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Do Natural Resources Really Cause Civil Conflict? Evidence from the New Global Resources Dataset

Michael Denly[1], Michael G. Findley[1], Joelean Hall[2], Andrew Stravers[3], and James Igoe Walsh[4]

Abstract

Scholars have long examined the relationship between natural resources and conflict at the country level. More recently, researchers have turned to subnational analyses, using either individual countries or subnational data for a small number of resources in sub-Saharan Africa. We introduce a new sub-national dataset of 197 resources that adds many resource types, locations, and countries from Africa, the Middle East, Asia, Latin America, and Europe. To demonstrate the value of the new dataset, we examine how conflict incidence varies with the value of the collective set of resources in a given location using world prices. We then introduce new country-specific price data, which are more relevant for conflict dynamics. Since country-specific prices can be endogenous to conflict, we instrument country-specific prices using U.S. and world prices. We find that sub-national resource wealth is associated with higher levels of conflict using some specifications, though the results vary widely by data source and world region. Using an instrumental variables strategy lends the strongest support to this positive relationship, but only for African countries.

[1]University of Texas at Austin, Austin, TX, USA
[2]Technical University of Munich, Munich, Germany
[3]Clements Center for National Security, University of Texas at Austin, Austin, TX, USA
[4]University of North Carolina at Charlotte, Charlotte, NC, USA

Corresponding Author:
Michael G. Findley, University of Texas at Austin, 158 W. 21st ST STOP A1800, Batts Hall 2.116, Austin, TX 78712, USA.
Email: mikefindley@utexas.edu

Notably, across all of our models, we find that resources are negatively associated with conflict in Latin America, suggesting heterogeneity of effects worth future exploration.

Keywords
natural resources, civil conflict, civil wars, political violence

Over the last two decades, social scientists have devoted significant scholarship to the "resource curse"— the proposition that an abundance of non-renewable natural resources has negative political, social, and economic consequences (e.g., van der Ploeg 2011; Ross 2015). A large segment of existing resource curse scholarship has focused on the links between natural resources and violent conflict (De Soysa 2002; Fearon and Laitin 2003; Collier and Hoeffler 2004; Ross 2004b, 2006; Humphreys 2005; Cotet and Tsui 2013; Lei and Michaels 2014; Bell and Wolford 2015; Esteban, Morelli, and Rohner 2015; Paine 2016; Menaldo 2016). To date, the role of oil wealth in fomenting conflict at the national level has received the most scholarly attention from the resource-conflict literature. The focus on oil at the national level is logical: oil is the world's most valuable commodity, data on national oil production and reserves are readily available,[1] and some national-level studies analyzing multiple resources have found few links between countries' resource wealth and conflict (e.g., Bazzi and Blattman 2014).

However, much recent research on natural resources and conflict has taken a decidedly micro turn, emphasizing that oil and other resources, such as diamonds and gold, may promote violent conflict at the local level (Nillesen and Bulte 2014). The reason underpinning the micro-level turn is that many conflicts are local in nature, yielding high violence in specific regions while the rest of the country experiences little violent contention. Accordingly, Koubi et al. (2014, 12) suggest that "the analysis of disaggregated data that are also able to capture the location and spatial aspects of resources clearly seems to be the most effective approach" for advancing knowledge. Such spatial natural resources data have proved crucial for understanding local conflict dynamics (Aragón and Rud 2013; Dube and Vargas 2013; Mähler and Pierskalla 2015; Maystadt et al. 2014), the incentives for national leaders to tolerate conflict (Koubi et al. 2014), how resources influence secessionist conflicts (Ross 2012; Asal et al. 2016), and how profiting from resources by rebel groups influences conflict dynamics (Fearon 2004; Conrad et al. 2019; Walsh et al. 2018).

Primarily due to the limitations of existing natural resource datasets, only a few published studies have analyzed how natural resources influence violence at the local level in multiple countries (Berman and Couttenier 2016; Berman et al. 2017; Harari and La Ferrara 2018; Christensen 2019).[2] To help researchers develop more general conclusions on the resource-conflict nexus as well as the resource curse more broadly, in this article we introduce the Global Resources Dataset (GRD). It is the first time-varying, open-source dataset with spatial information about natural resources for a wide range of resources (197) and countries (116). This article describes version 1 of the GRD and reports on the results of statistical analysis examining the resource-conflict relationship.[3]

Extant spatial natural resources data sets from Balestri, Lujala, and their colleagues provide useful data for gold, diamonds, gemstones, and petroleum (Gilmore et al. 2005; Lujala, Gleditsch, and Gilmore 2005; Lujala 2009, 2010; Balestri 2012; Balestri and Maggioni 2014; Balestri 2015). These data sources are among the most widely-employed in the study of resources and conflict at the local level, in part because they are open source and included in the PRIO-GRID dataset (Tollefsen, Strand, and Buhaug 2012).[4] By the same token, the coverage of these natural resource datasets is limited in comparison to the GRD (see Table 1).

A spatial natural resources dataset with a larger geographical reach is the Mineral Resources Dataset (MRDS) from the United States Geological Survey (USGS), which Harari and La Ferrara (2018) and Adhvaryu et al. (2021) use profitably. Aside from now being defunct, a main challenge with the MRDS relates to the fact that approximately 88% of its spatial points pertain to the United States.[5] Like the aforementioned datasets—but unlike the GRD introduced in this article—the MRDS is also not time-varying.

Other researchers have made important contributions to the resource-conflict literature using proprietary data that measures time-varying local resource endowments across countries (Berman and Couttenier 2016; Berman et al. 2017; Christensen 2019). However, these data sources are not widely available to many researchers, still include only a small number of resources, and are limited in geographical scope to Africa. Berman et al. (2017), for example, include fourteen minerals in Africa. While the replication data for Berman et al. (2017) are available, they aggregate across multiple resources and only provide data for the main mineral in each grid cell. Other researchers thus cannot use the Berman et al. (2017) data to identify the specific locations of resource extraction sites or disaggregate details within a grid cell.

Most sub-national analyses of the resource curse use as their key independent variable the existence of a natural resource extraction site, but they lack information on sites' output and the value of this output. This is a potentially important gap, since it is reasonable to expect that a site's output value influence relevant economic, political, and social outcomes. With the exception of the GRD and Berman et al. (2017), all of the datasets in Table 1 lack information about world prices of the non-renewable resources that they document. World prices for many widely-traded commodities are now available and used in research (e.g., Bazzi and Blattman 2014), and the GRD systematically joins world price data to resource locations. Furthermore, it includes data on the output of each site, allowing researchers to calculate the value of resources produced.

Table 1. Spatial Natural Resource Datasets.

Dataset	Countries	Spatial Unit	Time-Varing	Output	World Prices	Country-Specific Prices	Resources
Global Resources Dataset	116	Point	Yes	Yes	Yes	Yes	197 resources
Berman et al. (2017)	52	Grid cell	Yes	No	Yes	No	14 resources
USGS Mineral Resources Dataset	166	Point	Start only	No	No	No	183 resources
Balestri (2015)	110	Point	Start only	No	No	No	Gold
Lujala, Gleditsch, and Gilmore (2005)	52	Point	Start only	No	No	No	Diamonds
Lujala, Röd, and Thieme (2007)	107	Polygon	Start only	No	No	No	Oil and gas
Lujala (2009)	107	Point	Start only	No	No	No	Gemstones
Buhaug and Lujala (2005)	86	Polygon	Start only	No	No	No	Coca bush, opium, poppy, cannabis

A potentially more significant omission of existing datasets than their lack of world prices—and perhaps even more than resource output data—are the country-specific prices of the resources. The reason is that country-specific values of the resources likely exert a more powerful influence on conflict dynamics. As data from Table 2 corroborate, not all countries receive world prices for all resources, and local actors likely take into account the country-specific values of its respective natural resources when choosing whether to engage in conflict.[6]

To demonstrate the analytic value of the GRD, we examine how the collective value of resources in a given location relates to the incidence of conflict. To that end, we pool the different resource types and use relevant multipliers to produce comparable values, such that we can understand better the overall value of non-renewable resources in a given location. In conducting this main analysis, we find mixed results. When examining sub-Saharan African countries only using the Armed Conflict Location and Event Dataset (ACLED) and Georeferenced Event Dataset (GED) measures for conflict, the likelihood of conflict incidence tends to increase with natural resource values in a location. This finding is consistent with much of the work on sub-national resources and conflict, which has focused primarily on sub-Saharan Africa (e.g., Berman et al. 2017).

We then extend our analysis by using country-specific price data. Although country-specific prices are likely more relevant to actors on the ground, country-specific prices are also likely endogenous to conflict dynamics. Accordingly, we instrument country-specific prices using U.S. and world prices. Both the former and the latter correlate highly with the country-specific prices but are not drawn from the same distribution, which makes our instrument appropriate (see Table 2 and Appendix B). In extending the analysis to use U.S. and world prices as instruments for country-specific prices, we find strong evidence that higher natural resource values increase conflict incidence in African countries.

However, that result does not hold for other world regions or in a global perspective. In most other models across world regions, the results are null. For Latin America and the fully pooled model of all coded countries, the relationship between resources and conflict is negative and significant—i.e., fully opposite of the results for Africa. This finding suggests that future research could profitably explore why natural resources have a heterogeneous effect on conflict.

The paper proceeds as follows. First, we provide an overview of the GRD, including information about its many attributes, such as resource locations as well as price information. Second, we outline how researchers can use the GRD to examine many extent questions pertaining to the resource-conflict nexus. Third, we carry out an investigation of the effects of natural resource values on civil conflict. As part of this exercise, we implement an instrumental variables strategy that future researchers can easily mimic for other analyses. Finally, we sum up with concluding thoughts about what the use of more expansive data and analysis implies for future research on natural resources and conflict.

Table 2. Pairwise Correlations between World, US, and Country-specific Resource Prices.

	World Price	Log World Price	US Price	Log US Price
Country-Specific Price	0.78 ($n = 3,429$)		0.74 ($n = 4,764$)	
Log Country-Specific Price		0.88 ($n = 3,429$)		0.87 ($n = 4,764$)
World Price			1.00 ($n = 3,540$)	
Log World Price				1.00 ($n = 3,540$)

Note: The unit of analysis is the unique value of the Global Resource Dataset (GRD) country-resource-year. All price data are deflated to 2010 U.S. dollars and are expressed in the same measurement unit for each resource. World prices correspond to World Bank Global Economic Monitor prices for the resources in each respective year. Country-specific prices correspond to UN Comtrade export prices for the resources in each respective country-year. US prices correspond to USGS prices for the resources in each respective year. The sample size is greater for the USGS-UN Comtrade correlation because there are more matching country-resource-years with price information.

The Global Resources Dataset (GRD)

Dataset Overview

This section provides an overview of the GRD and complements our complete Codebook in Appendix D. The GRD documents the spatial location (i.e., latitude and longitude) and values of individual natural resource extraction sites and production facilities from 1994 to 2015. Each row in the dataset provides information for a single production location of a resource in a single year—i.e., a location-year. For each site or facility, the dataset records the resource, location, output, country-specific and global prices, as well as many other attributes.

Primary sources. The dataset is based on country reports of most countries' mineral industries produced by the National Minerals Information Center of the United States Geological Survey (USGS).[7] USGS experts, who maintain links with their counterparts in industry and government agencies, compile the respective country reports. Since USGS experts do not present the country reports in a way that facilitates spatial analysis, multiple coders read each of these reports and extracted the information into a machine-readable format.[8]

Spatial location. The USGS country reports most often simply give the name of the location or the city/general vicinity in which it is located. These are the locations in the dataset. To code these location-years, we first recorded the facility or location name in the dataset. We then took this information and used Geonames, Google Maps, Mindat as well as other databases to identify the most precise longitude/latitude possible.[9]

Precision of spatial location (precision code). To denote how close the recorded latitude/longitude is to the exact location of the mine, field, extraction site, or production facility, the GRD contains a precision code. We recorded a "1" when the exact site was within the above dataset itself, which corresponds to about 44% of GRD observations. When the most precise spatial information available was the city in which/near the site was located, we recorded a "2" (37% of observations). Less precise measures include a "3" or a "4," indicating instances in which we could be no more precise than the district or province in which the site is located (16% of observations). Similarly, when we are unsure of the location of the site altogether, we recorded a "9" (2% of observations).[10]

Countries and years. With respect to country coverage, the GRD includes information for all countries in Africa, the Middle East, and Latin America, as well as most countries in Asia and some European countries. Overall, the GRD contains information from 116 countries. The time-varying data extend from 1994 to 2015, but USGS country reports with spatial data are not available for all years, so country coverage of the GRD varies according to Table D2.

Resources. Based on current country coverage, the GRD identifies 197 unique natural resources in their spatial locations. These resources include not only "natural" resources such as diamonds, oil, and gold, but also downstream products such as petrochemicals, steel, and cement. Tin, copper, cobalt, uranium, iron ore, and phosphates encompass just some of the additional resources in the GRD. Table D1 provides a full list of all resources,[11] and Figures 1 and 2 depict the distribution of relevant resources globally and regionally in Africa.

Output, prices, and values. The GRD's inclusion of output for the above marks an advance over existing natural resource datasets (see Table 1), but researchers often want to estimate the value of such output, which requires price data. To respond to this need, the GRD provides up to three prices for each natural resource. The first price corresponds to the US price of the resource using data from the USGS (Matos 2015). The second price corresponds to the world price, obtained from the World Bank Global Economic Monitor (World Bank 2018) and, in some cases, Multicolour.[12] The third price corresponds to the country-specific export prices of each resource obtained from the UN Comtrade database (United Nations Statistics Division 2018). Since the initial output units often do not match the initial price units, we created numerous multipliers so as to ensure congruence between outputs and prices.[13] With these congruous output and price data, we calculated the value of each resource-location-year in 2010 US dollars.

Ownership of extraction sites/mines and production facilities. Not only do we code whether the site is a mine, field, refinery, or production facility, but we also code the ownership structure of the site as well.[14] Ownership is crucial to any natural resources dataset, because ownership influences the intensity of resource curse

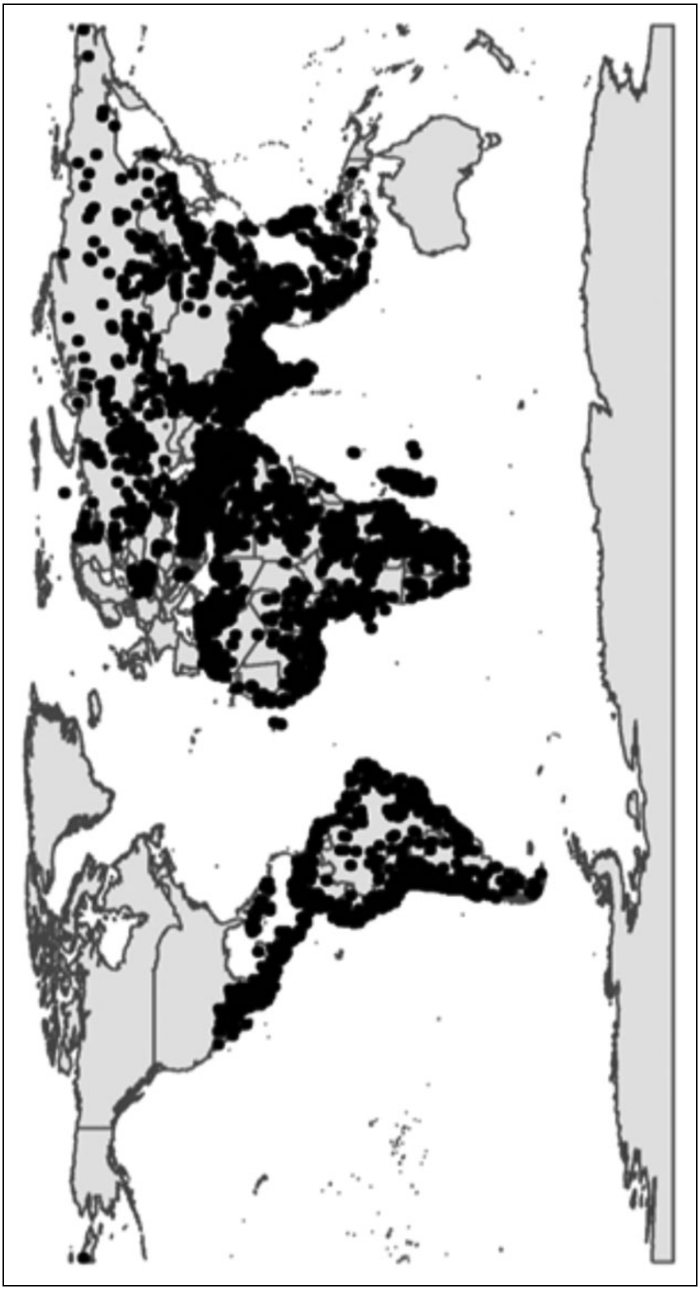

Figure 1. Natural resource locations in the Global Resource Dataset.

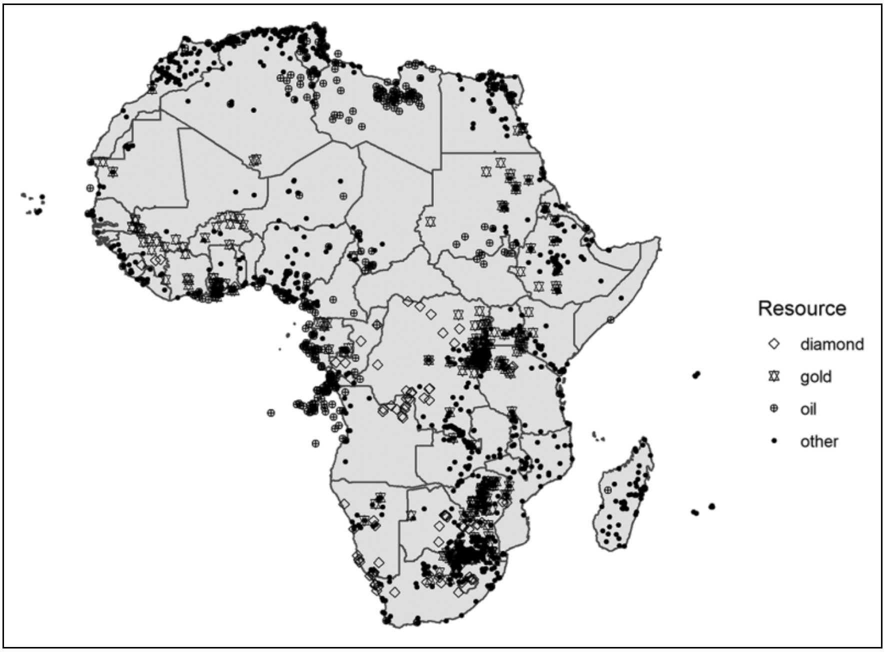

Figure 2. Natural resource locations in Africa.

effects as well as whether resources contribute to economic growth (Jones Luong and Weinthal 2010; Khanna 2017). The USGS country reports identify the ownership structure of many but not all resource locations in the GRD. When not available in USGS country reports, we researched the individual names of the companies, state-owned enterprises, or group operating the site to determine the ownership structure. We classify the ownership of a location according to the type of entity that owns more than a 50% stake. When the site entails a 50-50 public-private partnership, we classified it as such.

Potential New Uses of the GRD for Conflict Scholars

Before moving to our analysis of the data, we briefly outline existing and new research questions related to conflict that could be investigated with the GRD; in the conclusion, we suggest additional research questions not related to conflict that could be investigated.

Capital-intensive resources and sites. Much work on the resource-conflict link has focused on resources that can be "looted" by rebel groups because they do not require much human or physical capital to extract, or have a high price-to-weight ratio. Examples include secondary diamonds, minerals extracted with artisanal

Table 3. Overview of the Global Resources Dataset.

Description	Total	Percent
Countries	116	
Resources	197	
All Records	77,782	100%
Records with Geographic Coordinates	77,782	100%
Records with Output/Production Status	70,869	91%
Records with Country-Specific (UN Comtrade) Export Price	41,843	54%
Records with World Bank Global Economic Monitor World Price	34,612	44%
Records with Multicolour World Price	1,584	2%
Records with USGS US Price	49,476	63%
Records with Any One of the Above Prices	63,757	82%

methods, and narcotics. But rebel groups also capture or extort capital-intensive resources, and this may lead to distinct conflict dynamics. A recent example is the Islamic State's capturing and exporting fuel from Syrian and Iraqi oil facilities, which according to estimates earned the organization up to US $1.5 million a day. Further examples are not hard to find, with the Movement for the Emancipation of the Niger Delta (MEND) group in Nigeria launching repeated attacks on oil facilities in that country. Algeria saw a similar attack from Al Qaeda in the Islamic Maghreb in 2013 on the In Amenas petroleum processing facility. During the 1990s and into the 2000s, Chechen rebels targeted oil pipelines and oil transport vehicles. With the GRD, researchers can analyze conflict dynamics driven by capital-intensive resources as well as downstream refining and processing facilities.

New countries, regions, and causal heterogeneity. The GRD allows researchers to understand the location-specific effects of natural resources on conflict well beyond Africa (Table 3). In the process, the field will have the opportunity to better understand the conditions under which natural resources produce causal heterogeneity or heterogeneous treatment effects. Of course, the canonical example of causal heterogeneity in the resource curse literature is that Norway, Canada, United States, and other wealthy countries mostly benefit from oil, but those effects are far from uniform (Ross 2012, Chapter 1). With the GRD, researchers can develop a better sense of the causal mechanism in terms when exactly resources turn from a curse to a blessing. It is likely that such a transition is dependent on the specific resources and structural conditions of the relevant countries.

Price dynamics and market access. As we show in Table 2, not all countries follow the United States and are able to obtain the world prices for their natural resource exports. Using the GRD, researchers can disentangle the source(s) of these discrepancies (quality, transport costs, competition, risk, etc.) and see how they figure into conflict dynamics. It is possible, for example, that rebels refrain from attacking or seeking to control some mines because they know it will not be possible for them to offload relevant spoils at profitable world prices.

(Potentially) lootable versus non-lootable resources. The GRD enables more research on gold, gemstones, and other "lootable" resources, which are traditionally defined as having high value and low barriers to entry (Snyder 2006; Findley and Marineau 2015). Although the GRD cannot classify lootability as precisely as Gilmore et al. (2005) do for diamonds, we undertook the preliminary exercise of determining which resources are *potentially* lootable. More specifically, we classified all 197 minerals in the dataset according to whether they could *potentially* have high values and low barriers to entry.[15] Clearly, the approach is not perfect, as it can only fully identify non-lootable resources. Gemstones, for example, can have both high and low barriers to entry, depending on the location of the mine, so researchers may have to supplement the GRD with their own analyses. By the same token, the GRD will enable researchers to carry out studies similar to Sanchez de la Sierra's (2020) examination of how rebels' access to lootable and non-lootable resources foments different conflict and governance dynamics.[16] The effects of phosphates in Morocco/Western Sahara and uranium in the Democratic Republic of the Congo constitute only a couple of examples of minerals that deserve further analysis along such lines.

Research Design and Theoretical Expectations

We examine the question of whether natural resources make the incidence of violent armed conflict more likely, an idea that is now broadly accepted. As this is primarily a data introduction paper, we focus on the general relationship between natural resources and violent armed conflict rather than on specific theoretical mechanisms. To test the relationship between the value of natural resources and conflict incidence, we merged our new dataset based on spatial locations of the extraction sites and production facilities with UCDP GED, ACLED, and PRIO-GRID databases (Tollefsen, Strand, and Buhaug 2012).[17] The PRIO-GRID data divides the world into 0.5 degrees of longitude by 0.5 degrees of latitude squares (roughly 55 km *x* 55 km at the equator) to form a "grid."

The GRD includes all countries in sub-Saharan Africa, Latin America, and the combined Middle East and North Africa region, as well as additional set of non-random Asian and European countries. We thus estimate separate models for each region as well as a pooled model combining all countries across all regions.

Variables: Response, Explanatory, and Controls

The operationalization of violent armed conflict warrants some discussion. Based on a now broad literature, expectations about the effects of natural resources have centered primarily on the onset or dynamics of civil wars (Ross 2004a, 2004b;

Fearon 2004; Lujala 2010) and have mostly taken an aggregate country-level approach. Scholars are in the midst of a micro-turn towards examining how natural resources shape the *incidence* of violent or non-violent events (Berman et al. 2017; Christensen 2019), whether that be some aggregation of incidence or counts of violent events. This focus is in line with the much larger local turn in the literature on armed conflict, which takes incidence within subnational regions as the key indicator (Nillesen and Bulte 2014). Given our disaggregated dataset, we follow suit and also examine the incidence of armed conflict events, focusing on the two most prominent subnational datasets: the Armed Conflict Locations and Event Dataset (ACLED) measure, which includes events with and without direct deaths; and the UCDP Georeferenced Events Dataset (GED), which only includes events in which direct deaths occurred (Raleigh et al. 2010; Croicu and Sundberg 2016; Firchow and Ginty 2017). As will become clear in our analysis below, the choice of dataset is critically important: with the ACLED measure there is a positive relationship between natural resources and conflict incidence in sub-Saharan Africa and North Africa, meaning natural resources are associated with increased conflict. However, that relationship does not hold when using UCDP data. For purposes of geographic comparison, we can only use the UCDP GED measure for other regions of the world, as ACLED data for regions beyond Africa and the Middle East are not sufficiently available. We specify conflict incidence primarily as a dummy variable, capturing conflict incidence in a grid cell during a given year as recorded by each of these datasets.

Our primary explanatory variable is the overall value of the collective set of resources in a grid cell, represented in constant 2010 USD. One advantage of the GRD over many existing datasets is that it includes both output and price information for a wide range of resources, allowing us to calculate the total value of resources produced at a location in a year. This contrasts with existing studies that rely on dichotomous measures of the existence of a resource, or that include only price but not output information (e.g., Berman et al. 2017). Measuring the total value of resources produced at a location is important because existing theory leads one to expect that changes in these values influence incentives for conflict.[18] To do so, for a given resource we multiply the overall production amount in the year by the value of the resource in that year, and then repeat and sum for all resources in the grid cell. Following this approach allows us to capture some information about the full set of resources in a grid cell, whereas most existing studies focus on a single resource or small group of resources. Given the dispersion in the resource values, we logged the data. And to address some of the challenges with contemporaneous measurement, we lagged the data by one year.[19]

We supplement the world values measures based by using country-specific values, which are likely more theoretically relevant for most theories of resources and conflict. The country-specific value variable is the export value of the resource in 2010 USD. It is based on the unit output for the resource extraction site in UN Comtrade prices, where the resulting values differ by country. This measure is not without challenges. Most notably, it likely responds to changes in conflict, while possibly also motivating conflict. We thus need to develop a causal identification strategy that minimizes the endogeneity in this measure, which we do below.

Finally, our study attempts to control for several potential confounders. These variables are at the grid-cell level. For data on ethnicity, we use the measure on excluded ethnic groups within each grid cell from Vogt et al. (2015). We take grid-cell (log) population data from HYDE (Goldewijk et al. 2017). We also control for level of democracy using V-Dem's polyarchy score (Coppedge et al. 2020) and level of development using nighttime lights data. In particular, we use the mean calibrated nighttime lights density at the grid-cell level, as measured by satellite imagery (Elvidge et al. 2014). As we show below, the model uses fixed effects at the grid-cell level, which explains the absence of a series of other traditional time-invariant control variables, such as distance to borders (Caselli, Morelli, and Rohner 2015) and mountainous terrain (Fearon and Laitin 2003). Finally, we also generate spatially lagged conflict variables using the conflict data referenced above.

Spatial HAC Estimation

Given that Berman et al. (2017) is one of the most recent and highest profile works in this area, we model the effects of natural resources on conflict in a similar manner to provide some basis for comparison. Accordingly, we estimate our main models using a spatial heteroskedastic and autocorrelation consistent (HAC) model. Following Hsiang (2010), the spatial HAC model takes the following form:

$$y_{kt} = \alpha + \beta_0 + \beta_p X_p + FE_k + FE_{it} + \varepsilon_{kt} \tag{1}$$

where cell(k), time(t), and country(i) are all specified, FE_k are grid cell-level fixed effects, and FE_{it} are additional country and year fixed effects. As should be apparent, the advantage of the spatial HAC is that it can account for multiple fixed effects. In addition, spatial HAC models estimate Conley (1999) standard errors that properly account for spatial dependence, and the Stata .ado routine of Hsiang (2010) allows us to specify spatial and serial correlation cutoffs. Although the spatial HAC model uses Ordinary Least Squares (OLS), and we have a binary dependent variable, our large dataset contributes to the statistical consistency of our estimates, making them (arguably) asymptotically unbiased. Again, Berman et al. (2017) use a similar approach.

Identification through Instrumental Variables

In our primary models, discussed above and reported below in Tables 4 and 5, we lag the natural resource value variable, which is an important though not sufficient step towards avoiding endogeneity. As a further step against potential endogeneity, we introduce an instrumental variables approach.[20] Our two-stage least squares approach centers on instrumenting the endogenous, country-specific natural

Table 4. Main Spatial HAC and 2SLS IV Model Results for ACLED Outcome on SSA (Three-way Fixed Effects).

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	0.0031***	0.0019***		
	(0.0004)	(0.0005)		
Resources 1st Order Spatial Lag		0.0006***		0.0003
		(0.0002)		(0.0002)
Resources 2nd Order Spatial Lag		-0.0000		0.0001
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0151		-0.0547**
		(0.0104)		(0.0213)
Number of Excluded Ethnic Groups		-0.0008		0.0027
		(0.0039)		(0.0034)
Nighttime Lights		-0.8740***		0.4342***
		(0.1660)		(0.0686)
V-Dem Democracy Index		11.7420		0.0106
		(2.0e+03)		(0.0126)
Spatially Lagged Conflict Measure		0.0305***		0.0777***
		(0.0022)		(0.0026)
Natural Resource Value w/ Instrumented Country-Specific Price			0.0121***	0.0087***
			(0.0012)	(0.0019)
Constant			0.0765***	0.0248***
			(0.0004)	(0.0054)
Observations	162315	146063	162315	146063
R^2	0.001	0.004		
Adjusted R^2	0.001	0.004		

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

resource values using the exogenously-determined values of the natural resources on world and US markets. In Appendix B, we discuss how the instrument meets the necessary first-stage, monotonicity, the stable unit treatment value (SUTVA), exclusion restriction, and ignorability/independence assumptions (see Angrist, Imbens, and Rubin 1996).

Results: Natural Resource Values and Civil Conflict

We proceed by reporting the results in a series of steps. To compare with past studies, we begin by reporting the analysis for Sub-Saharan Africa when using the ACLED measure as our dependent variable (see Table 4).[21] We first report the results using the country-specific resource values without and with controls (Models

Table 5. Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on SSA (Three-way Fixed Effects).

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	0.0000	0.0001		
	(0.0002)	(0.0003)		
Resources 1st Order Spatial Lag		-0.0002*		-0.0003**
		(0.0001)		(0.0002)
Resources 2nd Order Spatial Lag		-0.0001		-0.0003**
		(0.0001)		(0.0001)
Presence of Lootable Resources		-0.0049		-0.0179
		(0.0072)		(0.0160)
Number of Excluded Ethnic Groups		0.0097***		0.0078***
		(0.0029)		(0.0027)
Nighttime Lights		0.1190		0.0750
		(0.1635)		(0.0456)
V-Dem Democracy Index		-4.9955		-0.0564***
		(1.9e+03)		(0.0122)
Spatially Lagged Conflict Measure		0.0175***		0.0299***
		(0.0017)		(0.0019)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0009	0.0000
			(0.0007)	(0.0013)
Constant			0.0316***	0.0415***
			(0.0002)	(0.0054)
Observations	162315	146063	162315	104380
R^2	0.000	0.001		
Adjusted R^2	-0.000	0.001		

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

1 and 2 respectively) and then using the instrumented country-specific price variable without and with controls (Models 3 and 4 respectively).[22]

Continuing with the ACLED conflict measure, we then expand the analysis to include the entire African continent (Table A2). The results of all of these analyses show that the value of natural resources in a given grid cell are positively associated with the incidence of conflict, a result that is consistent with past studies, notably the comprehensive Berman et al. (2017) study.[23]

Given that the GRD has broad coverage and allows for estimation outside of sub-Saharan and North Africa, we investigate the broader effects of natural resources on conflict incidence. Specifically, because the GRD includes complete data for the Middle East, Latin America, most Asian countries, and even some European countries, we fit relevant models for each region as well as overall models that encompass all regions.

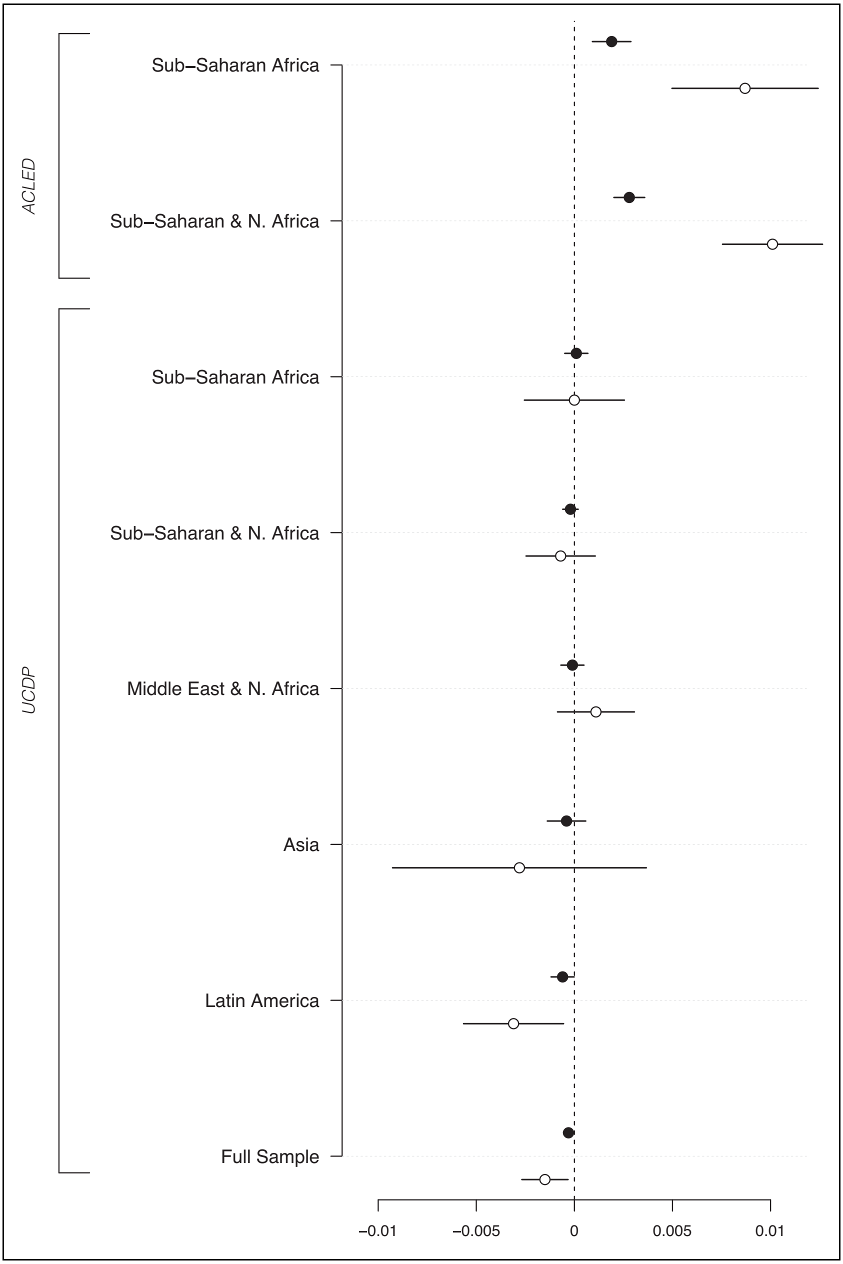

Figure 3. Results across all models. Solid dots represent base regression models with controls, but no instruments. The hollow dots represent the instrumental variable models.

Unfortunately, the ACLED data are not available for most countries outside of Africa for a sufficiently long time period. As such, we need to shift to a different measure for armed conflict that is available more broadly: the UCDP's Georeferenced Event Dataset (GED). For comparability with the ACLED models, we re-estimate the Sub-Saharan Africa results using UCDP and report those results in Table 5 (compare to ACLED results in Table 4), then extend out in successive analyses capturing Sub-Saharan Africa and North Africa (see Table A3 and compare to Table A2). With that benchmark, we move to analyses of all of the Middle East and Latin America, as well as most of Asia.

What is clear from these analyses using the UCDP measure is that the results are no longer straightforward. In the main models, estimated on sub-Saharan Africa and North Africa, there are either null or negative relationships. The instrumental variables model results are also inconsistent with those of ACLED. Notably, the model without controls indicates a negative relationship between resources and conflict, and the Sub-Saharan Africa models using the instrumented country-specific value is positive but not statistically significant. Overall, then, the results with UCDP raise some difficult questions about the conditions under which natural resources cause conflict, even in African countries (Figure 3).

Everything about the setup of these models is identical to the earlier models save for the different operationalization of conflict. The different results could simply imply that natural resources only robustly predict certain types of conflict but not others. Along these lines, there are a number of key differences between ACLED and UCDP that largely reflect differences in scope. For example, ACLED captures a wider variety of violent and non-violent events with and without casualties, whereas UCDP is confined to fatality-producing violent events (Eck 2012), though there is often much overlapping information as well (Donnay et al. 2019). The results of these models with UCDP do not provide a robust story, though the instrumented SSA model with controls is consistent, which is an important comparison point (See Table 5).

Once we turn to the remaining UCDP models outside of the African context, the overall story becomes even more complicated. The results for the Middle East and North Africa (see Table A4), Asia (see Table A5), Latin America (see Table A6), and then all countries globally that we have coded thus far (see Table A7) indicate that natural resources are not associated with conflict. In Latin America and Asia, natural resources are even negatively associated with conflict (see Tables A5 and A6), suggesting important limitations to the narrative tying resources to conflict.

External Validity

External validity refers to how the "inferences drawn from a given study's sample apply to a broader population or other target populations" (Findley, Kikuta, and Denly 2021). Characterizing external validity entails an assessment of a study's various dimensions, particularly mechanisms across settings, treatments, outcomes, units, and time (M-STOUT). In this study, we examine how natural resources affects conflict across different regions (settings), a large set of resources (treatments), two measures of conflict (outcomes), for grid-cells in 116 countries (units) across many years (time). The results of the study suggest different inferences relative to many past studies, especially with respect to the settings, treatments, outcomes, and units under consideration.

Given the heterogeneous treatment effects that we have documented across regions and conflict measures, future research could profitably focus on developing more fine-grained explanations of the contextual factors and salience of mechanisms that lead to positive relationships between resource wealth and conflict at the local level (see also, O'Brochta 2019; Vesco et al. 2020). For example, we find that the relationship between resources and conflict is negative in Latin America but positive in Africa. This is consistent with other work that has found that natural resource wealth has distinct effects in Latin America (e.g., Dunning 2008). The scope and comprehensiveness of the GRD also provides a strong basis to investigate heterogeneous relationships between resource abundance and outcomes of interest at lower levels of spatial aggregation along the lines of Dube and Vargas (2013) and Mähler and Pierskalla (2015).

Conclusion

In this paper, we report on a new data set of 197 natural resources, georeferenced across 116 countries. While the natural resource data could be used for many purposes, we used them here to examine its relationship to conflict. We estimated a basic set of models connecting natural resource values to conflict using different prices. The results show that, in some cases, natural resources are positively correlated in Africa. However, the result does not carry over to other regions. Moreover, the effect changes based on whether one uses the ACLED or GED measure of conflict. We then shifted to calculating natural resource value with country-specific price data, instrumented with U.S. and world prices, in order to address endogeneity concerns. These results indicate that for the ACLED outcome, but not the GED outcome, natural resources strongly and positively predict violence in Africa but not elsewhere. Notably, across all of our models, we find that resources are negatively correlated with conflict in Latin American countries, suggesting heterogeneity of effects worth future exploration.

While our empirical analysis here has focused on the links between resources and conflict incidence at the local level, the GRD could be used to address many additional research questions by scholars of conflict and of other issues. For conflict researchers, the data should lend itself to a better understanding of the intensity of conflict; the type of conflict events (i.e., battles between government and rebel forces or violence against civilians); protests (Christensen 2019); how changes in prices influence conflict (Dube and Vargas 2013); where rebel groups originate and establish bases and sanctuaries; human rights abuses by government and rebel forces

(Weinstein 2007); and patterns of territorial control (Aronson et al. 2021). A partial list of research questions beyond the domain of armed conflict that could be investigated with the GRD includes government capacity at the local level; the incidence of corruption; public goods provision (e.g., Denly and Hall 2021); and voting behavior. As both the most in-depth dataset on natural resources to date, as well as the most wide-ranging, the opportunities for making advancements using these new data are numerous.

Authors' Note

The perspectives, opinions, results, and conclusions reported here are only attributable to the authors and not to the U.S. Army or the U.S. Department of Defense.

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ORCID iDs

Michael G. Findley https://orcid.org/0000-0002-4830-1828
James Igoe Walsh https://orcid.org/0000-0002-5833-1705

Supplemental Material

The supplemental material for this article is available online.

Notes

1. See, for example, Ross and Mahdavi (2015).
2. O'Brochta (2019), Vesco et al. (2020), and Blair, Christensen, and Rudkin (2021) proffer relevant meta-analyses as well, but their studies are not uniquely based on subnational data.
3. Coding of additional countries and years is underway and we expect version 2 of the dataset to have nearly all countries for the last couple of decades.
4. Other authors have put forth some limited sub-national data of some key resources as well (e.g. Gervasoni 2010; Diaz-Rioseco 2016; Hong 2018), but these data are not systematically available for many countries and resources.
5. Systematic updates to the MRDS ended in 2011. As the documentation for the MRDS notes, the dataset was intended to document resource locations in the United States "completely", and that "its coverage of resources in other countries is incomplete." See: https://mrdata.usgs.gov/metadata/mrds.faq.html.
6. As we explain in Section 1.2, in this paper we do not hypothesize about the reasons why only some countries receive world prices for their natural resources. Scholars who are interested in examining such a question can profitably use the Global Resources Dataset to do so.
7. Available at https://www.usgs.gov/centers/nmic/international-minerals-statistics-and-information.
8. We implemented safeguards to ensure high quality data collection from the USGS country reports. First, we conducted two rounds of coding for all countries. At the end of the second round of coding, the coders randomly sampled each other's work and performed some triple-checks. A senior coder then performed spot checks throughout and adjudicated all difficult cases that were not initially clear from the documents produced by the USGS.
9. Additional sources include Mining Atlas, USGS MRDS, Conicyt Chile, The Diggings, Price Waterhouse Coopers, PEMEX Mexico, and Wiki Mapia.
10. In such instances, we chose the center of the respective area for the latitude and longitude. Often, these entries do not have large numbers of decimals. By contrast, entries with lower precision codes tend to have more decimals given the given the greater certainty about the location.

11. Of course, not all of these resources are in every country, and some resources only show up in rare cases, but nonetheless, we include the full catalog from USGS for the countries that we coded.
12. Multicolour is a Hong Kong-based auction house that provides pricing information on many rare gemstones that are not available in other datasets. Those wishing for these data may contact its owner, David Weinberg, via email: info@multicolour.com
13. Refer to the Codebook in Appendix D for more details.
14. See the Codebook in Appendix D for details.
15. For example, we code gold as potentially lootable, because although sometimes dredging equipment is needed to extract it, other times it can be mined through placer techniques. By contrast, we code different types of ferroalloys as not potentially lootable: even though some ferroalloys are valuable, their extraction and sale entail high barriers to market entry.
16. In his study of rebel groups in the Congo, Sanchez de la Sierra's (2020) finds that rebel groups who rely on bulky commodities such columbite-tantalite (coltan) tend to act as stationary bandits, whereas rebels that focus on lootable resources like gold tend operate as roving bandits and provide less state-like services to their members. For more on the distinction between roving and stationary bandits, see Olson (1993).
17. For convenience, the public version of our dataset includes the PRIO-GRID cell ID number corresponding to the latitude and longitude of each extraction site or production facility. In addition, we have included the latitude and longitude of each grid cell's centroid as well. For more information, refer to the Codebook in Appendix D.
18. To calculate the value for resource extraction site, we compared the units for the output from USGS and the units for the prices by the World Bank, USGS, UN Comtrade and Multicolour. When the units did not match, we created a multiplier for the units to match. Then, we deflated our results using 2010 USD.
19. The appropriate lag structure for the data is not immediately evident, and moving forward some theorizing is needed about the timescale on which natural resource extraction and production can be expected to translate into any conflict-inducing behavior.
20. Future research may benefit from employing a similar IV approach. Indeed, including an approach to obviate potential endogeneity between natural resources and conflict is a specific recommendation of a recent literature review from Koubi et al. (2014).
21. Summary statistics for the covariates, based on estimation of Model 2, are reported in Table A1 of the Appendix.
22. Note that, for these models, we use a set of common controls, but do not include a covariate for population. Including a population covariate reduces the number of observations substantially. As such, we report the results in the paper without the population variable, but estimate them separately and include those models in the replication data. Although a lot of observations drop out, the results are qualitatively similar across our models.
23. We carried out a replication of the Berman et al. (2017) study using only the fourteen resources, limiting analysis to a main resource in each grid cell, and then using prices rather than values— but for the resource and activity we coded, not Berman et al.'s (2017)

proprietary dataset. In doing so, we find that the constituent price and active mine variables are positive and significant, but the interaction term is not at conventional levels, which is different from their study that stresses the interaction as the key result. (Results are included in replication files.) The difference in results are likely due to the different coding of resource presence and mine activity. In the GRD, which is substantially larger than any other spatial natural resource dataset (see Table 1), we have a different constellation of resources and different measures of mine activity. Future research may want to consider a broader comparison across different data sets, perhaps as part of a meta-analysis similar to Blair, Christensen, and Rudkin (2021). Given that the GRD has price and production information, including country-specific prices, we proceed with the much more direct and applicable value measure of price × production.

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