or 1990, depending on the timing of the road network data.
[12] Note the cross-sectional robustness check in Appendix A4.8.



(a) Road network (b) State access

(c) Internal connectedness (d) Relational state capacity

Figure 1: Measuring state access, internal connectedness, and relative state capacity in the Democratic Republic of the Congo 1966. Figures (b)–(d) are based on Equations 1–3; plotted values are logged.

and

3. *state events*, which denote conflict events in which the state fights directly with challengers.

We geographically encode these variables by counting unique armed actors and violent events in ethnic groups' settlement areas.[13] This geographic approach to coding our dependent variables allows us to analyze the full set of ethnic groups in Africa. However, it comes at the risk of attributing armed actors and the violence they engage in to ethnic groups from which they did not originate from originally. This blurs our measures in particular where rebel groups and militias expand their activities beyond their geographic cores.

[13] All variables are coded on the basis of the interaction codes provided by ACLED.

We log-transform ($ln(y+1)$) our three outcome variables to account for their skewed distribution. In a series of robustness checks in Appendix A4.1, we first disaggregate the composite of challengers into rebels groups and militias. This addresses the danger that the results are driven by the subset of militias that are allied with a state's government.[14] We also consider other functional forms and types of political violence, and use data from alternative sources.

Empirical Strategy

In a first set of analyses, we test our hypotheses by estimating the impact of RSC measured in 1966 on conflict-related outcomes in the 1997-2016 period. This long temporal lag between treatment and outcome is used to minimize the risk of reverse causality, i.e, the risk of road networks reflecting anticipated future conflict.

We estimate linear models with country-year fixed effects. This setup effectively controls for all phenomena that are constant within country-years. To mitigate the risk of omitted variables at the group-level, we add two sets of controls. First, we control for $\textsf{state access}_g^{foot}$ and $\textsf{internal connectedness}_g^{foot}$. These variables are analogous to the ones defined in expressions 1–2, but calculated exclusively on the 'foot-path' network. Hence, they do not contain any road network information. These measures capture the impact of all non-road related determinants of accessibility, in particular the location of an ethnic group's settlement area relative to the population distribution, as well as its state's capital and borders. These controls allow us to empirically separate the impact of the road network from that of geographic and demographic features.

Second, we include a vector of geographic controls that may plausibly affect the presence of roads and conflict risk: groups' distance to the closest border, coastline, and navigable river, a dummy indicating whether a group's settlement area includes the capital, local resource wealth in the form of a mineral deposit dummy (Schulz and Briskey 2005) as well as the soil suitability for general agriculture (Ramankutty et al. 2002) and cash crop production,[15] the local climate (mean temperature, precipitation, evapotranspi-

[14] As such we argue that the mere existence of an alliance between a local militia and the government is already a clear sign of a loss of the official state's local monopoly of violence. Unfortunately, no data on such alliances is available at the moment.

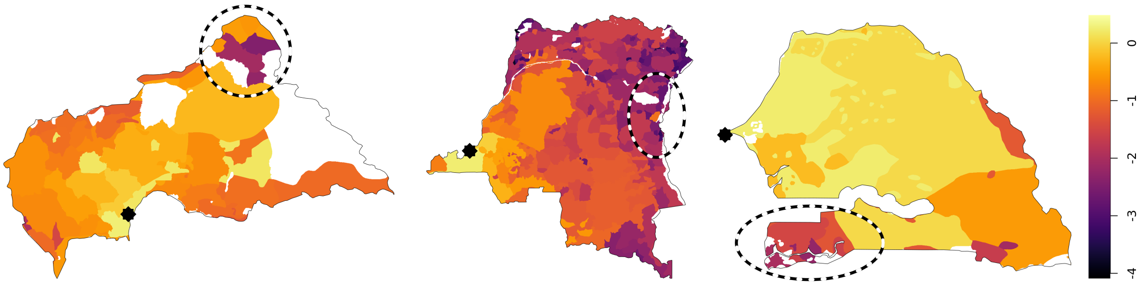
[15] We compute this metric by taking the maximum suitability (from FAO 2015) for growing one of eight

ration), and the altitude and roughness of a group's settlement area (from FAO 2015). We also control for groups' contemporary total population and urban population (CIESIN and ITOS 2013), as well as the size of their settlement area (see e.g. Buhaug and Gates 2002; Buhaug and Rød 2006). We add and subtract control variables in a series of robustness checks summarized in Appendix A4.4. To account for error dependence, we cluster standard errors at the country level.

Results

Before turning to the quantitative results, we discuss three cases that underline the face validity of our argument: the Central African Republic, the Democratic Republic of the Congo, and Senegal. Figure 2 depicts the distribution of RSC within these countries. Dark shades indicate ethnic groups with low levels of RSC, many of which staged violent challenges to state power in the recent past.

In the Central African Republic, RSC is lowest in the northern region Vakaga from where Seleka rebels toppled the government in 2013. Cut off from the capital during the rainy season but internally highly interconnected, Vakaga is outside the government's reach, and its inhabitants rarely use the national language and currency (International Crisis Group 2007, 2015). In the DRC, we find that RSC is up to 350% higher among groups located in the west of the country compared to those in the Eastern Kivu region. In line with our argument, civil wars have raged in the Kivus for years. Many areas are



(a) Central African Republic (b) Democratic Republic of the Congo (c) Senegal

Figure 2: RSC (logged) in 3 African countries, based on expression 3. Highlighted regions are discussed in the text.

cash crops: cotton, coffee, cocoa, groundnuts, oil palms, sugarcane, tea, or tobacco (see also Roessler et al. 2018).

ruled and competed over by militias and rebel groups rather than the state (Sanchez de la Sierra 2018). In the nominally much stronger Senegal, the Casamance constitutes another area that features low levels of RSC and long-lasting conflict. As in the eastern part of the DRC, rebel groups in the Casamance have established governance structures that compete with the state and tax the local population – activities facilitated by their high levels of social control (Humphreys and ag Mohamed 2005; Evans 2004).

Table 1: Effect of the components of RSC, OLS

	Dependent variable (logged)		
	Challengers	Challenger Events	State Events
	(1)	(2)	(3)
β_1: State access '66 (log)	-0.157^{***}	-0.111^{**}	-0.138^{***}
	(0.038)	(0.044)	(0.046)
β_2: Internal connectedness '66 (log)	0.186^{***}	0.161^{***}	0.133^{***}
	(0.036)	(0.041)	(0.035)
State access; foot '66 (log)	0.036	-0.006	0.011
	(0.029)	(0.035)	(0.033)
Internal connectedness '66; foot (log)	-0.130^{***}	-0.117^{***}	-0.103^{***}
	(0.030)	(0.034)	(0.030)
$\beta_1 + \beta_2$	0.03	0.05	0
	(0.04)	(0.05)	(0.04)
Country-year FE:	yes	yes	yes
Controls:	yes	yes	yes
Mean DV	0.21	0.17	0.15
F-Stat:	22.83	20.33	15.99
Observations	31,760	31,760	31,760
Adjusted R^2	0.399	0.370	0.313

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

Turning to the statistical analysis, Table 1 presents estimates of the effect of ethnic groups' state access and internal connectedness on the three main outcomes.[16] The results align with our expectations. Higher levels of state access are associated with lower numbers of challengers (Model 1), less violence among them (Model 2), and less fighting between them and the government forces (Model 3). Conversely, internal connectedness is associated with more challengers and conflict events. Across the three models, the two coefficients

[16]Note that we log all RSC-related variables to account for decreasing marginal effects for high values of accessibility and connectedness.

are precisely estimated and have opposite effects. Indeed, the difference between the two estimates' absolute values is not significantly different from zero. This implies that we can substitute these two regressors with logged RSC (as defined in expression 3) without much loss of information.[17]

Table 2: Relational state capacity and violence in Africa 1997–2016: Main Results, OLS

	Dependent variable (logged)		
	Challengers	Challenger Events	State Events
	(1)	(2)	(3)
RSC 1966 (log)	-0.174^{***}	-0.141^{***}	-0.135^{***}
	(0.032)	(0.036)	(0.033)
State access 1966; foot (log)	0.048^{*}	0.015	0.009
	(0.026)	(0.031)	(0.027)
Internal connectedness 1966; foot (log)	-0.122^{***}	-0.103^{***}	-0.104^{***}
	(0.029)	(0.032)	(0.030)
Country-year FE:	yes	yes	yes
Controls:	yes	yes	yes
Mean DV	0.21	0.17	0.15
F-Stat:	22.84	20.33	16.01
Observations	31,760	31,760	31,760
Adjusted R^2	0.398	0.370	0.313

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

Table 2 summarizes the results obtained when using the combined RSC metric. There is a lower number of challengers in ethnic groups with high levels of RSC, less conflict among them, and less fighting between challengers and the state. In substantive terms, the coefficients of RSC are sizeable, precisely estimated, and similar across the three outcomes. The models associate a 10% decrease of RSC with an increase in the number of violent challengers and events by between 1.4 and 1.8 percent.[18] Returning to DR Congo, our estimates suggest that the 350% increase in RSC when moving from ethnic groups in the Kivus in the east to groups around Kinshasa in the west translates into a decrease in the number of challengers by 60 percent. Along the same route, the number of violent

[17] Note that Equation 3 implies:
$ln(\mathsf{RSC}_g) = ln(\mathsf{state\ access}_g) - ln(\mathsf{internal\ connectedness}_g)$.

[18] These percentage estimates are approximate due to the unit constant added to the outcome prior to taking the log. For low baseline values of the outcome, the actual effect is larger.

events is predicted to decrease by about 50 percent.

In Appendix A4 we check whether these findings are robust to changes in the baseline model specification. We first alter the specification of our dependent variables and the functional form of the estimated models. A disaggregation of the composite of 'challengers' to local state rule into rebel groups and militias shows that RSC has a very similar effect on the number and battles associated with both types of violent actors (Appendix Section A4.2). Using dummies instead of counts as outcomes, using fatalities instead of events, and sourcing the outcome variables from alternative data sets (UCDP GED, Sundberg and Melander 2013, and SCAD, Salehyan et al. 2012) yields estimates substantively equivalent to the baseline results (A4.1). The same applies when using logistic or negative binomial models instead of linear specifications (A4.2).

In a series of further robustness checks, we find that the results hold when we employ the 1990 road network data (A4.3). They are also robust to either dropping all control variables or expanding them, including precolonial and geographic characteristics of ethnic settlement areas (A4.4). Adding fixed effects for 10'000 'bins' of ethnic groups of the same country and a similar geographic distance to the capital, distance between inhabitants, and population size produces equally consistent results (A4.4). Dropping groups that are very small or cross national borders (A4.5), using different ethnic settlement data as units of analysis (A4.6), or conducting a country-by-country jackknife does not significantly change the results either (A4.7). Finally, cross-sectional analyses show that the results are not due to our panel setup or potentially endogenous movements of borders and capitals since independence (A4.8).

Beyond the caveats addressed above, a causal mechanism other than states' and challengers' social control may explain the relationship between our road-based proxy of RSC and conflict. We test two such alternative explanations in Appendix A4.9. The first alternative is that roads connect markets, foster growth and economic development, which can bring peace and stability. The second explanation is that roads to the capital capture generally higher levels of connectedness of an ethnic group with the entirety of its country. The resulting strength of inter-ethnic ties might curb the risk of rebellion. We find that controlling for these two alternative mechanisms barely reduces the size of the estimated effect of RSC.

An instrumental variable approach

The potential endogeneity of road networks is the most important limitation of the above analysis. In particular, it is plausible that there are unmeasured group-level characteristics that have affected colonial road building and recent conflict.[19] If, for example, unobserved resource endowments caused ethnic groups to have better connections to capitals and at the same time increase the risk of conflict (e.g. Lujala, Gleditsch and Gilmore 2005; Berman et al. 2017), we would underestimate the effect of RSC. In contrast, ethnic favoritism can lead governments to build roads towards their ethnic kin but not powerless ethnic groups (Burgess et al. 2015), which are more likely to rebel (e.g. Cederman, Gleditsch and Buhaug 2013). This biases the estimated effect of RSC upwards. To address such endogeneity, we implement an instrumental variable (IV) approach based on simulated road networks.

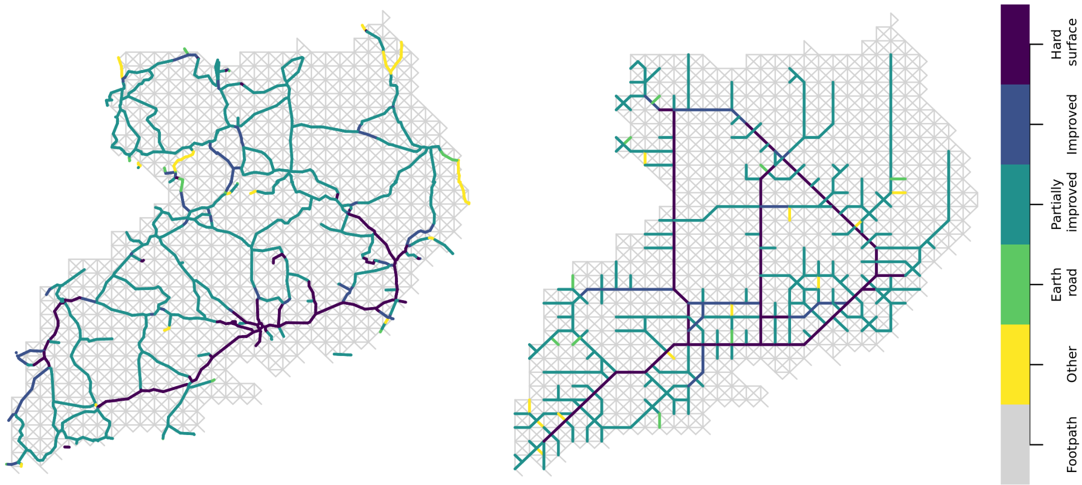
An instrument for road networks

We construct an instrument for our observed RSC metric in two steps. First, for each country in our sample, we construct an "optimal" road network using only information that is plausibly exogenous to contemporary conflict. Building on the literature on optimal transport networks (e.g. Los and Lardinois 1982) our road-building algorithm only takes a country's population distribution in 1880 (from Goldewijk, Beusen and Janssen 2010) and its total type-specific (highways, dirt roads, etc.) road mileage in 1966 as inputs.[20] It then constructs a road network that minimizes the average traveling time between any two inhabitants of the country. The road-budget constraint ensures that the total length and composition of the simulated networks is, with small rounding errors, the same as in the observed networks. For details on the simulation algorithm, see Appendix A5. In a second step, we use these simulated networks to recompute the state access and internal connectedness metrics introduced above. These new variables serve as instruments for our observed measure of RSC.

For this IV strategy to be effective, two conditions need to be met. First, the instruments need to be predictive of the endogenous treatment, which implies that the simulated

[19] Another potential source of endogeneity is systematic bias in the Michelin maps' accuracy.

[20] Note that the results barely change if we use the road mileage from 1990 as an input in Appendix A4.3. However, because protracted conflict (or peace) might have had a reverse effect on the overall extent of road networks, we deem the use of the data from 1966 more suitable for avoiding reverse causality.



(a) Observed network (b) Simulated network

Figure 3: Observed and simulated road network in Uganda, 1966. For further examples, see Appendix A5.

road networks need to be sufficiently similar to their observed counterparts. Indeed, we find that this is the case. While real-world road building is obviously more complex than minimizing inter-citizen traveling times, our simulated networks are still fairly realistic, the reason being that some network configurations are more effective at interconnecting a country's population than others. As an example, consider the simulated and observed networks for Uganda in Figure 3. The algorithm places the highest-quality roads between the most populated areas in the Southwest, center, and Southeast of the country. As in the observed network, the algorithm also produces trunk- and feeder-roads that facilitate travel towards the adjoining areas of a main road. The next Section reports quantitative evidence that our (simulated) RSC instruments are predictive of observed RSC.

Second, our instruments have to satisfy the exclusion restriction, i.e. they need to be exogenous to contemporary conflict, and may not affect conflict through any other channel than observed state access and internal connectedness. Exogeneity requires that the inputs to the simulation algorithm – population distributions, country borders, and total road mileage – are themselves exogenous. We bolster the credibility of this assumption by basing the simulations on historical data, i.e. 1880 population counts and 1966 road stocks,[21] and by including country-fixed effects in the IV regression. The latter measure eliminates

[21]For a similar approach, see Jedwab and Storeygard (2016).

any potential endogeneity of population counts or road mileage on the country-level, and ensures that all identifying variance originates from groups' relative location vis-à-vis the country's borders and population. Another threat to the exclusion restriction arises if our instruments simply pick up group-level population counts or other demographic and geographic information. To counter this risk, we include three sets of controls in the IV regression. The first set is comprised of footpath-based versions of state access and internal connectedness, now based on the 1880 population distribution used for the simulation. The second set consists of the inputs to the simulation: ethnic groups' population count in 1880, and their distance to the country-border. The third set is the vector of geographic controls from our baseline analysis.

In sum, our IV design exploits the fact that some groups feature low RSC because building straight roads to access them from the capital is inefficient, but building roads that make them internally connected pays off. The design thus builds directly on Herbst's (2000, ch. 5) observation that some African countries' geographies are ill-suited for constructing road networks that benefit local state rule.

Results

We implement our IV strategy using 2SLS models. Unlike the baseline analyses above, the instrumentalized version measures observed RSC based on the 1990 roads data. Assuming that our instrument is valid, we no longer need to rely on historical road network data. Since road networks and population distributions are highly persistent, our instruments (simulated with 1966 road mileages)[22] are still highly predictive of 1990 state access and internal connectedness. The IV results strongly support the predictions of Hypotheses 1 and 2 that low levels of RSC facilitate the emergence of challengers to state power and leads to violent competition between them. Offering more mixed support for Hypothesis 3, the result indicate that these dynamics also lead to increased violence between challengers and state forces. While such fighting decreases with instrumented RSC, this result is not stable across all robustness checks and mainly driven by the state access component of RSC. We discuss the implications of this finding after presenting the results.

[22]Note the robustness check with road networks simulated based on countries' road stock in 1990 in Appendix A4.3.

Table 3: Instrumental Variable Approach: Reduced Form

	Dependent variable (logged)		
	Challengers	Challenger Events	State Events
	(1)	(2)	(3)
State access 1880 (sim; log)	-0.221^{***}	-0.155^{***}	-0.090^{*}
	(0.046)	(0.052)	(0.047)
Internal connectedness 1880 (sim; log)	0.123^{***}	0.098^{***}	0.023
	(0.028)	(0.030)	(0.028)
State access 1880; foot (log)	0.062^{**}	0.012	-0.029
	(0.030)	(0.036)	(0.032)
Internal connectedness 1880; foot (log)	-0.054^{**}	-0.032	-0.002
	(0.027)	(0.030)	(0.026)
Country-year FE:	yes	yes	yes
Controls:	yes	yes	yes
Mean DV	0.21	0.17	0.15
F-Stat:	21.87	19.63	15.5
Observations	31,280	31,280	31,280
Adjusted R^2	0.391	0.364	0.309

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

Table 3 presents the reduced form estimates. As expected, states' access to ethnic groups on the simulated network relates negatively and statistically significantly to the number of challengers, fighting between them, and battles between challengers and state forces ($p = .057$). Conversely, the simulated internal connectedness of ethnic groups has a positive effect on the number of challengers and fighting between them. However, the measure does not have a significant or large effect on battles between challengers and the state. With the exception of violence between the state and its challengers, these effects are precisely estimated and coincide with our baseline results. In particular the consistent negative effect of state access underlines the importance of Herbst's (2000) work for understanding contemporary political development and conflict in Africa. Indeed, violent competition over local power is more prevalent in peripheral ethnic groups that cannot be easily penetrated by the state.

Table 4 presents the main 2SLS models. The explanatory power of our two instruments

Table 4: Relational state capacity and violence in Africa 1997–2016: Main Results, 2SLS

	Dependent variable (logged)			
	Stage 1	Stage 2		
	RSC 1990	Challengers	Challenger events	State events
	(1)	(2)	(3)	(4)
State access 1880 (sim; log)	0.645***			
	(0.063)			
Internal connectedness 1880 (sim; log)	−0.262***			
	(0.032)			
RSC 1990 (log)		−0.370***	−0.269***	−0.128*
		(0.077)	(0.081)	(0.070)
State access 1880; foot (log)	0.261***	0.168***	0.092*	0.0002
	(0.040)	(0.051)	(0.056)	(0.048)
Internal connectedness 1880; foot (log)	−0.210***	−0.113***	−0.069*	−0.037
	(0.030)	(0.036)	(0.039)	(0.032)
Country-year FE:	yes	yes	yes	yes
Controls:	yes	yes	yes	yes
Mean DV	-1.11	0.21	0.17	0.15
F-Stat:	267.09	21.18	19.38	15.49
F-Stat Stage 1:		61.99	61.99	61.99
Observations	31,280	31,280	31,280	31,280
Adjusted R^2	0.891	0.371	0.356	0.307

Notes: 2SLS-IV models. Control variables consist of the total population in 1880 (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, and the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

in the first stage is high, yielding a F-statistic of 62.[23] As expected, state access^{sim} has a positive effect on RSC, while internal connectedness^{sim} impacts the measure negatively. Both coefficients are statistically significant.

The second stage shows substantive effects of RSC on the number of challengers, violence among them, and violence between them and the state. The coefficients for instrumented RSC in 1990 are statistically significant and of greater absolute size than the baseline estimates for the number of challengers and violence between them. In substantive terms, the IV-estimates suggest that a decreasing RSC in 1990 by 10 percent increases the

[23] Specifically, we can reject the weak instrument null under a maximum size of 10% of a 5% Wald test of $\beta_{\mathsf{RSC}} = 0$ (Stock and Yogo 2005, p. 101). The first stage holds across different size-bins of ethnic groups and countries (see Appendix A6.1). Because our simulations are imprecise in small areas, the instruments are weak for small ethnic groups and have no predictive power in the smallest countries in the sample.

number of local challengers by 3.7 and violent events between them by 2.7 percent. The same decrease in RSC raises the number of battles between challengers and the state by 1.3 percent, an estimate that is similar in size than the baseline result but associated with somewhat greater uncertainty ($p = .066$).[24] As highlighted by the reduced form estimates in Table 3 and confirmed by estimating the effects of state access and internal connectedness instrumented separately (Table A7 in Appendix A6), the effect of RSC on state-challenger battles is mainly driven by states' access to ethnic groups. The estimated effect of groups' internal connectedness is half the size and associated with a large standard error.

To assess the robustness of the IV analysis, we implement the same robustness checks as for the uninstrumented analysis and discuss the results in detail in Appendix A4. The estimated effect of RSC on the number of challengers and violence between them is robust across all alternative specifications, thus providing further support to Hypotheses 1 and 2. The more imprecisely estimated effect of the instrumented measure of RSC on fighting between states and their challengers generally coincides with the effect reported in Table 4, although with a few exceptions. These exceptions pertain to (1) the effect of RSC on the number of fatalities in battles between the state and its challengers, (2) the number of such battles as measured by UCDP GED, and (3) the number of state-challenger battles in ethnic settlement areas from GREG (Weidmann, Rød and Cederman 2010). In these three specifications, the estimated effect of RSC is smaller than in the baseline models and statistically insignificant. Furthermore, they turn insignificant when we analyze the data in a cross-sectional manner, although here, the point estimates are indistinguishable from the baseline analysis. Finally, the effect of RSC on state-challenger fighting is mainly driven by observations from the DR Congo. Despite being the proto-typical case in which we expect Hypothesis 3 to hold, this casts further doubt on its validity. The results are consistent with those reported above in all other specifications.

The results thus show consistent and strong support for Hypotheses 1 and 2 that low levels of RSC allow rebels and militias to mobilize and compete violently over local power. We find more mixed support for Hypothesis 3 that states fight their challengers more often in ethnic groups with low levels of RSC. In light of the consistent findings on

[24] Again, these percentage estimates are approximate due to the unit constant added to the outcome prior to taking the log. For low baseline values of the outcome, the actual effect is larger.

the number of and fighting between challengers, this raises two questions in particular. The first concerns whether our geographic counting of state-challenger battles accurately captures conflict dynamics between the center and the periphery. The second relates to potentially heterogeneous incentives of governments to confront peripheral rebellions.

First, while fighting among challengers to the state is most likely to occur in the ethnic settlement areas they compete over, this is not necessarily the case for fighting between rebels and the state. Peripheral rebel groups and militias that grow strong will fight with state forces not only in the settlement area of 'their' ethnic group, but also elsewhere, in particular on their way to the state's capital. Such spatial patterns are not captured by our measurement. Instead and as mentioned above, we attribute the respective battle events to ethnic groups from which such rebel groups and militias did not originate.

Second, there might be substantial heterogeneity in the circumstances under which states invest the resources to fight their peripheral challengers. As noted above, some rulers might choose to not fight them at all, due to their inability to control the respective ethnic groups in the long run, logistical difficulties to stage a successful military campaign, or presuming that the rebels do not threaten their survival. In other cases, the threat of peripheral challengers will pose too much of a risk to governments' survival, thus motivating them to take up arms and defend their rule. These heterogeneous incentives to repress peripheral rebellions highlight important questions for future research on the effects of relational state capacity on the geography of civil wars.

Conclusion

The civil war literature correctly highlights state weakness as a central conflict determinant. Yet, past research on the effect of state capacity on conflict has relied on a set of incomplete theoretical arguments and empirical measurements. While shifting the theoretical focus from the rebel side to structural properties of the state, Fearon and Laitin's (2003) influential formulation leaves the interaction between governments and non-state actors mostly implicit. Subsequent work has either proposed better country-level proxies for state capacity or turned to the local level, without fully capturing the state-society nexus that is at the heart of conflict processes.

In order to bridge this gap, we have proposed a relational theory of state capacity and conflict that builds on Mann (1984, 1993) and Migdal (1988), as well as Herbst's (2000) previous work on road networks in Africa. Our theory of opportunities specifies that state weakness cannot be understood without considering it directly in relation to the social control maintained by non-state actors that compete for power both among themselves and at the expense of the state. The crucial realization is that road networks, which we use to proxy for social control, do not merely serve as radial power projectors of the central government, but also constitute the potential backbone in challengers' attempts to exert control. For each kilometer of roads paved, and by extension, for each radio station, cell phone tower, or internet cable built, the state may provide the tools with which its competitors can outgovern it.

We have found empirical support for this dual perspective on governance. Focusing on ethnic groups in Africa, we have measured relational state capacity (RSC) as the difference between groups' accessibility from the capital and their internal connectedness. Our baseline analysis suggests that RSC decreases the number of challengers to state power, the risk of political violence among them, and between them and state forces. We address potential endogeneity biases through an instrumental variable approach that exploits credibly exogenous variation in road networks, which we capture with a novel network simulation strategy. The results bolster the baseline estimates, with the exception of the effect of RSC on the number of battles fought between the state and its challengers, which is positive in the main IV specification but not robust in a number of sensitivity analyses.

There are good reasons to believe that our results generalize beyond Africa. For example, Scott (2009) highlights similar dynamics in his work on how state penetration in Southeast Asia forced peripheral ethnic groups to flee into inaccessible terrain. This process turned into conflict when states tentacles impeded future escape and ethnic groups mobilized against the state. Historically, Hechter's (1975) account of "internal colonialism" and Weber's (1977) analysis of French nation building illustrate the pivotal role of road building in extending the state's social control into its entire territory. The problem of dual technologies of social control is also not limited to road networks. In recent work on civilian targeting in Syria, Gohdes (2019) highlights that the Internet presents rulers with a very similar dilemma than we have emphasized here: it provides information that improves their ability to target rebels, but at the same time allows rebels to organize and mobilize.

Moving forward, our argument about the opportunity-driven effect of relational state capacity on violent conflict needs to be extended to encompass motives of the state and it violent challengers at the local level. Under what conditions will states choose to fight their peripheral challengers? And under what conditions does extending RSC, necessarily at the expense of local actors, affects their readiness to take up arms in defense of their realm? This question is of particular importance, since extending states' social control does not necessarily imply inclusive rule and good governance, but may instead lead to repression and 'internal colonialism' (Hechter 1975). In that regard, the different strands of the literature on the motivations for armed conflict can offer a good starting point to explore how RSC can be increased without causing violent backlash.

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Supporting Information
'Roads to Rule, Roads to Rebel'

Table of Contents

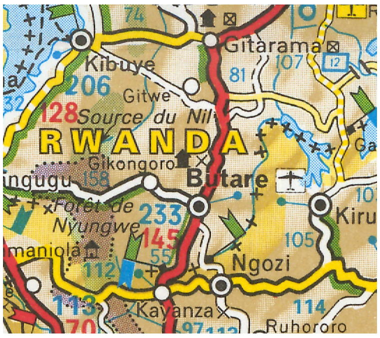


Figure A1: Small excerpt from the 2003 Michelin map for Southern Africa, showing southern Rwanda.

A1 Digitizing road maps

A1.1 The Michelin map corpus

Our source for road network data is the African Michelin map corpus, a collection of large topographical maps at a resolution of 1:4,000,000, showing detailed information on transport infrastructure with a consistent cartographic symbology. While coverage before the 1960s is sporadic, Michelin has covered the entire African continent at intervals of at most 5 years beginning in 1966. This makes the Michelin corpus an unparalleled source for time-variant road-network information. In the present paper, we make use of the 6 maps published in 1966 and 1990.

We digitize this map collection automatically. Apart from being relatively cheap, the automatic digitization approach features a number of additional benefits:

- *Consistency:* The cartographic information is extracted in a highly consistent manner, avoiding errors due to human fatigue and less-than-perfect inter-coder reliability.
- *Replicability:* The entire data set can be reproduced at will.
- *Extendability:* After the initial system is set up, the marginal costs of adding new cartographic material (including from other sources) are negligible.

A1.2 Map digitization as a computer vision task

A critical first step for extracting information from geospatial imagery is to distinguish between areas representing objects of interest and background.

Roads in the Michelin maps are drawn as complex features with multiple color and line-patterns, and often interrupted by other objects (see Figure A1). Therefore, heuristic algorithms that distinguish only colors or lines fail to classify roads correctly. Instead, we implement a method that "looks at" entire map segments at once, and is able to distinguish between lines and other object types using contextual visual information.

To do so, we borrow from recent advancements in the machine learning literature and implement a *Convolutional Neural Network*-based system for road network extraction.

Convolutional Neural Networks (CNNs) have recently emerged as a powerful method for computer vision applications, outperforming other approaches across a variety of classification problems (LeCun, Bengio and Hinton 2015). Fundamentally, CNNs are feedforward artificial neural networks (ANNs). They consist of multiple layers of neurons, each neuron representing a non-linear function associated with a trainable weights vector, accepting a linear combination of inputs from the previous layer, and outputting a scalar that is passed on to the next layer.[25] In the language of ANNs, the vector of predictors associated with a single observation is then called the "input layer", whereas the prediction produced by the ANN is called the "output layer". Note that in computer vision problems, the input layer typically consists of raw image data, structured as a pixel-image with multiple color bands.

While the most basic variants of feedforward ANNs feature fully connected architectures where each neuron accepts inputs from *all* neurons of the previous layer, *convolutional* neural networks restrict the visual receptive field of each neuron to a small, spatially contiguous patch of input data, thus retaining the spatial structure of the inputs. Moreover, CNNs feature a shared-weights architecture, whereas neurons reuse the same set of parameters to "look" at all locations of the input image. This ensures that CNNs are shift-invariant: They are able to detect objects regardless of their spatial location in the input image.

Neurons in CNNs typically implement two types of operations. A *convolution* operation, computing the dot product between a patch of input data and the neuron's weights, and a pooling operation, which downsamples the input image to a lower resolution by some given factor. Productive CNNs typically feature multiple convolution- and pooling-layers in succession, giving rise to a complex non-linear function that transforms a given input image into a series of images with decreasing resolution, but higher depth, called *feature maps*.[26] This architecture gives rise to the key advantage of CNNs: their ability to learn features relevant for classification from raw, unprocessed input imagery (Zeiler and Fergus 2014). Hence, instead of the researcher having to pre-process the input data and extract variables that are useful for classification (e.g. whether particular shapes or color patterns are present), CNNs are capable of learning important features by themselves. The layers close to the input image recognize low-level features such as edges or blobs of a particular color, which are then fed to the higher-level layers that capture more complex features at lower resolutions, like specific line patterns or shapes with particular textures.

For image segmentation, Shelhamer, Long and Darrell (2017) have recently proposed what they call a *fully convolutional* approach. Here, the feature maps produced by the regular convolutional and pooling layers are used as inputs for a set of upsampling, or *deconvolutional* layers. These consist of neurons that implement a reverse convolutional operation, mapping lower resolution feature maps onto higher resolution outputs via a

[25] The following discussion of ANNs and CNNs draws from Bengio, Goodfellow and Courville (2016, ch. 6 & 9).

[26] Here, "depth" refers to the third dimension of an image. An RGB image has depth 3.

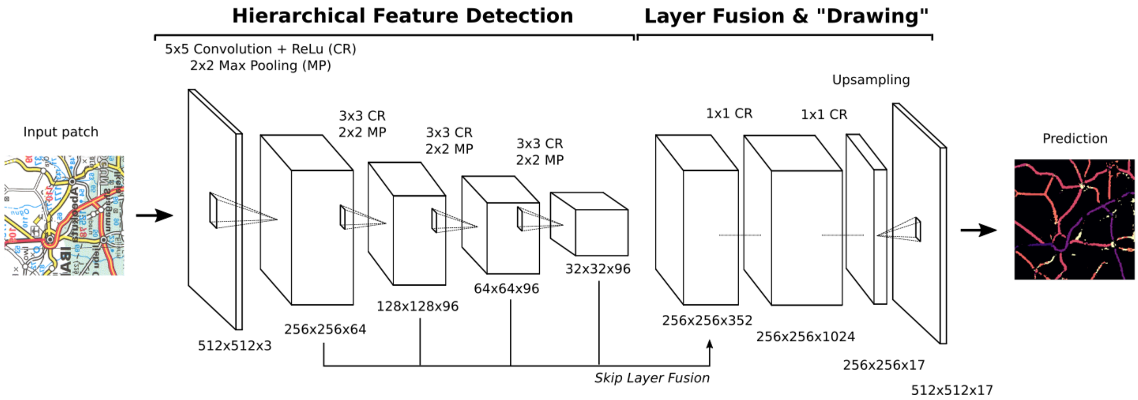


Figure A2: Architecture of our custom fully convolutional neural network.

trained interpolation function. Hence, fully convolutional neural networks (FCNNs) have an "abstraction stage", where convolutional and pooling layers learn to recognize complex image features, and a "drawing stage". Here, the information from the lower-resolution feature maps is mapped back onto the scale of the original input image, yielding a full semantic segmentation.

A1.3 Our FCNN: Architecture and training

To solve the semantic segmentation problem on the Michelin map material we implement a version of Shelhamer et al.'s FCNN model that takes RGB image patches of dimension $512 \times 512 \times 3$ pixels as input, and maps them onto output segments of size $512 \times 512 \times 17$. The output image depth arises from the fact that Michelin identifies 16 road categories.[27] The precise architecture of our model is shown in Figure A2. The model is described in canonical notation, see Bengio, Goodfellow and Courville (2016) and Shelhamer, Long and Darrell (2017) for more information.

We pursue a transfer-learning approach and pre-train the FCNN on 2000 artificial map images.[28] These are color-images of dimension $512 \times 512 \times 3$ that superficially look like real road maps, but which we create programatically by drawing arbitrary planar networks together with other map-like shapes and text labels of arbitrary color, size, orientation, etc. Each simulated map image is paired with a "ground truth" label of dimension $512 \times 512 \times 2$ that highlights the location of the road-network to be detected. With the pre-trained model, we then proceed to the training of the main model using actual, hand-annotated training data from the Michelin maps.[29]

Interpreting trained artificial neural networks is notoriously difficult, as the learned

[27] An additional reference category identifies background pixels.

[28] For pre-training, the outcome layer is only of depth two (instead of 17) because construct the artificial training labels such that they only identify the *presence* of roads, but not their type.

[29] All layers up to the second-to-last one (exclusive) are initialized with pre-trained weights, whereas the weights of last two layers are initialized randomly. For training both the initial "artificial" model as well as the final model, we use the stochastic gradient descent (SGD) based optimizer introduced by Kingma and Ba (2014) with a batch-size of 2.

parameters have little intuitive meaning by themselves. However, one commonly employed strategy is to show the neural activations of the network's feature maps for some input image. Six such feature maps shown in Figure A3 demonstrate how different neurons capture different types of information. The feature maps in the top row appear to recognize numbers, those in the bottom row identify road-related features. They also show that feature maps at lower resolutions tend to capture more abstract, higher-level objects, reflecting the hierarchical logic of feature detection in CNNs.

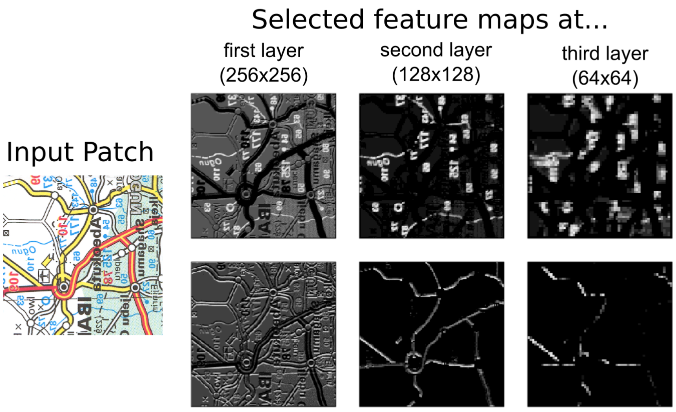


Figure A3: Selected feature maps from the trained FCNN.

Finally, it is instructive to demonstrate the trained FCNNs predictive performance visually. Figure A4 shows an excerpt from a 1966 map segment for Southern Nigeria (left panel), together with the corresponding road predictions obtained from the trained FCNN model (middle panel). The different colors in the predicted image correspond to different road types. We highlight that the FCNN is able to distinguish between even subtle differences in line types, e.g., lines of the same color, but with different border thickness.

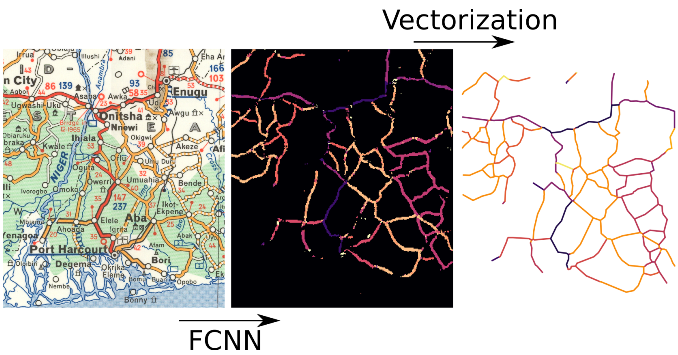


Figure A4: Predictive performance of the digitization procedure.

A1.4 Vectorization and results

Given the FCNN predictions, we implement and apply a four-step algorithm to convert the pixel-based FCNN output into vectorized road-network data:

	Binary	Categorical
Precision	0.988	0.888
Recall	0.986	0.964

Table A1: Evaluation statistics for the full digitization pipeline based on a hold-out sample.

1. The Zhang-Suen *topological thinning* algorithm is applied to the input images, leading to single-pixel-width road representations.
2. The thinned images are fed to a *line-tracing* algorithm, transforming the road network information to a vector-based representation.
3. A *line-splicing* algorithm is then applied to fill small, unlikely gaps in the vectorized road network.
4. A sequential, *hidden-Markov* style model is used to smooth the road type classification, leading to the removal of short segments with misclassified road types.

The right-most panel of Figure A4 illustrates the result of this vectorization procedure. To assess the accuracy of the digitization pipeline, we generate vectorized predictions for two hand-coded hold-out maps, each covering about 1000 square kilometers. We split the ground-truth and predicted networks into 5 km long road segments and calculate two evaluation metrics. *Precision* measures the proportion of predicted road segments that are proximate to a ground-truth road segment. *Recall* measures the proportion of ground-truth road segments that are proximate to a predicted road segment. We use 5 km error bands to establish whether two road segments are proximate. We also calculate variants of these metrics that take road types into account. Here, predicted and a ground-truth segments are only coded as proximate if they are also of the same road type.[30]

The result of this evaluation exercise is summarized in Table A1. We find that our digitization procedure is highly accurate. Over 98.8% of all extracted roads are present in the Michelin maps, and 98.6% of all Michelin roads are extracted. The corresponding figures are somewhat lower if we take road categories into account, but still 89.3 and 96.7, respectively. We note, however, that in those cases where the model misclassifies the road type, the error is typically small. Across all cases where roads are correctly extracted but assigned the wrong category, the mean absolute error on the ordinal road-type scale is 1.38. In other words, misclassifications typically take the form of a partially improved road erroneously being classified as an improved road, rather than an earth road being mislabeled as a highway. The lower category-precision is due to very small stretches of missclassified roads that should only marginally affect the estimates of travel times. In addition, we see no reason to believe that the FCNN introduces non-random errors.

[30]Note that for this evaluation, we employ the 6-category road type coding used in the paper, not the 16-category coding used during digitization.

A2 Constructing and validating road networks

A2.1 Network construction

We transform the Michelin data into a planar graph that uniformly covers each African country. We do so in a step-wise manner:

1. **Foot-path network:** The basis of our planar graph consist of a network of 8-connected 'foot-paths', shown for the case of Uganda in Figure A5a. The graph's nodes are the centroids of a raster of population estimates from the HYDE 3.1 data (Goldewijk, Beusen and Janssen 2010) for 1960 at a resolution of $.1667 \times .1667$ decimal degrees (or ca. 20 km at the equator). Each node is connected with a foot-path to its 8 nearest neighbors using queen moves. This setup allows for much more flexible applications than travel-query APIs such as Google Maps which do not process queries from/to points that are too distant from the next road.

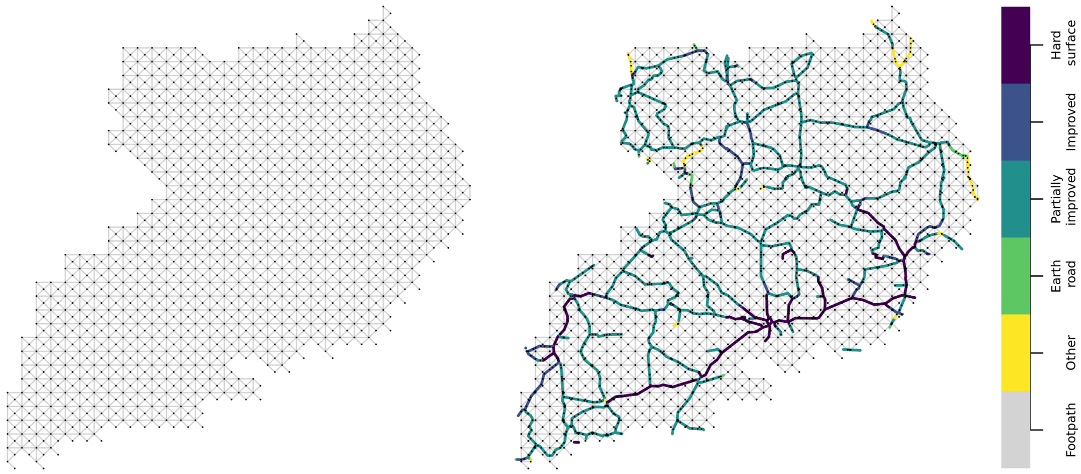
2. **Adding roads:** We overlay the basic foot-path network with the spatial lines extracted from the Michelin maps (see Figure A5b). We create additional nodes wherever two roads or foot-paths cross, thus retaining the planar graph property. These additional nodes' purpose is to serve as intersections. They are not associated with any population data. Hence, travel between two populated nodes will typically start by taking a foot-path to a road, and end by traveling from a road to the target node on another foot-path.

3. **Calculating edge weights:** Each edge on the network is associated with an edge weight which is equivalent to the estimated time it takes to traverse the edge. Before assigning these edge weights, we first collapse the 16 road types on the Michelin maps to 6 main categories. We obtain estimated travel speeds for each of these categories by querying the mapping tool on the Michelin website (`www.viamichelin.com`. For each road category, we identify a random selection of trips on roads of that category, and record the travel speed returned by the Michelin querying tool (see Figure A6a).[31] We set the traveling speed on foot-paths to 6 km (about 4 miles) per hour. This corresponds to walking-time estimates on `www.maps.google.com` (see also Jedwab and Storeygard (2016)).

A2.2 Validation

We validate the travel times computed on our Michelin-based network using the Google Maps API. Since Google only offers contemporary data, we base our comparison on road

[31] Note that the average speed returned for 'highways' is somewhat lower than that returned for 'hard surface' roads. Highways are almost non-existent in Africa. They constitute only .06 percent of the total road mileage observed in 1966 and cluster in the immediate neighborhood of large cities where speed is slowed by congestion. To preserve the rank-ordering of roads (which is important for our road simulation), we recode all highways as hard surface roads.



(a) Foot-path network

(b) ... adding Michelin roads observed in 1966

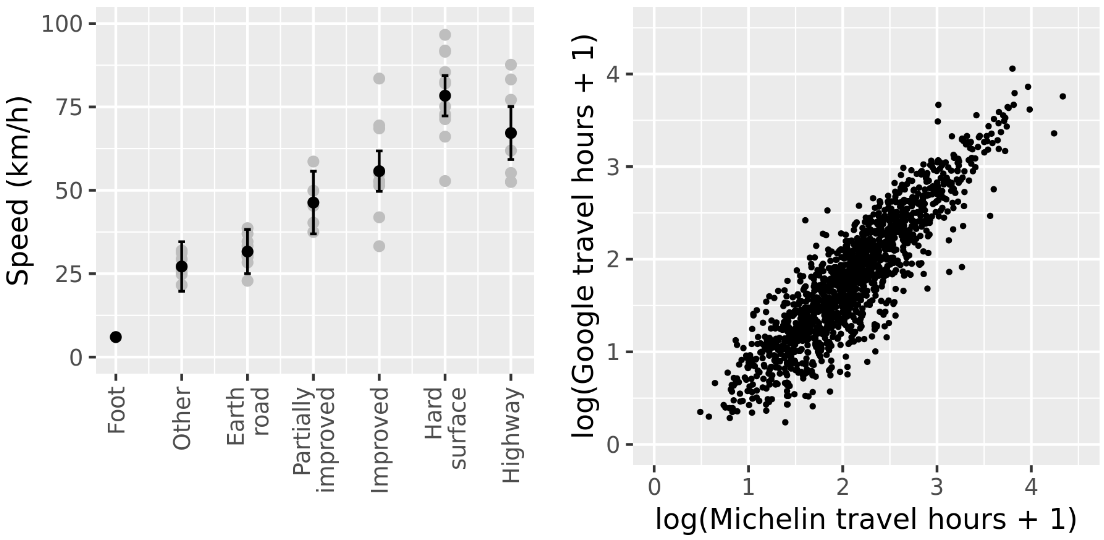
Figure A5: Constructing road networks that regularly cover geographical space. Additional vertices are added to the graph where foot-paths and roads intersect.

networks constructed with Michelin data from 2003, the most contemporary source at our disposal. For each country, we draw 50 source- and 50 destination nodes, each with a probability relative to a node's population size.[32] These nodes make up the start- and end-points of 50 paths, for which we compute both foot-travel and road-travel times on our network. We query the travel time between the two coordinates on the Google Maps API. Since the API allows only the search of geographical paths which start and end in close proximity to a road, only 60% of our queries are successful.

We compare the results from the 1,416 successful queries with our Michelin-based computations. Figure A6b plots the two data sources against each other. The figure shows a high correlation of ≈ 1 which is least precise at low travel times. This imprecision likely results from the fact that, in certain areas, Google Maps uses data on very small roads whereas our Michelin-based networks approximate such roads as 'foot-paths'.

This comparison does not only highlight the quality of our measurement of travel times. It also sheds light on one of the key shortcomings of Google Maps as an alternative resource for measuring travel times. Since Google Maps does not allow for querying paths between arbitrary coordinates, but makes such searches contingent on the presence of roads, it is impossible to use their services for our purposes.

[32]Fewer if the country in question does not have 50 populated nodes.



(a) Estimate of travel speed on different road types

(b) Comparison of travel times on the Michelin-based road network (roads from 2003) and travel times queried from the Google Maps API.

Figure A6: Construction and validation of edge-weights.

A3 Summary statistics

Table A2: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Challengers	31,780	0.51	2.41	0	128
Challenger Events	31,780	1.02	13.33	0	739
State Events	31,780	0.99	12.86	0	881
RSC 1966 (log)	42,878	−1.21	0.79	−4.09	0.49
State access 1966; road (log)	42,878	−2.76	0.72	−5.06	−0.06
Internal connect. 1966; road (log)	42,878	−1.55	0.59	−4.01	0.00
State access 1966; foot (log)	42,878	−4.22	0.81	−5.94	−0.23
Internal connect. 1966; foot (log)	42,878	−1.98	0.80	−4.88	0.00
State access 1880; road (sim; log)	42,196	−2.45	0.64	−4.40	−0.11
Internal connect. 1880; road (sim; log)	42,196	−1.35	0.67	−4.04	0.00
Distance to border	42,878	103.45	106.13	0.03	590.94
Capital dummy	42,878	0.03	0.16	0	1
Median altitude	42,851	601.64	452.68	3.80	2,427.10
Median slope	42,851	3.91	1.21	1.00	9.00
Evapotranspiration	42,851	1,617.84	274.68	1,073.75	2,509.15
Precipitation	42,851	1,166.26	554.99	3.24	3,217.60
Evapotranspiration / Precipitation	42,851	4.42	1.53	1.00	8.00
Temperature	42,851	24.85	2.89	11.32	29.94
Cash crop suitability	42,851	0.36	0.15	0.00	0.80
Agricultural suitability	42,851	0.35	0.25	0.00	0.99
Distance to coast	42,878	5.83	4.08	0.0001	16.10
Distance to nav. river	42,878	1.74	2.29	0.001	20.07
Mineral deposit	42,878	0.12	0.32	0	1
Area (1000 km^2)	42,878	17.35	64.23	0.11	1,311.14
Population (1000s)	42,878	463.54	1,846.02	0.003	37,581.51
Urban population (1000s)	42,878	178.03	1,159.41	0.00	30,564.21

A4 Robustness checks

We apply an extensive set of robustness checks to our main analysis. The following pages give an overview over the motivations, implementation, and results of each additional test. To facilitate interpretation, most robustness checks are presented as coefficient plots, in particular and unless otherwise noted, in Figure A7 below. Detailed reports will be available with the replication data.

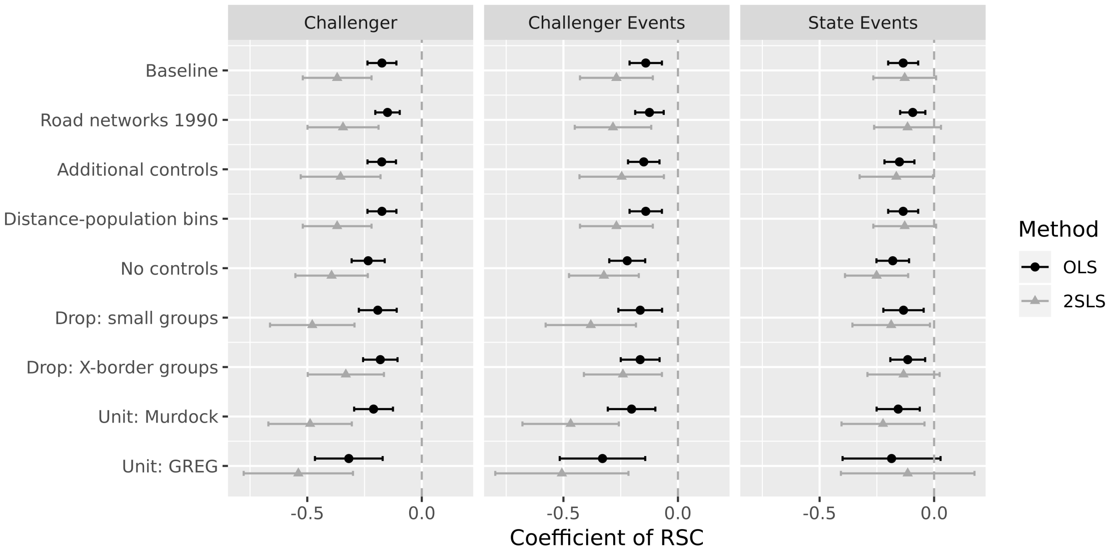


Figure A7: Coefficients of RSC in robustness checks. Bars indicate 95% confidence intervals.

A4.1 Alternative dependent variables

We first gauge whether our baseline effects on the number of and violent events associated with challengers to state power are driven by rebel groups or militias, defined as as ACLED's class of political and ethnic militias. In its three panels, Figure A8 plots the estimated effect of RSC on (1) the number of rebel groups and militias active in an ethnic settlement area (first and second row), (2) the number of battles between either rebel groups or militias with both, rebel groups and militias, as well as (3) the number of battles between state fores and rebel groups and militias. The results show that the baseline patterns found for the aggregate composite of 'challengers' are not solely driven by either rebel groups or militias.

We heed the advice of Hegre and Sambanis (2006) and subject our main model to (1) alternative specifications of our outcomes of interest and (2) additional outcomes from various datasets on political violence. Figure A9 plots the results for using (1) linear models of the probability that our main outcomes take a value > 0 and (2) the logged number of fatalities of the event types as the dependent variable. The respective results are consistent with those that are based on pure event counts. In addition, the Figure

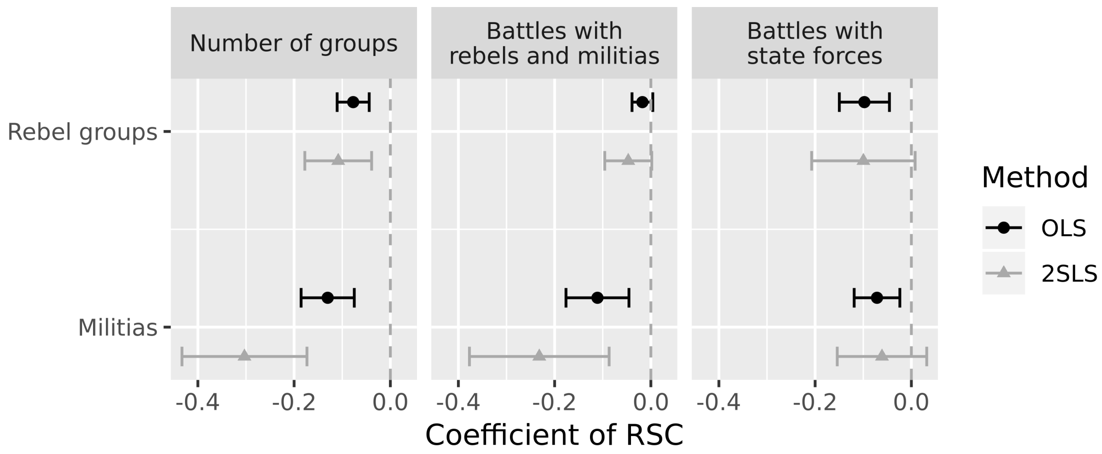


Figure A8: Coefficients of RSC when when disaggregating challengers to local state rule into rebel groups and militias.

shows results when conducting the repeating our analyis with alternative outcome data from the (3) ACLED (Raleigh et al. 2010), (4) UCDP GED (Sundberg and Melander 2013), and (5) SCAD datasets (Salehyan et al. 2012). The results show that low levels of relative state capacity are robustly associated with higher event counts across almost all categories of political violence.

Two classes of exceptions exist. First, the results show no evidence of an impact of RSC on remote violence, i.e. aerial bombings, as measured by ACLED. This is not too surprising, since these events are seldom and have little to do with physical accessibility. Also, We do not find effects of RSC on the number of violent incidents committed by pro-government militias taken from the SCAD data. These oftentimes happen in capitals, where RSC is by definition high. The second class of exceptions consist in that, in our instrumental variable approach, we find no evidence of an effect of RSC on (1) fatalities of state-challenger battles and (2) UCDP GED civil war events. Both exceptions relate to the generally more mixed results of the effect of RSC on fighting between challengers and state forces discussed in the respective section of the main text.

Notwithstanding these deviating patterns, the results from analyzing the effect of RSC on alternative measures of violent events in ethnic groups highlight that challenger-related violence in the periphery of a state also brings along other forms of political violence, most importantly violence against civilians.

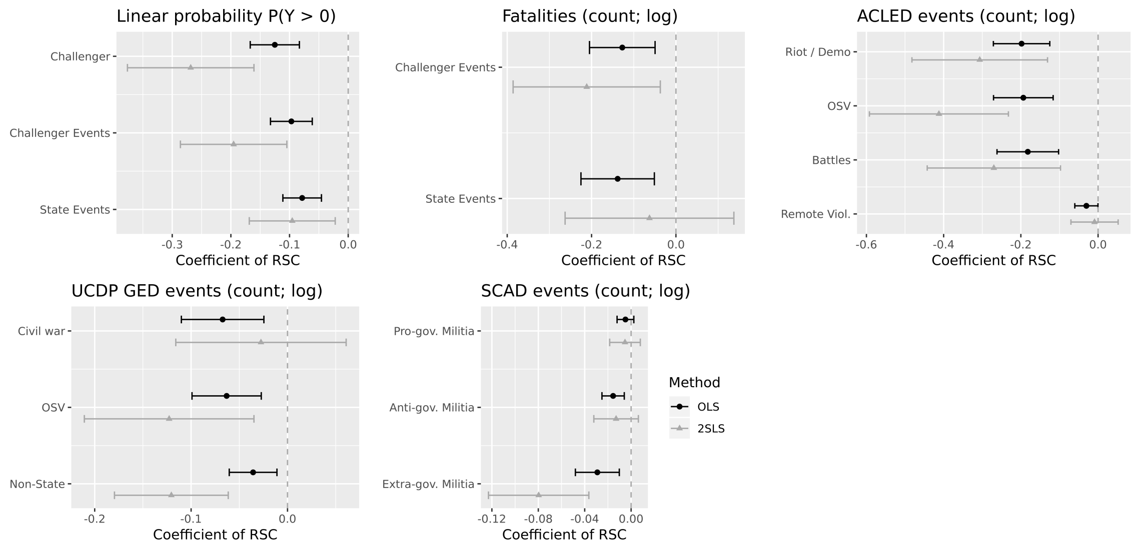


Figure A9: Effect of RSC on alternative outcome variables. Bars indicate 95% confidence intervals.

A4.2 Alternative functional forms

Although linear count models have the advantage of allowing for a very flexible specification of fixed effects, the bias introduced by the miss-specification of the distribution of the dependent variables might drive our results. Figure A10 therefore presents results based on logistic and negative binomial models that use the same vector of explanatory variables as our main model.[33] Due to computational complications in estimating such models with a large number of country-year dummies, we do control for country- and year-fixed effects rather than country-year fixed effects. Because our independent variables are cross-sectional in nature, this limitation has negligable effects. The results mirror the ones presented in the main paper, indicating that the latter are not due to the choice of linear count models.

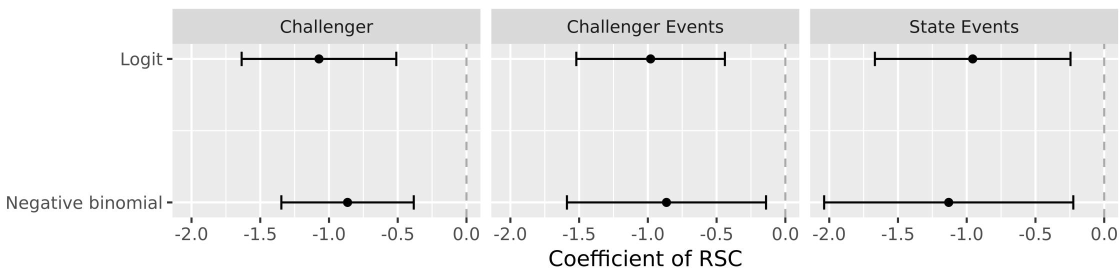


Figure A10: Coefficients of RSC when choosing different functional forms. Bars indicate 95% confidence intervals.

[33]We do not estimate Poisson models here because of the significant overdispersion of the dependent variables.

A4.3 Measuring RSC on 1990 road networks

In order to gauge whether the reliance on 1966 road network data significantly affects the results, we re-estimate the baseline specifications of the naive OLS and the instrumental variable analysis using data on the Michelin road network observed in 1990. For the IV-specification, this implies that we simulate a new set of road networks for each country using the road budget observed within a country's borders in 1990, and then using the simulation to instrument for RSC as measured on the 1990 road networks. The results of the resulting models are plotted in the second row of Figure A7 and show no significant deviation from the baseline estimates, except for the IV-estimate of the effect of RSC on the number of battles between the state and its challengers which slightly decreases in precision ($p = .11$) but comes with a point estimate that is equivalent to the baseline estimate.

A4.4 Adding and dropping control variables

To account for potential omitted variable bias, we include a set of additional control variables. These are:

- *Precolonial characteristics:* Data from Murdock (Murdock 1959, 1967) to account for precolonial characteristics of ethnic groups that might affect the extent and structure of colonial road building as well as contemporary conflict risk. In particular, we control for precolonial (1) economic practices – ethnic groups' dependence of hunting, fishing, animal husbandry, and agriculture –, (2) intensity of agriculture, and (3) political centralization.

- *Landcover:* Since landcover might affect conflict risk and the extend of transport infrastructure, we control for the percentage of ethnic groups' settlement areas that covered by (1) pasture land that is used for grazing, (2) savanna, (3) tropical woodlands, and (4) tropical forests (FAO 2015). With average values over 10 percent, these are the most prevalent land-cover types in Africa.

- *Characteristics of the area between an ethnic group and the capital:* Lastly, the quality of the road connection between an ethnic group and the capital is likely correlated with characteristics of the area between an ethnic group and the capital. Such characteristics might also conflict risk. For this reason, we compute the geographical area that lies between ethnic groups and their countries' capitals, recompute all baseline controls for these areas,[34] and add these new variables as controls.

The third row of Figure A7 shows that including these three vectors of control variables does not affect the baseline results.

[34] I.e, these areas' distance to the coast, their local climate (mean temperature, precipitation, evapotranspiration, and the ratio of the latter two), and their average altitude and roughness. We also include their contemporaneous (urban) population (both logged), as well as the logged size of their area.

In addition to the effect of potential omitted variables, the results reported above might be driven by non-linear effects of (1) pure geographic distances, in particular $\mathsf{state\ access}_g^{foot}$ and $\mathsf{internal\ connectedness}_g^{foot}$, and/or (2) population counts. To control for this caveat, we create yearly bins of ethnic groups that have similar values on these three dimensions. Within each country-year, we divide each of the three variables into bins of approximately 25 observations, which when all combined and interacted with make a total of 10'019 unique bins populated by observed ethnic groups. We then add one fixed effect per distance-population-country-year-bin to our baseline specification. Econometrically, this method is akin to matching observations from the same country-year on these three variables. The results of the re-estimated models are presented in the fourth row of Figure A7. The coefficients for RSC are similar those at the baseline and statistically significant. This further suggests that the negative effect of relational state capacity on conflict risk is not due to country-specific, nonlinear effects of (the combination of) pure geographic distances and population sizes.

Lastly, the fifth row of Figure A7 reports the results of estimating the main specifications without any control variables, except for foot-travel times to capitals and within ethnic groups. The results are not driven by the inclusion of the various controls. If at all, the specification shows that the inclusion of controls decreases the estimated effect of RSC, in particular its effect on the number of battles between state forces and challengers, which is now highly significant, both in the naive OLS and the IV-specification.

A4.5 Restricting the sample

Ethnologue lists (1) many very small ethnic groups, and (2) groups that are not strictly nested in (changing) country-borders. The first caveat may lead to internal connectedness measures that are hardly influenced by any roads. The second caveat produces small 'rump' groups where ethnic settlement patterns are cut by country borders, leaving potentially insignificant parts of an ethnic group on one side of a border. Such ethnic groups might inherently feature different types of conflict risks (Michalopoulos and Papaioannou 2011) which might bias our results.

To address both caveats, we restrict the sample of ethnic groups in two ways. The first is to drop ethnic groups with an area that is below the 25th percentile of the distribution of ethnic groups' areas (1295 km^2). The second robustness check drops ethnic groups that are divided by a state border. The results (Figure A7) of both tests are consistent with our main results. All coefficients are statistically indistinguishable from the baseline.

A4.6 Alternative units of analysis

Next, we reevaluate our hypotheses using two alternative data sets of ethnic settlement patterns, namely GREG (Weidmann, Rød and Cederman 2010) and Murdock's (Murdock 1959) ethnic map. GREG is based on the Soviet Atlas Narodov Mira, and Murdock's Atlas is coded on the basis of ethnographic evidence available in the 1950s and has been digitized by Nunn and Wantchekon (2011). Ethnic groups encoded in both data sets are on average bigger than those of the Ethnoglogue data. This might reduce potential bias introduced by very small ethnic groups (see also above, Subsection A4.5). The ensuing results, plotted in Figure A7, are mostly equivalent to the baseline results. As noted in the main text, this is with the exception of the IV-estimate of the effect of RSC on the number of state-challenger battles which does not decrease in magnitude but is estimated to be insignificantly different from zero. The respective naive OLS estimate is statistically significant at $p < .1$.

A4.7 Country-level jackknife

To assess the effect single countries have on our estimates, we implement a country-by-country jackknife approach, where we iteratively delete observations from each country from our sample. The estimates for the coefficient of relational state capacity RSC are plotted in Figure A11. No single country affects the statistical significance of the effect of RSC on the number of challengers and fighting between them. Not surprisingly however, we do see lower associations of RSC with our conflict-related outcomes when we drop countries such as the DR Congo, Ethiopia, Algeria, or Kenya. In particular the first two countries host peripheral ethnic groups which are prime examples of relatively weak relational state capacity leading to violent competition over local power. With regard to the third main outcome, battles between state forces and armed groups, Figure A11 shows that the baseline estimate of the IV specification are mainly driven by patterns of relational state capacity and conflict in the DR Congo. Although the country, in particular its Eastern part, hosts many proto-typical ethnic groups with low levels of relational state capacity and high levels of conflict, its influence on the results casts doubt on its representatives of conflict dynamics elsewhere on the continent. We discuss the implications of this finding in the main text.

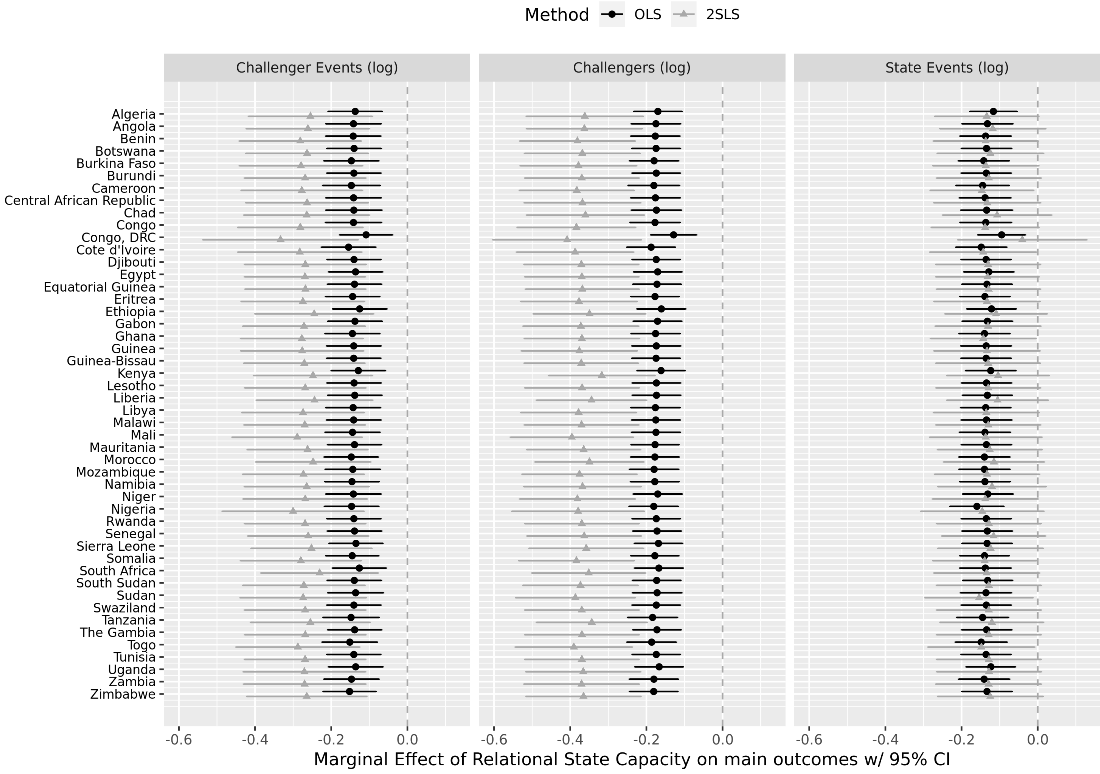


Figure A11: Country-by-country jackknife applied to main models (Table 2). Bars indicate 95% confidence intervals.

A4.8 Cross-sectional analysis

To reflect border changes in Africa after 1997,[35] we have so far analyzed panel data. Because such border changes might bias our results, we turn towards a cross-sectional analysis. The first cross-section is based on state borders and capitals observed in 1997 (the start of ACLED). The second cross-section chooses countries' borders and capitals locations at the time of their independence.[36] The dependent variables consist of the logged sums of our baseline outcomes between 1997 and 2016. Using the cross-sectional data, we estimate our main models with country-fixed effects, and base data for the population controls on the year 1966 (1990) for the first (second) cross-section.

The results of these analyses are presented in Figure A12. They show that the insights gained from our baseline models hold irrespective of the choice of a panel- or cross-sectional design. Only the IV-estimate of the effect of RSC on violence between the state and challengers turns statistically insignificant, but is associated with the a point-estimate

[35]Mainly the secession of South Sudan in 2011, but, where the SCAD and UCDP GED data is used, also the independence of Eritrea and Namibia.

[36]Dropping ethnic groups from Eritrea, South Sudan, and Namibia from the sample, and replacing them with the groups we would have observed had these countries not become independent from Ethiopia, Sudan, and South Africa.

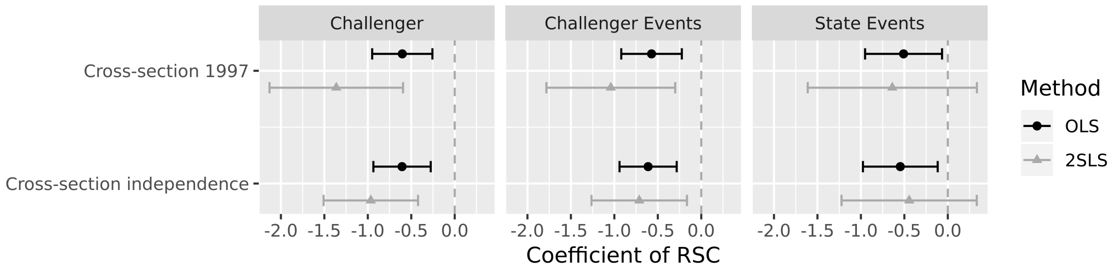


Figure A12: Coefficients of RSC in the cross-sectional analysis. Bars indicate 95% confidence intervals.

that is indistinguishable from the one derived from the respective naive OLS-estimate.[37] In sum, these patterns suggest that it is unlikely that the main results are due to endogenous, postcolonial changes of borders and capital locations.

A4.9 Alternative mechanisms

Our theoretical argument is that *RSC* affects conflict risk through social control. However, our empirical measure of RSC, being based on travel times, might affect conflict risks through different mechanisms. In the following, we test two such alternatives.

First, roads will increase market access and thus foster local development (e.g. Donaldson and Hornbeck 2016), which in turn increases the odds of peace. To control for this alternative causal mechanism, we control for (1) ethnic groups' nightlight emissions as a proxy for local development (Henderson, Storeygard and Weil 2012),[38] as well as (2) the total, quality-weighted road mileage present in an ethnic groups settlement area in 1966.[39] The latter controls for the historical level of economic development. After controlling for the length of the local road network, the RSC-measure picks up effects only due to the structure but not the local length of the road network. It therefore is a conservative test.

Second, ethnic groups that are well connected to the capital might also be well connected to entirety of the country's population. Such physical integration might promote socio-economic integration and increased trans-ethnic interactions, both of which may foster peace. To avoid picking up effects that are due to the general level of connectedness between an ethnic group and its country, we include a measure for the extent of 'external connectedness' of an ethnic group.[40]

Using the additional covariates to control for these two alternative causal mechanisms,

[37]Note however, that the size of coefficients is smaller than at the baseline, once they are standardized by the means of the dependent variables.

[38]We include the logged value of average nightlight emissions in a settlement area and a dummy for whether any light is emitted in a certain group-year. Data on nightlights is available from 1992 to 2015 from National Geophysical Data Center (2014). We substitute the missing 2016 values for data from 2015.

[39]This measure is simply the sum of all road kilometers multiplied by the average speed attainable on them.

[40]Specifically and similar to the computation of the measure *internal.connectedness* (Equation 2), we compute

Table A3: Alternative Mechanisms, OLS: Alternative mechanisms

	Dependent variable (logged)		
	Challengers	Challenger Events	State Events
	(1)	(2)	(3)
RSC 1966 (log)	-0.149^{***}	-0.115^{***}	-0.125^{***}
	(0.032)	(0.036)	(0.033)
State access 1966; foot (log)	0.020	-0.012	-0.016
	(0.027)	(0.033)	(0.028)
Internal connectedness 1966; foot (log)	-0.112^{***}	-0.095^{***}	-0.100^{***}
	(0.029)	(0.032)	(0.029)
External connectedness (log)	0.009	0.026	-0.011
	(0.056)	(0.061)	(0.063)
External connectedness; foot (log)	0.065	0.048	0.121
	(0.068)	(0.079)	(0.081)
Roads (km x quality)	-0.002	-0.004^{**}	-0.002
	(0.002)	(0.002)	(0.002)
Nightlights (log)	0.043^{***}	0.047^{***}	0.025^{***}
	(0.006)	(0.007)	(0.006)
Nightlights >0	-0.176^{***}	-0.208^{***}	-0.087^{***}
	(0.031)	(0.040)	(0.031)
Country-year FE:	yes	yes	yes
Controls:	yes	yes	yes
Mean DV	0.21	0.17	0.15
F-Stat:	24.1	21.42	16.49
Observations	31,740	31,740	31,740
Adjusted R^2	0.408	0.379	0.316

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

we re-estimate the baseline models (Table A3).[41] Of the additional variables, only our proxy for local development is consistently associated with challengers to state power and

$$external.connectedness_g = \left(\frac{1}{I_g * K_g} * \sum_{k=0}^{K_g} \sum_{i=0}^{I_g} time_{k,i} \right)^{-1},$$

where $i \in I_g$ denotes the inhabitants of the settlement area of group g that live at a distance of travel time $time_{k,i}$ from their compatriots $k \in K_g$ that live in all other ethnic settlement areas. To differentiate effects of pure geography from the effects of the road network, we again compute the measure external connectedness$_g^{foot}$ on the foot-path network and include it as a covariate.

[41] We do not implement this robustness check for the IV-analysis because the contemporary data (population and nightlights) would introduce post-treatment bias.

conflict. In particular, local nightlight emissions have a negative association with conflict at the extensive, and a positive one at the intensive margin. External connectedness has no discernible effect on conflict patterns. Importantly however, the estimate of the effect of relational state capacity remains almost unchanged from the baseline.

A5 Instrumental variable approach: Simulating road networks

To simulate realistic, yet simplified road networks based only on exogenous information, we assume that the road-builder aims to minimize the following objective function:

$$LOSS = \frac{1}{I^2} * \sum_{j=0}^{I} \sum_{i=0}^{I} time_{j,i}, \tag{4}$$

where $i, j \in I$ are the inhabitants of the territory on which roads are built. They are separated by a distance of travel time $time_{i,j}$. The road builder seeks to minimize the average travel time between any two inhabitants of the territory.[42] Population data are obtained from Goldewijk, Beusen and Janssen (2010). Since we want to avoid using data on population distributions that are affected by modern transport infrastructure, we use estimates of the African population distribution in 1880.[43] Road building is constrained by the road budget:

$$B_q = \sum_{k=q}^{Q} length_k^{observed}, \tag{5}$$

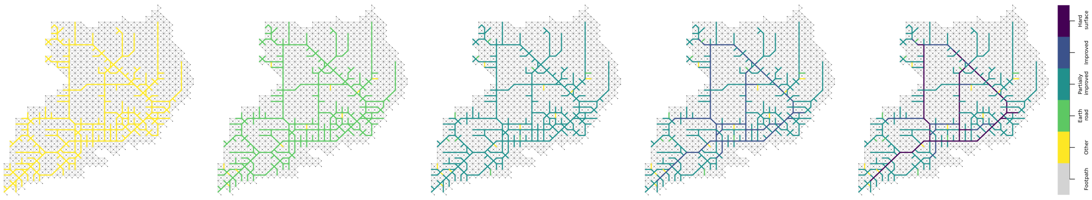
which consists of different qualities $q \in Q$ of roads, each of which corresponds to the observed Michelin road types (see A2). For each road type, the road-builder receives the road mileage of this type of road and all superior types of roads observed in the Michelin map of 1966.

Roads are 'built' on a pre-determined network of footpaths.[44] Given computational constraints in the repeated computation of the loss function (Eq. 4), we adjust the resolution of our baseline network to countries' size (see Table A4). As detailed by the following description of our road-building algorithm, the road-builder builds one type of road after the other, by upgrading existing roads sequentially. The budget constraint ensures that the total road mileage per type of road on the simulated network corresponds to the one

[42]Note that Burgess et al. (2015) add a distance penalty to each pair of citizens to the loss function for their simulation of 'optimal' road investment. In our IV-setup, this approach would introduce an additional parameter (distance) and further complicate the control for omitted variables.

[43]Note however that this estimate is based on a combination of current disaggregated population data and historical census data which is extrapolated to the past.

[44]These footpath-networks are of the same kind as the one used to transport the Michelin maps into networks. In particular, the networks consist of (1) vertices distributed in a grid-like manner in space, and (2) 8-connected 'foot-path'-edges.



(a) $q = 1$ (b) $q = 2$ (c) $q = 3$ (d) $q = 4$ (e) $q = 5$

Figure A13: Simulation of the Ugandan road network in 1966, using population data from 1880.

in the observed network.

Table A4: Mean of input values to road network simulation

Resolution	Countries	Example	Population	Vertices	B_1	B_2	B_3	B_4	B_5
0.083	11	Togo	$352,680.9$	450	1.5	1.5	1.0	0.8	0.2
0.167	33	Nigeria	$3,306,608.0$	$1,547.2$	11.6	11.6	8.2	7.4	2.9
0.25	22	DR Congo	$3,827,680.0$	$1,984.9$	21.5	21.5	15.9	14.6	7.7

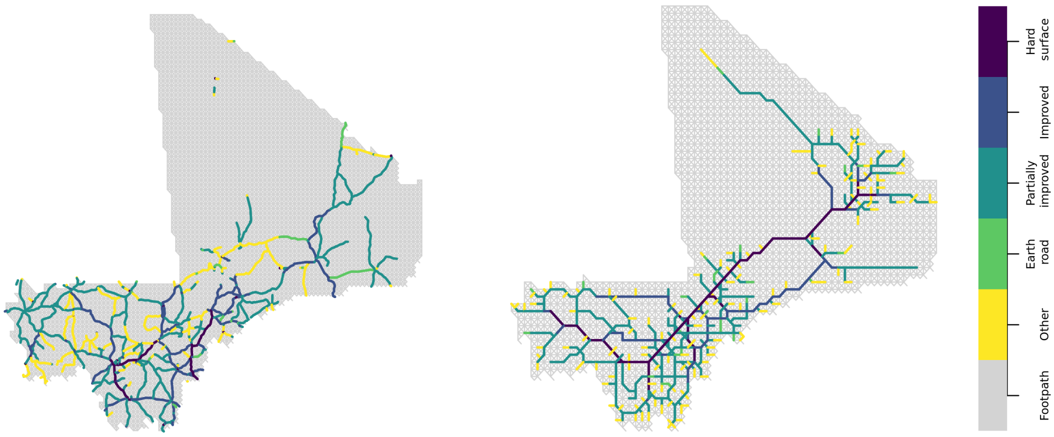
Networks' resolution is measured in decimal degrees and road budgets B_q in 1000 kilometers.

Algorithm:

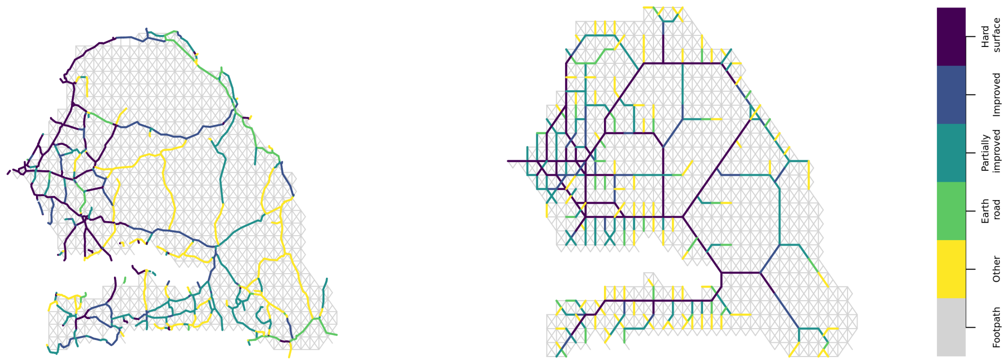
1. Round; $q = 1$
   (a) Draw 10 seed edges, upgrade to q
   (b) Select neighboring edges $q_e < q$ of all edges with quality $q_e = q$, evaluate and keep 10 most promising edges as E_p.
   (c) Upgrade edge $e \in E_p$ that minimizes $LOSS$. Select neighboring edges $q_e < q$ of e and add to E_p. Update $B_q = B_q - length_e$.
   (d) Repeat step (c), and, in every 10th round, step (b), until budget B_q is spent.

2.-5. Round; $q \in [2, 3, 4, 5]$
   (a) Select all edges with quality $q_e = q - 1$, evaluate and keep 10 most promising edges as E_p.
   (b) Upgrade edge $e \in E_p$ that minimizes $LOSS$. Select neighboring edges $q_e = q - 1$ of e and add to E_p.
   (c) Repeat step (b), and, in every 10th round, step (a), until budget B_q is spent.
   (d) Proceed to the next higher road quality and start again at (a).

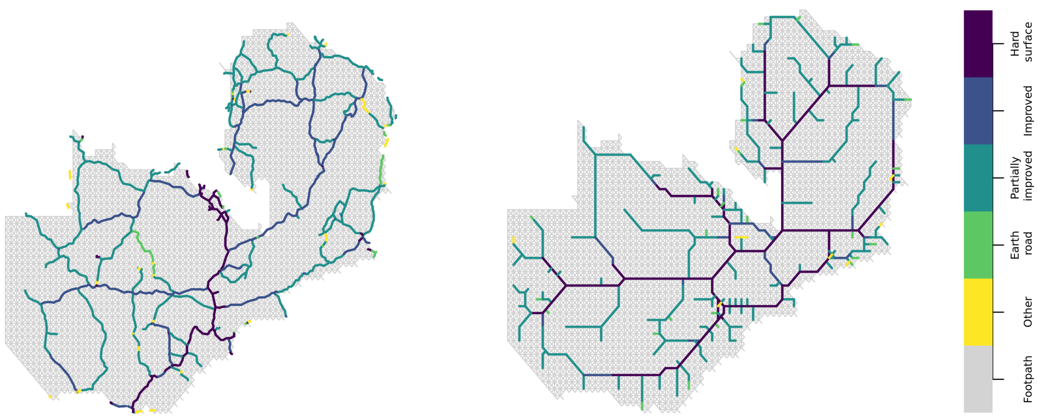
The algorithm generates realistic road networks (Figure A13 and A14) for all country-periods in Africa since independence. To speed up computation, we make use of a 90 CPU high performance computing cluster. While small countries can be simulated in



(a) Mali: Observed and... (b) ... simulated network

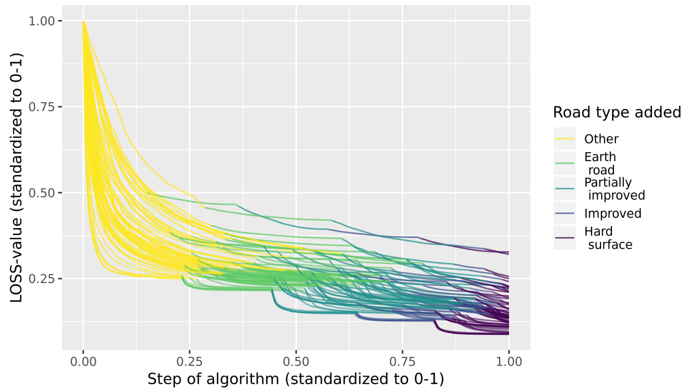


(c) Senegal: Observed and... (d) ... simulated network

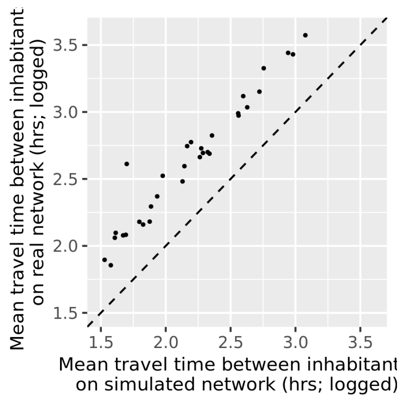


(e) Zambia: Observed and... (f) ... simulated network

Figure A14: Observed and simulated road networks in Mali, Senegal, and Zambia, 1966.



(a) Improvement of loss during application of road-building algorithm



(b) Comparison of loss on observed and optimized networks (both with population data for 1960).

Figure A15

minutes, bigger countries require up to 48 hours of run time, simply because each time we recalculate the loss value we have to compute up to 3415^2 shortest paths.[45]

Over subsequent iterations of edge-by-edge road building, the within-country connectedness increases and the LOSS improves (Figure A15a), but with decreasing marginal returns due to substantive scale effects of roads. Figure A15b compares the LOSS values achieved by the simulated networks and observed networks. The simulated networks are consistently better in connecting countries' populations.

A6 Instrumental variable approach: Additional robustness checks

In addition to the sensitivity analyses presented above, this section discusses robustness checks tailored specifically to the IV-approach.

A6.1 First stage by size of country and ethnic group

Because we vary the resolution of the road simulations depending on countries' size (see Table A4), our first stage results are driven by intermediate and large countries. In contrast, small countries do not feature enough variation in our instruments. Splitting up the sample along the three levels of resolution used for simulating road networks and estimating the first stage separately illustrates this pattern (Table A5). Our two instruments possess no significant explanatory power in the 11 very small countries (think of Burundi or Lesotho) in our sample. However, in the remaining bulk of countries, our instruments behave as expected.

[45]We make use of a path updating algorithm with $\mathcal{O}(|V^2|)$ efficiency.

Table A5: First stage estimation across resolutions of optimized networks

	Dependent variable: RSC 1990 (log)		
	(1)	(2)	(3)
State access 1880 (sim; log)	−0.039	0.479***	0.914***
	(0.365)	(0.070)	(0.109)
Internal connectedness 1880 (sim; log)	−0.241	−0.276***	−0.258***
	(0.179)	(0.040)	(0.047)
Resolution (dec. degrees):	0.083	0.167	0.25
Country-year FE:	yes	yes	yes
Controls:	yes	yes	yes
Mean DV	-0.68	-1	-1.38
F-Stat:	84.23	329.3	375.02
Observations	1,740	19,045	10,495
Adjusted R^2	0.919	0.897	0.902

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

Table A6: First stage estimation across geographic size of ethnic groups

	Dependent variable: RSC 1990 (log)			
	(1)	(2)	(3)	(4)
State access 1880 (sim; log)	0.539***	0.530***	0.771***	0.925***
	(0.107)	(0.097)	(0.116)	(0.121)
Internal connectedness 1880 (sim; log)	0.019	−0.186***	−0.463***	−0.367***
	(0.072)	(0.051)	(0.066)	(0.074)
Group area quartile:	1	2	3	4
Country-year FE:	yes	yes	yes	yes
Controls:	yes	yes	yes	yes
Mean DV	-1.58	-1.29	-0.98	-0.59
F-Stat:	48.82	79.05	98.48	95.11
Observations	7,485	7,910	7,950	7,935
Adjusted R^2	0.814	0.885	0.901	0.916

Notes: OLS models. Control variables consist of the total and urban population (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

In a similar vein, it might be argued that only very large ethnic groups drive the first stage. We therefore split the sample along the quartiles of the total geographic area of ethnic groups and re-estimate the first stage regression. Table A6 shows that the first stage results are not driven only by large ethnic groups. Indeed, although the coefficient size of our first instrument, state access^{sim} increases with group size, its precision does not. For the smallest quartile of ethnic groups, where we expect least variation in the internal connectedness, our second instrument, internal connectedness^{sim} does not have explanatory leverage over RSC. However, it does have such power for the three remaining quartiles. These results show that our first stage estimation is not driven by the biggest ethnic groups although, as one would expect, the first stage is strongest there.

A finial finding worth discussing is that across country and group sizes, the coefficient for the state access instrument is larger than that of the internal connectedness instrument. This difference is due to the manner in which we construct our road graph, in which the observed road networks are superimposed on the 8-connected 'foot-path' network. This superposition implies that to travel on the road network, each traveler has to first 'walk' the next road network vertex. This walk inflates within-group travel times proportionally more than travel towards capitals. Because this extra 'walk' is not necessary on the simulated networks, the coefficient for the internal connectedness instrument is pushed towards zero.

A6.2 Disaggregated relational state capacity

To test whether it is indeed the combination of ethnic groups' internal connectedness and state access, coined RSC, that drives the results, we conduct a robustness check where we instrument for both constituents of RSC separately. Table A7 shows that both instruments are valid for the respective endogenous variable. The instrumented measures of state access and internal connectedness are consistently related to the number of challengers and violence among them. In these two models, we can also not reject the null that the coefficients of state access and internal connectedness are of equal absolute size. This supports the use of our aggregated measure of RSC. Mirroring the results of the reduced form estimates reported in the main text in Table 3, the results show that the number of battles between state forces and armed group decreases with state access to ethnic groups ($p = .057$), but does not increase with their internal connectedness. The coefficient of internal connectedness is half the size of that of state access, and associated with a large standard error. Please refer to the main text for further discussion of the implications of this pattern.

Table A7: Effect of the components of RSC, 2SLS

	Dependent variable (logged)				
	Stage 1		Stage 2		
	State access	Internal connectedness	Challengers	Challenger events	State
	(1)	(2)	(3)	(4)	(5)
State access 1880 (sim; log)	0.665***	0.020			
	(0.051)	(0.060)			
Int. connect. 1880 (sim; log)	−0.077***	0.185***			
	(0.024)	(0.033)			
β_3: State access 1990; (log)			−0.348***	−0.246***	−0.137*
			(0.084)	(0.088)	(0.072)
β_4: Int. connect. 1990; (log)			0.517***	0.428***	0.065
			(0.154)	(0.159)	(0.143)
State access 1880; foot (log)	0.273***	0.012	0.151***	0.074	0.007
	(0.032)	(0.038)	(0.056)	(0.061)	(0.050)
Int. connect. 1880; foot (log)	0.053***	0.262***	−0.171***	−0.132**	−0.012
	(0.017)	(0.031)	(0.064)	(0.066)	(0.058)
$\beta_3 + \beta_4$			0.17	0.18	-0.07
			(0.16)	(0.16)	(0.14)
Country-year FE:	yes	yes	yes	yes	yes
Controls:	yes	yes	yes	yes	yes
Mean DV	-2.6	-1.49	0.21	0.17	0.15
F-Stat:	445.97	120.14	20.56	19	15.46
F-Stat Stage 1 (state):			185.93	185.93	185.93
F-Stat Stage 1 (internal):			39.81	39.81	39.81
Observations	31,280	31,280	31,280	31,280	31,280
Adjusted R^2	0.932	0.786	0.352	0.343	0.307

Notes: 2SLS-IV models. Control variables consist of the total population in 1880 (log), groups' area (log), the mean annual temperature, precipitation, evaporation, the ratio of precipitation and evaporation, and the mean altitude and slope of a group's settlement area, its cash crop and agricultural suitability, a mineral deposit dummy, as well as groups' logged distance to the coast, navigable river, and border. Two-way clustered standard errors in parentheses (ethnic group and country-year clusters). Significance codes: *p<0.1; **p<0.05; ***p<0.01.

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