Do Natural Resources Really Cause Civil Conflict? Evidence from a Global, Subnational, Georeferenced Database*

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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 subnational resource wealth is associated with higher levels of conflict using some specifications, though the results vary widely by data source and world region. Using the instrumental variables strategy lends the strongest support to this positive relationship, but that is only the case for African countries.

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, 2004*b*, 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).

[1] See, for example, Ross and Mahdavi (2015).

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).

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).[3] 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. (2020) 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.[4] Like the aforementioned datasets—but unlike the GRD introduced in this article—the MRDS is also not time-varying.

[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] 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.

[4] 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.

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

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 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 also includes data on the output of each site, allowing researchers to calculate the value of resources produced.

A potentially more significant omission of extant datasets than their lack of world prices—and perhaps even resource output figures—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.[5]

[5] We leave the source of the delta for future research.

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.

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 compute 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. 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 imply for future research on natural resources and conflict.

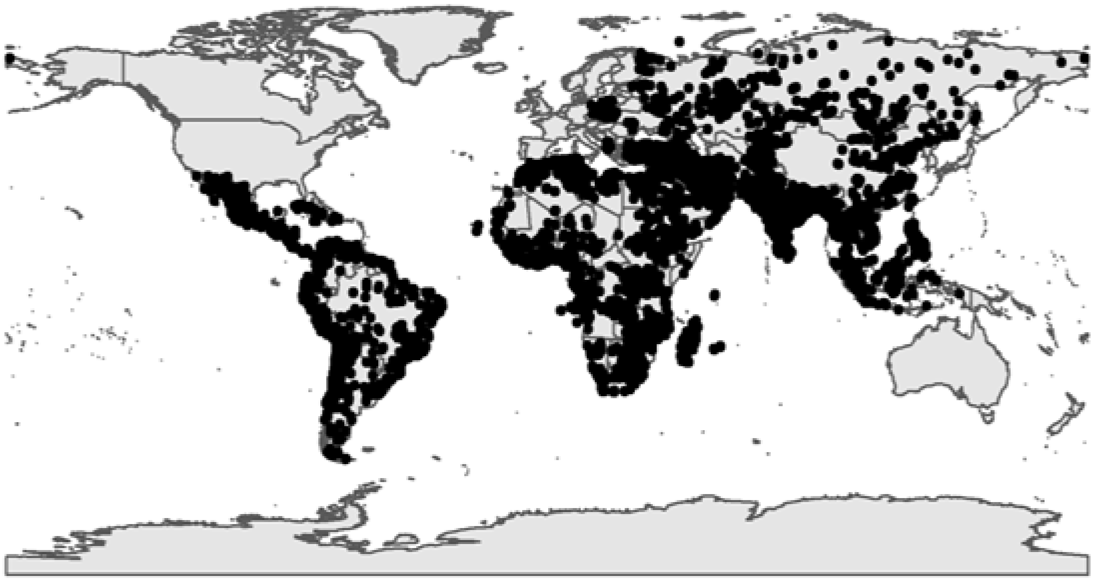
1. The Global Resources Dataset (GRD)

1.1. 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 over time. 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

Figure 1: Natural Resource Locations in the Global Resource Dataset (GRD)



Geological Survey (USGS).[6] 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.[7]

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 location-years constitute the unit of analysis for 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.[8]

[6] Available at https://www.usgs.gov/centers/nmic/international-minerals-statistics-and-information.

[7] 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.

[8] Additional sources include Mining Atlas, USGS MRDS, Conicyt Chile, The Diggings, Price Waterhouse Coopers, PEMEX Mexico, and Wiki Mapia.

Table 3: Overview of the Global Resources Dataset (GRD)

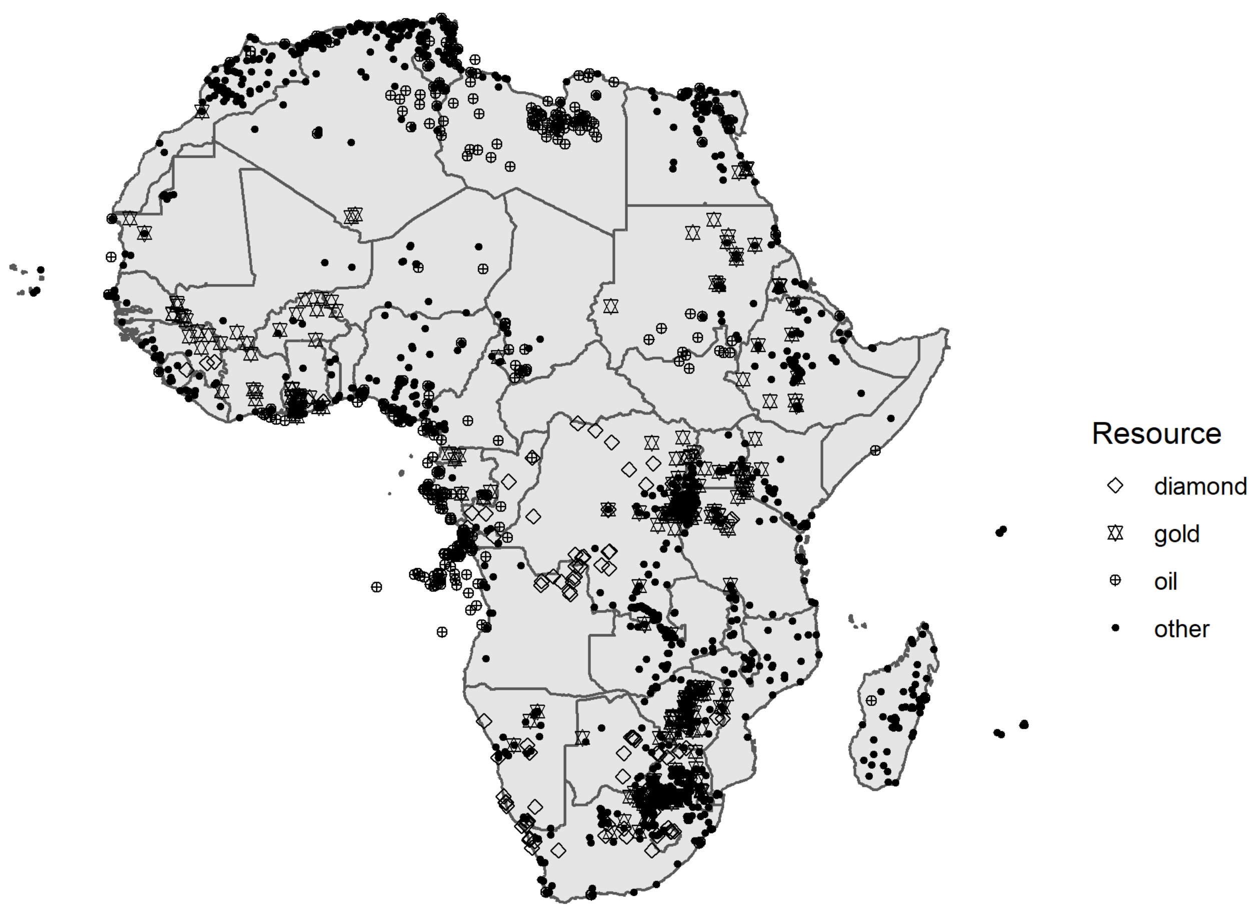
Description	Total	Percent
Countries	116	
Resources	197	
All Records	77,782	100%
Records with Geographic Coordinates	77,782	100%
Records with Output/Production Status	70,869	91%
Records with Country-Specific (UN Comtrade) Export Price	41,843	54%
Records with World Bank Global Economic Monitor World Price	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%

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 databases itself, which corresponds to about 44% of GRD observations. When the most precise we could be 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).

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

Figure 2: Natural Resource Locations in Africa



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,[9] 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.[10] 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.[11] 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. Ownership is crucial to any natural resources dataset, because ownership influences the intensity of resource curse effects (Jones Luong and Weinthal, 2010). 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

[9] 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.

[10] 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

[11] Refer to the Codebook in Appendix D for more details.

entails a 50-50 public-private partnership, we classified it as such.

1.2. 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 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. 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 offload relevant spoils at profitable world prices.

(Potentially) Lootable Vs. 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.[12] 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 resesarchers 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.[13] The effects of phosphates in Morocco/Western Sahara

[12] 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.

[13] 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).

and uranium in the Democratic Republic of the Congo constitute only a couple of examples of minerals that deserve further analysis along such lines.

2. 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).[14] 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."

Because we have coded all countries in sub-Saharan Africa, Latin America, and the Middle East. we present the results for these three regions separately. We have coded an additional non-random set of Asian and European countries. Because we do not have a random or complete sample in these regions, we estimate a pooled model with all countries across all regions and report those following the sub-Saharan Africa, Middle Eastern, and Latin American country models.

2.1. 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

[14] 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.

primarily on the onset or dynamics of civil wars (Ross, 2004*a*,*b*; 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 database, we follow suit and also examine the incidence of armed conflict events, and examine the two most prominent databases: the Armed Conflict Locations and Event Data set (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, but 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. As with Africa, there is not a positive relationship between natural resources and conflict incidence in other regions of the world individually or when pooling all regions together. We specify conflict incidence primarily as a dummy capturing conflict incidence in a grid cell during a given year as recorded by each of these datasets.[15]

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

[15] We checked the main model using a count of events, estimated with a negative binomial model, and the result is qualitatively the same (positive and significant).

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 (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.[16] 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, and then finally log that number. 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.[17]

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, based on the unit output for the resource extraction site from USGS and prices from UN Comtrade, 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 development using nighttime lights data. In particular, we use the mean calibrated nighttime lights density at the grid-cell

[16] 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.

[17] 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.

level, as measured by satellite imagery (Tollefsen, Strand and Buhaug, 2012; Elvidge et al., 2014). As is shown 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.

2.2. 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:

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

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.

2.3. 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 that future researchers may easily employ in resource-curse studies using the GRD.[18] Our two-stage least squares approach centers on instrumenting the endogenous, country-specific natural 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).

3. 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). We first report the results using the country-specific resource values without and with controls (Models 1 and 2 respectively) and then using the instrumented country-specific price variable without and with controls (Models 3 and 4 respectively). Continuing with the ACLED conflict measure, we then expand the analysis to include the entire African continent (Table A1). 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.[19]

[18] 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).

[19] We carried out a true 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

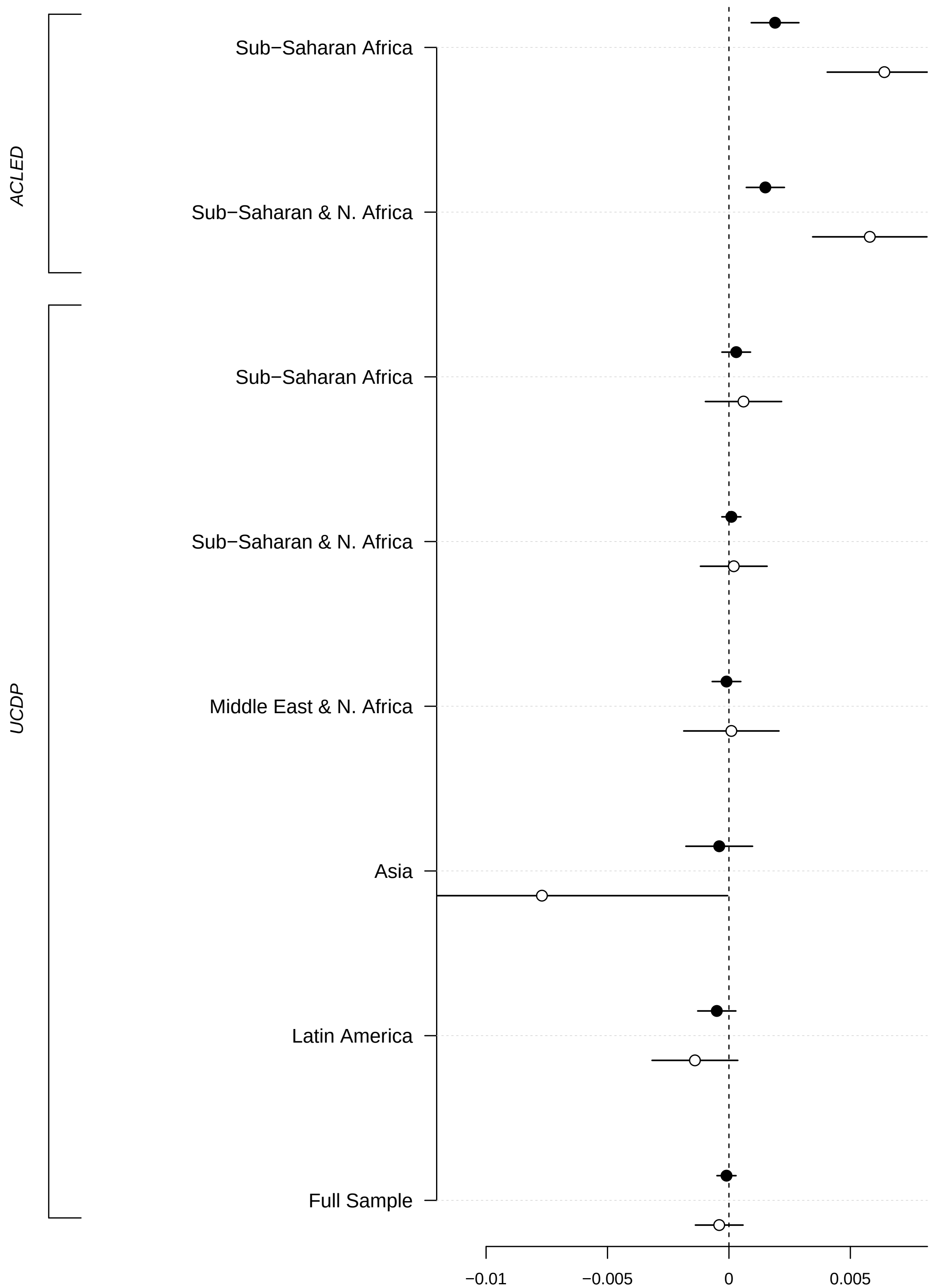


Figure 3: Results Across All Models. Solid dots represent base regression models with controls, but no instruments. The hollow dots represent the instrumental variable models.

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		
		(0.0104)		
Number of Excluded Ethnic Groups		-0.0008		0.0025
		(0.0039)		(0.0034)
Nighttime Lights		-0.8740***		0.4324***
		(0.1660)		(0.0666)
V-Dem Democracy Index		11.7420		
		(2.0e+03)		
Spatially Lagged Conflict Measure		0.0305***		0.0778***
		(0.0022)		(0.0026)
Natural Resource Value w/ Instrumented Country-Specific Price			0.0121***	0.0064***
			(0.0012)	(0.0012)
Constant			0.0765***	0.0290***
			(0.0004)	(0.0030)
Observations	162315	146063	162315	146063
R^2	0.001	0.004		
Adjusted R^2	0.001	0.004		

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

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, and most Asian countries (and even some European countries), we fit relevant models for each region as well as overall models that encompass all regions.

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, and accordingly, we use data from 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 A2 and compare to Table A1). 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, negative in the models without controls, and positive for Sub-Saharan Africa using the instrumented country-specific value model. Only one out of eight models match the results from the ACLED models, although arguably that one model is the most critical model to match. As we have argued, the instrumented version is likely to be the most accurate specification from the perspective of internal validity.

that the constituent price and active mine variables are positive and significant, but the interaction terms is not, which is different from their study in which the interaction is the key result. (Results are included in replication files.) The difference in results are due to the different coding of resource presence and mine activity. In our database, which is substantially larger than any others, as discussed in the introduction, 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 we have price and production, including country-specific prices, we proceed with the much more direct and applicable value measure.

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. 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. We now consider whether the results are similar (no effect) outside of Sub-Saharan African and North Africa when using the UCDP measure. The results for the Middle East and North Africa (see Table A3), Asia (see Table A4), Latin America (see Table A5), and then all countries globally that we have coded thus far (see Table A6) indicate that natural resources are not associated with conflict, or are even negatively related (conflict less likely). A key caveat here is that while we have coded the African continent, the Middle East, and Latin America in their entirety, we have only coded a non-random set of countries in Asia (see Table D2).

Moving to the Middle East region, Asia, and Latin America, as well as the entire sample (Table A3), all of which rely on the UCDP measure given that the ACLED data are not available, resources are not significantly associated with conflict incidence. In some cases, resource values are negatively associated with conflict. The story is similar for Asia and Latin America (see Tables A4 and A5). When pooling across all regions, the results remain mixed at best. In all of these additional models, resources are never positively associated with conflict, suggesting important limitations to the narrative tying resources to conflict.

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 (0.0002)	0.0003 (0.0003)		
Resources 1st Order Spatial Lag		-0.0001 (0.0001)		-0.0002 (0.0002)
Resources 2nd Order Spatial Lag		0.0000 (0.0001)		-0.0001 (0.0001)
Presence of Lootable Resources		-0.0004 (0.0080)		
Number of Excluded Ethnic Groups		0.0077** (0.0035)		0.0147*** (0.0030)
Nighttime Lights		0.1222 (0.2187)		0.0124 (0.0471)
V-Dem Democracy Index		-1.0057 (668.5990)		
Mean Population Density		0.0001 (0.0001)		0.0000 (0.0001)
Spatially Lagged Conflict Measure		0.0143*** (0.0017)		0.0231*** (0.0018)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0009 (0.0007)	0.0006 (0.0008)
Constant			0.0316*** (0.0002)	0.0169*** (0.0041)
Observations	162315	104380	162315	104380
R^2	0.000	0.001		
Adjusted R^2	-0.000	0.001		

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

4. External Validity

As Findley, Kikuta and Denly (2021) explain, "external validity captures the extent to which inferences drawn from a given study's sample apply to a broader population or other target populations", and part of that entails an assessment of a study's various dimensions: mechanisms, settings, treatments, outcomes, units, and time (M-STOUT). In this study, we present results involving a large time-series on substantially more units (countries) and treatments (resources) than previous literature on the spatial effects of natural resources on conflict. We also consider two different, but related, conflict incidence outcome measures: ACLED and UCDP. Given the heterogeneous treatments 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).

5. 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 carried out a basic set of models connecting natural resource values (using different prices) to conflict and show that, in some cases, natural resources are positively correlated in Africa. However, the result does not carry over to other regions and indeed changes based on whether one uses the ACLED or GED measures. 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.

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 so on. 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 include the incidence of corruption; public goods provision (e.g. health, environmental protection); 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.

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A. Additional Results

Table A1: Main Spatial HAC and 2SLS IV Model Results for ACLED Outcome on SSA and NA (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	0.0041*** (0.0004)	0.0015*** (0.0004)		
Resources 1st Order Spatial Lag		0.0002 (0.0002)		0.0001 (0.0002)
Resources 2nd Order Spatial Lag		-0.0000 (0.0001)		-0.0003*** (0.0001)
Presence of Lootable Resources		0.0015 (0.0110)		
Number of Excluded Ethnic Groups		0.0084* (0.0047)		0.0104*** (0.0039)
Nighttime Lights		-0.9945*** (0.1960)		0.5881*** (0.0556)
V-Dem Democracy Index		4.0908 (753.6384)		
Mean Population Density		0.0002** (0.0001)		0.0002** (0.0001)
Spatially Lagged Conflict Measure		0.0180*** (0.0022)		0.0374*** (0.0023)
Natural Resource Value w/ Instrumented Country-Specific Price			0.0142*** (0.0010)	0.0058*** (0.0012)
Constant			0.0657*** (0.0004)	0.0211*** (0.0043)
Observations	208815	134345	208815	134345
R^2	0.002	0.002		
Adjusted R^2	0.002	0.002		

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

Table A2: Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on SSA and MENA (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	-0.0003	0.0001		
	(0.0002)	(0.0002)		
Resources 1st Order Spatial Lag		-0.0002*		-0.0002**
		(0.0001)		(0.0001)
Resources 2nd Order Spatial Lag		0.0000		-0.0000
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0031		
		(0.0072)		
Number of Excluded Ethnic Groups		0.0079**		0.0146***
		(0.0035)		(0.0030)
Nighttime Lights		-0.1313		-0.0291
		(0.1547)		(0.0385)
V-Dem Democracy Index		-0.1494		
		(668.8244)		
Mean Population Density		0.0000		0.0000
		(0.0001)		(0.0001)
Spatially Lagged Conflict Measure		0.0126***		0.0202***
		(0.0016)		(0.0016)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0013**	0.0002
			(0.0006)	(0.0007)
Constant			0.0294***	0.0191***
			(0.0002)	(0.0029)
Observations	208815	134345	208815	134345
R^2	0.000	0.001		
Adjusted R^2	0.000	0.001		

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

Table A3: Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on Middle East and North Africa (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	0.0001 (0.0003)	-0.0001 (0.0003)		
Resources 1st Order Spatial Lag		-0.0002 (0.0002)		-0.0003 (0.0002)
Resources 2nd Order Spatial Lag		-0.0000 (0.0001)		0.0005*** (0.0001)
Presence of Lootable Resources		-0.0081 (0.0099)		
Number of Excluded Ethnic Groups		0.1143*** (0.0255)		-0.0492** (0.0211)
Nighttime Lights		-0.0259 (0.1094)		0.5764*** (0.0658)
Mean Population Density		0.0001 (0.0000)		0.0001** (0.0001)
Spatially Lagged Conflict Measure		0.0011 (0.0036)		-0.0002 (0.0038)
Natural Resource Value w/ Instrumented Country-Specific Price			0.0012 (0.0009)	0.0001 (0.0010)
Constant			0.0437*** (0.0005)	0.0124 (0.0082)
Observations	99140	61646	99140	63921
R^2	0.000	0.005		
Adjusted R^2	-0.000	0.005		

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

Table A4: Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on Asia (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	-0.0006	-0.0004		
	(0.0005)	(0.0007)		
Resources 1st Order Spatial Lag		-0.0004		-0.0003
		(0.0004)		(0.0005)
Resources 2nd Order Spatial Lag		0.0008**		0.0010***
		(0.0003)		(0.0004)
Presence of Lootable Resources		-0.0354*		
		(0.0189)		
Number of Excluded Ethnic Groups		0.0596***		-0.0755***
		(0.0146)		(0.0125)
Nighttime Lights		-0.0149		-0.0125
		(0.0670)		(0.0435)
V-Dem Democracy Index		-0.3653		
		(29.9738)		
Mean Population Density		-0.0000		0.0000
		(0.0001)		(0.0001)
Spatially Lagged Conflict Measure		0.0116		-0.0064
		(0.0101)		(0.0080)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0021	-0.0077*
			(0.0021)	(0.0039)
Constant			0.0336***	0.0716***
			(0.0006)	(0.0133)
Observations	125538	80964	125538	80964
R^2	0.000	0.001		
Adjusted R^2	0.000	0.001		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on Latin America (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	-0.0004*	-0.0005		
	(0.0002)	(0.0004)		
Resources 1st Order Spatial Lag		-0.0005***		-0.0005**
		(0.0002)		(0.0002)
Resources 2nd Order Spatial Lag		-0.0003**		-0.0002
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0060		
		(0.0069)		
Number of Excluded Ethnic Groups		-0.0004		-0.0034**
		(0.0011)		(0.0014)
Nighttime Lights		0.5538***		-0.0517
		(0.1540)		(0.0332)
Mean Population Density		-0.0002*		-0.0003**
		(0.0001)		(0.0001)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0012*	-0.0014
			(0.0006)	(0.0009)
Spatially Lagged Conflict Measure				0.0000
				(.)
Constant			0.0163***	0.0395***
			(0.0004)	(0.0051)
Observations	158440	101049	158440	101166
R^2	0.000	0.002		
Adjusted R^2	0.000	0.002		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Main Spatial HAC and 2SLS IV Model Results for UCDP Outcome on Full Sample (Three-Way Fixed Effects)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Natural Resource Value in Cell (Time Lag/Log)	-0.0002*	-0.0001		
	(0.0001)	(0.0002)		
Resources 1st Order Spatial Lag		-0.0002***		-0.0002**
		(0.0001)		(0.0001)
Resources 2nd Order Spatial Lag		0.0000		0.0001**
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0017		
		(0.0041)		
Number of Excluded Ethnic Groups		0.0201***		0.0031
		(0.0030)		(0.0028)
Nighttime Lights		0.0541*		0.0601***
		(0.0286)		(0.0146)
V-Dem Democracy Index		-0.6214		
		(55.9867)		
Mean Population Density		-0.0000		0.0000
		(0.0000)		(0.0000)
Spatially Lagged Conflict Measure		0.0126***		0.0173***
		(0.0016)		(0.0017)
Natural Resource Value w/ Instrumented Country-Specific Price			-0.0008*	-0.0004
			(0.0004)	(0.0005)
Constant			0.0206***	0.0151***
			(0.0001)	(0.0024)
Observations	870532	549827	870532	552219
R^2	0.000	0.001		
Adjusted R^2	0.000	0.001		

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

B. Instrumental Variable

B.1. Criterion 1: First-Stage Assumption

First, a valid instrument must have a first-stage relationship: $COV(D, Z) \neq 0$. For our instrument, there must be a relationship between the endogenous variable (country-specific values, D) and the instrument (U.S./world values, Z). In our case, log country-specific values correlate with the instrument at 0.74 (see Table 2). The correlation between the country-specific exports prices from UN Comtrade and world is 0.78 (see Table 2). Conventionally, instruments are thought to be strong if the F-statistic is above 12. In all of our models with control variables (other than for Asia), the F-statistic ranges from 93 to 326. In the Asia model, the F-statistic is 12, even so meeting the basic threshold. In most of the models, therefore, the instrument is strong.[20]

B.2. Criterion 2: Monotonocity

Second, the instrument must satisfy the monotonicity assumption: $Pr(D_1 \geq D_0) = 1$ (Kern and Hainmueller, 2009).[21] Monotonicity means that the instrument is shifting outcomes in countries in the same direction; alternatively, in the language of Imbens and Angrist (1994), there are no "defiers".[22] In this case, higher U.S./world resource values for natural resources mostly fuel civil conflict. Ross (2012) points out that there is some causal heterogeneity in the resource curse for wealthy countries such as Canada and Norway, but that is mainly not the case in Africa and the other developing countries in our sample.

[20] All first-stage results available with replication files.

[21] Recent studies from, for example, de Chaisemartin (2017) and Heckman and Pinto (2018) challenge whether monotonicity is indeed necessary, but we present the assumption for the sake of completeness.

[22] Technically, it is possible to have an instrumental variable in which there are only "defiers" and no "compliers", but this is not the norm. For more on the compliers and defiers distinction, refer to Imbens and Angrist (1994) and Angrist, Imbens and Rubin (1996).

B.3. Criterion 3: Stable-Unit Treatment Value Assumption (SUTVA)

Third, the instrument must satisfy the stable-unit treatment value assumption (SUTVA): $Y_i \perp\!\!\!\perp D_j \; \forall \; i \neq j$ and $Y_i = Y_{1i}D_i + Y_{0i}(1 - D_i)$. For SUTVA to hold, units must not interfere with each other, and potential outcomes must be well-defined. One could perhaps argue that mine discoveries in one grid cell could catalyze exploration and discovery of mines in neighboring grid cells. However, any spatial spillovers are prone to time lags given that discoveries and extraction in neighboring grid-cells will not happen immediately. As Menaldo (2016) shows, natural resource extraction requires significant technology, capital, and investment. Additionally, the sites of natural resources tend to be located in rural areas, which in many countries means that there is no road access, etc.

B.4. Criterion 4: Exclusion Restriction

Fourth, the instrument needs to satisfy the exclusion restriction: $P(Y_{1d} = Y_{0d}|D) = 1 \in [0, 1]$ (Kern and Hainmueller, 2009, 384). Our proposed instrument would violate the exclusion restriction if: (a) U.S./world values (Z) are endogenous to local conflict (Y); or (b) there are alternative pathways connecting the country-specific resource values (D) to local conflict (Y) other than the country-specific value of the resource (D).

Regarding the potential endogeneity of US/world values and conflict, very prominent recent studies by Berman et al. (2017) and Christensen (2019) contend that world resource prices are exogenous to local conflict (see also Humphreys, 2010; Carter, Rausser and Smith, 2011; Rossen, 2015). According to these authors, a commodity super-cycle has been in place since roughly 1996. As many countries have become richer and more populous, world demand for minerals has spiked considerably, creating large demand-side shocks that facilitate exogeneity of resource prices to conflict. Whether these demand-side shocks from the commodity super-cycle are so large as to offset any supply-side incentives of higher resources prices potentially fueling rebel attacks of extraction sites is difficult to test empirically. Nevertheless, in this paper we furnish (to our knowledge) the first evidence to show that natural resource companies spend significant amounts of their resources on preventing rebel attacks (see Appendix C). Rebels are generally thus not able to affect the global price at will, and there are significant safeguards in place at industrial mines to avoid rebel-induced interruptions in the flow of minerals onto the world market. In turn, on a process level, local conflicts are insulated from global prices except through the mediation of country-specific prices.

With respect to the potential alternative pathways that may confound the effect of the country-specific resource values, they are hard to imagine. It may be theoretically possible that governance mediates the resource values. However, such effects would not be relevant for our grid-cell level estimation, and introducing a country-level governance variable (a universal, local-level governance measure does not exist) would simply lead to collinearity and unstable estimates. Additionally, as we show in Appendix C, companies take the security of mines and extraction sites seriously. Accordingly, it is difficult to envisage a scenario nowadays in which, most of the time, governance mediates or distorts the effect of the country-specific resource values (D) to local conflict (Y).[23]

B.5. Criterion 5: Independence/Ignorability

The fifth criterion that an instrument must satisfy is the independence or ignorability assumption: $Z_i \perp\!\!\!\perp (Y_{i1}, Y_{i0}, D_{i1}, D_{i0})$. Essentially, the instrument needs to be independent of potential outcomes and the endogenous variable in its different treatment states (Morgan and Winship, 2015, 307). In this case, the independence assumption would not hold if the US/world values (Z) are a function of local conflict (Y) or the country-specific resource values (D). We addressed the potential non-independent relationship between Y and Z in the previous section on the exclusion restriction.

Whether the relationship between Z and D suffers from Betz, Cook and Hollenbach (2018) call "spatial simultaneity" merits further discussion. For our instrument, the country-

[23] For relevant recent studies on mediation, see Imai et al. (2011) and Imai, Tingley and Yamamoto (2013).

specific resource values that we calculate from UN Comtrade prices do not constitute any form of an average or aggregate up to the US/world values that we calculate from USGS and the World Bank—and, in some cases, Multicolour (see above). In fact, none of these datasets come from the same distribution. USGS prices correspond to US resource values, which are outside our sample. Despite the literature's ubiquitous use of the world prices from the World Bank (e.g. Berman et al., 2017), the latter institution mostly draws their price data from OECD countries outside our sample (World Bank, 2018). Accordingly, our instrument does not suffer from the same concerns as the spatial averages that Betz, Cook and Hollenbach (2019) critique at length.

Betz, Cook and Hollenbach (2019) further raise the issue of spatial interdependence among outcome variables. In order to control for the possibility of spillover effects among outcome variables in neighboring units, they recommend the use of spatial two-stage least squares (S-2SLS). The latter creates a first-stage equation to predict outcome variables in neighboring cells, and it then uses the predicted values in the second-stage equation. Much of what the S-2SLS model accomplishes in practical terms is the creation of a spatial weights matrix in order to perform the two-stage equation. However, S-2SLS does not lend itself to panel data.

To address this issue, in the creation of this data set, we constructed a series of spatial weights matrices for each year of the data. After the construction of each year's spatial weights matrix, we simply appended the data from each year to produce time-series data that also contained spatially lagged variables. This simple work around allows the creation of both spatial and time-series lags, and so we included a spatially *and* temporally lagged dependent variable of conflict on the right-hand side of the equation.

Noticeably, the above procedure skips the first-stage of S-2SLS, but we posit this has some advantages. First, whereas S-2SLS uses predicted values from neighboring cells, we use the actual values of conflict in the neighboring cell that are both spatially and temporally lagged. This has the advantage of more realistically modeling diffusion and avoids simultaneity. Second, a predicted value from a neighboring cell relies on good model fit for an accurate prediction. Even if the prediction model is well-fit, the predicted value's relationship to the actual value should be unbiased. Thus, the use of the actual value would produce similar results to the use of predicted values. If the prediction equation is not well-fit, then the use of actual values will create results that are more accurate than biased results from a poorly fit predicted value. In some cases, the use of actual values may even be an overly conservative test for our primary independent variables, as the first-stage value may under-predict conflict, because of poor model fit. Thus, the use of actual values for temporally and spatially lagged dependent variables on the right-hand side appears to be an appropriate solution to the concerns about spatial interdependence.

C. DRC Case Study of Exclusion Restriction

The case of mining operations in the Democratic Republic of Congo (DRC) provides plentiful evidence that mining companies devote significant resources to protecting mines from outside forces. The most direct evidence comes from a mining company called Anvil Mining Limited. In 2009, it operated the Kinsevere Copper Project in Katanga Province of the DRC. During this time period, the company spent roughly $158,000 per month on direct security costs for the Kinsevere site alone (Booth et al., 2010). The Kinsevere Mine is a relatively average mining site in the DRC with an annual value of roughly $366 million per year, compared to the average location across all observations in the DRC of $365 million. It also has only a slightly higher annual output than the mean of all mines within the DRC. As such, it represents a typical mining location, and the mining company spent almost $2 million a year on direct site security for the Kinsevere site alone.

These direct costs are also only part of the broader picture of mine security costs. Mine security in the DRC is a complex issue that involves numerous government agencies, with side payments and informal agreements between the mining company and armed groups—both government and rebel. For instance, Anvil Mining was also reported to pay roughly $5,000 per month to local administrative and security officials to maintain their support in the area around the Dikulushi Mine north of Kilwa (Rights and Accountability in Development and Action Contre l'Impunité pour les Droits Humains, 2005). The same report indicates that informants claimed local administrators and sector chiefs each received roughly $420 per month. All of these payments stand in addition to the existing repatriation agreement, where the company repatriates 40% of proceeds from the mine site for use by the DRC government. For this mine site alone, that agreement amounted to the repatriation of $76 million in 2008 (Institute of Developing Economies, 2019). Other reports indicate that, while the central government agrees to provide security in return for a share of the mining profits, local officials do the same. At times, tacit agreements are formed with local commanders or even individual soldiers in return for the provision of security (De Koning, 2010).

In addition, there are tacit agreements at mine sites, which allow local authorities to use company security equipment when they need it for security purposes. In one instance, local authorities used mine security equipment to raid a local town that was supposedly harboring rebels. This shows that the mine site was heavily armed and prepared to defend against rebel groups. In fact it was even more heavily armed than government forces in the area, and so heavily armed that it was used a repository for those local security officials to conduct offensive operations against neighboring rebel groups. Furthermore, the company paid for the stationing of DRC troops and army intelligence at the mine site itself as a protective measure. It was only after the incident that the company requested additional security forces from the government in order to prevent the need for local security forces to requisition equipment from the company (Czernowalow, 2004).

All of these items indicate that mine security is taken very seriously across even medium-sized sites of average value, to prevent disruptions in the supply of raw materials to the world market. Because companies are determined to protect their resources through the direct provision of security and through explicit and implicit agreements with local officials, local prices of the resource at the mine site are unlikely to see significant shocks. Rather, what we generally see are steady operations at industrial sites that occasionally shut down for technical issues, which affects local prices but not global prices.

Furthermore, it is worth exploring the idea that global prices influence conflict on their own without the mediation of local prices. This is unlikely for a variety of reasons, but the main issue is that many minerals require a significant investment in infrastructure for them to be taken to the world market. They must enter the global market in order to be incorporated into supply chains and the process of adding value through conversion, transformation, refinement, or combining with other elements to produce finished products.

For instance, in the case of the same mine, the Dikulushi Mine in Southeast DRC, the minerals extracted are copper and silver. In order to bring these minerals to market, they must first be refined and finished. The company built pontoon ferries across 27 miles of Lake Mweru and then drive another 1,600 miles to a company processing facility in Namibia for refining. From there, the processed product would then need to be transported to an international port for loading onto ships and transport to facilities that apply further manufacturing techniques in Europe and Asia.

Rebels have very little ability to apply this process on their own, and even looted resources must be sold at local prices for them to be taken into the global market by others. Due to the technical nature of extraction and the need for significant infrastructure to transport many minerals to a point of sale, it is highly unlikely that rebels would ever be able to realize a world price rather than a local price.

Thus, because of the nature of many minerals—both their need for further value-added and the necessity of large-scale infrastructure on the ground in order to realize any value, local conflict is relatively insulated from world prices. Since companies that do the mining also expend significant time and money guarding the resource sites, local conflicts are insulated from both supply- and demand-side shocks from the global market. Therefore, the instrument meets the exclusion restriction.

D. Codebook

D.1. Overview

This codebook describes the process of coding variables for the Global Resources Dataset.

D.2. Coding process

The unit of observation is the mine, resource extraction site, or resource processing facility in each year. The data are coded from annual country fact sheets produced by the United States Geological Survey (USGS) website.

We undertook a number of safeguards to ensure high quality data. First, we undertook an initial round of coding. Next, especially since geolocations are not always clear with higher level precision codes, we undertook a second round of coding to check all of the entries for accuracy. At the end of the second round of coding, the coders randomly sampled each other's work and performed some triple-checks. In the third round of coding, coders performed an initial coding of each location-year, with another coder double-checking over each coded entry. Senior coders also performed spot checks throughout and adjudicated all difficult cases that were not initially clear from the PDF documents produced by the United States Geological Survey (USGS). After the second and third rounds of coding, we further examined instances in which the same location was given different latitudes and longitudes for different location-years. Accordingly, an expert coder then re-checked those locations and assigned a final latitude and longitude to them ex post.

D.3. Variables

This section outlines the variables in the dataset.

D.3.1. resource

This information is taken from United States Geological Survey (USGS). Details on the individuals resources covered in this dataset are found in Table D1. In total, there are 192 different resources in the dataset.

Table D1: Resources in the Global Resources Dataset (GRD)

Resource	Number of Observations
alumina	674
aluminum	1,614
aluminum floride	11
amazonite	2
amber	7
amethyst	21
ametrine	7
ammonia	198
ammonium nitrate	1
andalusite	65
anhydrite	14
antimony	386
antimony trioxide	15
apatite	28
aquamarine	14
arsenic	7
arsenic trioxide	10
asbestos	179
asphalt	16
attapulgite	22
barite	655
basalt	19
bauxite	1,027
bentonite	98
beryl	3
beryl and emerald	4
beryllium	1
bismuth	158
black carbon	46
borax	6
boron	308
bromine	12

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Table D1: Resources – *continued*

Resource	Number of Observations
cadmium	17
calcite	6
calcium carbonate	216
carbon dioxide	10
caustic soda	18
celestite	9
cement	10,043
chlorine	3
chromite	1,026
chromite ferrochromium	15
chromium	55
citrine	3
clay	206
coal	3,288
cobalt	386
coke	175
copper	4,092
copper sulfate	32
diamond	1,015
diatomite	49
diesel	6
dolomite	63
emerald	74
feldspar	189
ferro-chromium	106
ferro-manganese	4
ferro-molybdenum	17
ferro-nickel	29
ferro-silicon	50
ferro-vanadium	14
ferroalloys	1,077
fertilizer	753
fluorspar	559
gallium	19
garnet	37
gasoline	54
gemstones	73
germanium	11
glass	53
gold	5,196
granite	73
graphite	434

Continued on next page

Table D1: Resources – *continued*

Resource	Number of Observations
guano	2
gypsum	830
helium	49
indium	51
iodine	93
iron	2,676
iron and steel	249
iron oxides	18
iron pyrites	22
kaolin	422
kerosene	6
kyanite	84
labradorite	46
lapis	15
lead	1,424
lignite	110
lime	422
limestone	569
liquified natural gas	182
liquified petroleum gas	24
lithium	49
lithium chloride	11
lithium hydroxide	10
magnesite	183
magnesium	77
manganese	946
marble	327
mercury	62
methane	6
methanol	69
mica	110
molybdenum oxide	18
morganite	7
naphtha	4
natural gas	2,392
nickel	948
niobium	243
niobium and tantalum	207
nitrates	102
nitrogen	333
nitrogen ammonia	78
nitrogen urea	24

Continued on next page

Table D1: Resources – *continued*

Resource	Number of Observations
oil	8,323
onyx	4
opal	9
palladium	259
peat	49
perlite	45
petroleum products	1,096
phosphate	1,192
phosphoric acid	226
phosphorite	40
platinum	714
potash	76
potassium	12
potassium chloride	16
potassium nitrate	27
potassium sulfate	7
pozzolan	62
pozzolana	13
pumice	90
pyrophyllite	74
quartz	74
quartzite	4
rare earths	39
rebar	1
rhenium	34
rhodium	258
rhyolite	1
ruby	56
ruthenium	38
salt	1,149
sand	103
sand and gravel	62
sandstone	13
sapphire	128
selenium	52
sepiolite	4
silica	269
silicomanganese	1
silicon	17
silver	1,860
soapstone	12
soda ash	140

Continued on next page

Table D1: Resources – *continued*

Resource	Number of Observations
sodium	1
sodium nitrate	15
sodium silicate	19
sodium sulfate	68
sodium tripolyphosphate	4
steel	4,896
stone	308
strontium	36
sulfur	408
sulfuric acid	320
synthetic fuels	25
talc	140
tantalite	8
tantalum	84
tanzanite	64
tellurium	34
tin	1,706
titanium	583
tourmaline	39
travertine	46
tuff	108
tungsten	496
turquoise	12
uranium	197
urea	73
vanadium	44
vanadium pentoxide	70
vermiculite	60
wolframite	12
wollastonite	13
zeolite	48
zinc	2,161
zircon	3
zirconium	257
Total	77,782

D.3.2. country

This variable identifies the country in which a resource location-year observation is located. Table D2 lists the countries included in the GRD, the first and last year for which data is included, and the total number of resource location-years for each country. Number in parentheses after the country name indicates the number of years for which data is missing. In most cases, this is because there is no USGS country report for that year. Most missing observations occur before 2004.

Table D2: Country-Years in the Global Resources Dataset

Country	Beginning Year	Ending Year	Observations
Afghanistan	2008	2015	163
Albania	1994	2015	826
Algeria (3)	2001	2015	1418
Angola	2002	2014	437
Argentina	1994	2015	1369
Armenia (1)	1994	2015	422
Bahrain	2006	2015	239
Bangladesh	2006	2015	418
Belize	2005	2015	30
Benin	2004	2015	39
Bhutan	2006	2015	59
Bolivia (7)	1994	2015	1727
Botswana (2)	2003	2015	162
Brazil	1994	2015	8866
Burkina Faso (1)	2002	2012	100
Burundi	2004	2015	320
Cambodia	2006	2015	93
Cameroon (1)	2003	2015	80
Cape Verde (3)	2004	2014	11
Chad	2004	2015	121
Chile (1)	1994	2015	3787
China	1994	1996	320
Colombia (1)	1994	2014	1029
Costa Rica (6)	1994	2014	172
Cote d'Ivoire	2002	2012	114
Cuba	2007	2014	190
Democratic Republic of Congo (2)	2003	2014	1014

Continued on next page

Table D2: Country-Years in the Global Resources Dataset – *continued*

Country	Beginning Year	Ending Year	Observations
Djibouti (1)	2004	2015	67
Dominican Republic (7)	1994	2015	127
Ecuador	2005	2014	246
Egypt (4)	1994	2015	1359
El Salvador (2)	2001	2015	95
Equatorial Guinea	2005	2015	132
Eritrea	2002	2015	81
Ethiopia	2002	2015	574
French Guiana	2013	2013	9
Gabon (5)	1994	2014	408
Ghana (3)	1994	2014	445
Guatemala (2)	1994	2014	308
Guinea	2002	2014	178
Guyana	1994	2014	251
Honduras (3)	1994	2014	141
India	1994	2015	4135
Indonesia (2)	1994	2016	1401
Iran (3)	2000	2014	2025
Iraq (2)	2001	2014	605
Israel	2001	2014	530
Jamaica (6)	1994	2015	166
Jordan	2003	2014	453
Kazakhstan (20)	1994	2014	106
Kenya (1)	2004	2014	400
Kuwait (6)	1994	2014	557
Kyrgyzstan	2007	2013	370
Laos	2007	2016	316
Lebanon	2004	2013	148
Lesotho	2006	2014	34
Liberia (3)	2004	2014	24
Libya (1)	2004	2014	679
Madagascar	2001	2014	444
Malawi	2002	2014	194
Malaysia	1994	2015	1141
Mali (2)	2002	2014	95
Mauritania (2)	2002	2014	118
Mauritius (1)	2002	2014	33
Mexico	1994	2015	3271
Moldova	1994	2016	89
Mongolia	2006	2015	209
Morocco (2)	2002	2014	840

Continued on next page

Table D2: Country-Years in the Global Resources Dataset – *continued*

Country	Beginning Year	Ending Year	Observations
Mozambique	2001	2014	316
Myanmar (Burma)	2005	2014	227
Namibia (1)	2003	2014	319
Nepal	2006	2015	82
Nicaragua (3)	1994	2014	110
Niger (2)	2002	2014	71
Nigeria (5)	1994	2014	530
Oman	2006	2012	362
Pakistan	2005	2014	551
Panama (5)	1994	2014	55
Paraguay	2004	2014	44
Peru	1994	2015	2224
Philippines (3)	1994	2015	675
Poland	1994	2015	2721
Qatar (3)	2001	2014	532
Republic of Congo (1)	2004	2014	289
Reunion (2)	2002	2013	9
Russia (6)	1988	2014	4127
Rwanda	2002	2014	281
Saudi Arabia (7)	1994	2015	842
Senegal (1)	2002	2014	133
Seychelles	2006	2013	17
Sierra Leone (1)	2002	2014	75
Somalia	2002	2003	14
South Africa (1)	2002	2014	4220
South Sudan	2011	2015	30
Sri Lanka	2006	2015	150
Sudan	2002	2015	353
Suriname (1)	1994	2015	184
Swaziland (Eswatini)	2006	2015	26
Syria	2004	2015	836
Taiwan	1994	2015	551
Tajikistan	1994	2015	750
Tanzania	2002	2015	513
Thailand	1994	2015	1410
Togo	2002	2015	105
Tunisia	2004	2015	809
Turkey	2007	2015	1704
Uganda	2001	2015	348
United Arab Emirates	2006	2015	718
Uruguay (10)	1994	2015	60

Continued on next page

Table D2: Country-Years in the Global Resources Dataset – *continued*

Country	Beginning Year	Ending Year	Observations
Venezuela	1994	2015	1248
Vietnam	2002	2015	1076
Western Sahara (3)	2002	2015	14
Yemen (4)	2001	2015	339
Zaire	1994	1994	20
Zambia	2006	2015	479
Zimbabwe (7)	1998	2015	903

D.3.3. year

This information is taken from United States Geological Survey (USGS). Years range from 1994–2015. Data availability varies by country. Details on the individuals country-years covered in this dataset can be found in Table D2.

D.3.4. COW_code

This variable corresponds to the Correlates of War (COW) country code.

D.4. gwno

This variable corresponds to the Gleditsch-Ward country code.

D.4.1. wb_ccode

This variable corresponds to the World Bank/ISO3 country code.

D.4.2. region_wb

This variable corresponds to World Bank region of the mine location or resource extraction site. There are five regions in the dataset: (Subsaharan) Africa; Middle East and North Africa; Latin America and Caribbean; South Asia; and East Asia and Pacific.

D.4.3. continent

This variable corresponds to the continent of the mine location or resource extraction site. The dataset contains observations from Asia; Europe; the Americas (South and Central America); and Africa.

D.4.4. gid

This variable corresponds to the grid-cell ID from the PRIO-GRID (see Tollefsen, Strand and Buhaug, 2012). In line with Tollefsen, Strand and Buhaug (2012), we performed the relevant spatial join with the WGS84 coordinate reference system, using the sf package in R (Pebesma, 2018).

D.4.5. gid_centroid_latitude

This variable corresponds to the latitude of the grid-cell centroid from the PRIO-GRID. In line with Tollefsen, Strand and Buhaug (2012), we performed the relevant spatial join with the WGS84 coordinate reference system

D.4.6. gid_centroid_longitude

This variable corresponds to the longitude of the grid-cell centroid from the PRIO-GRID. In line with Tollefsen, Strand and Buhaug (2012), we performed the relevant spatial join with the WGS84 coordinate reference system.

D.4.7. standard_measure

This variable identifies the standard unit of measure for each resource. Information is taken from United States Geological Survey (USGS). Data are recorded using the following units: 42-gallon barrels, 42-gallon barrels per day, billion cubic meters, carats, cubic meters, kilograms, metric tons, metric tons per day, million 42-gallon barrels, million bricks, million cubic meters, million cubic meters per day, million metric tons, square meters, thousand 41-gallon barrels, thousand 41-gallon barrels, thousand 42-gallon barrels per day, thousand 42-gallon barrels per day, thousand bricks, thousand carats, thousand cubic meters, thousand metric tons, and thousand square meters.

D.4.8. comtrade_unit

This information is taken from UN Comtrade. It describes the unit measure for the respective UN Comtrade prices. Prices are expressed in carats, cubic meters, kilograms, and liters.

D.4.9. wb_unit

This information is taken from the World Bank's Global Economic Monitor. The variable describes the unit corresponding to the world price of the respective mineral or resource. Prices are expressed in 42-gallon barrels, metric tons, troy ounces, and mmbtu.

D.4.10. usgs_unit

This information is taken from the United States Geological Survey (USGS). The variable describes the unit corresponding to the US prices of the respective mineral or resource. Prices are expressed in metric tons.

D.4.11. multicolour_unit

This is information is taken from Multicolour. The variable describes the unit corresponding to the world price of the respective mineral or resource. All Multicolour prices are given in carats. For more inquiries on Multicolour prices, please contact David Weinberg at Multicolour: info@multicolour.com.

D.4.12. APIforoil

Table D3: API Gravity to Density Conversions

API Gravity Measure	**Corresponding Density (kg/m^3)**
20	933.993
25	904.152
30	876.161
35	849.850
40	825.073
45	800.8

This information refers to the American Petroleum Institute (API) gravity measure for oil/petroleum or products thereof. It is the industry standard for expressing density, as compared to the density of water. Higher API gravities entail lower densities, which in turn return higher prices on commodity spot markets. When oil has a lower API gravity/higher density, yielding a heavier 42-gallon oil barrel/drum, it requires additional processing steps to make the oil usable.

Table D3 provides the densities in kg/m^3 corresponding to the API gravity measures for a sample of API gravities used in this dataset. The data availability for API gravity based on oil field assays is limited. Thus, when we were unable to find the API gravity each oil field, we approximated the API gravities by country based on information here, here, here, here, here, other websites, and:

Awadh, Salih Muhammed, and HebaSadoon Al-Mimar. 2013. "Statistical Analysis of the

Relations between API, Specific Gravity, and Sulfur Content in the Universal Crude Oil." *International Journal of Science and Research* 4(5): 1279-1284.

D.4.13. SGforoil

This variable pertains to the specific gravity of oil/petroleum and products thereof. The specific gravity can be calculated as follows:

$Specific\ Gravity = 141.5/(131.5 + API\ Gravity)$

D.4.14. density

This information refers to the density of variables for which output data is expressed in terms of mass but price data is given in volume or heat content—or vice-versa. Table D4 provides the relevant densities (kg/m^3) used in this dataset. Note that densities are only relevant when converting between mass, volume, or heat content units.

Table D4: Density by Resource

Resource	**Corresponding Density (kg/m^3)**
clay (bricks)	1900
gasoline	719.7
granite	2075
helium	147
limestone	2360
liquefied petroleum gas	550
liquefied natural gas	450
marble	2700
natural gas	0.8
oil	see Table D3
salt	1025
stone	2515

D.4.15. heat_content

This variable describes the heat content of certain resources in MMBtu/bbl. Refer to Table D5 for the resource for which it was necessary to have heat content information due to conversions between mass, volume, and heat content units. Heat contents by resource can be found on the website of the Society for Petroleum Engineers.

Table D5: Heat Content by Resource

Resource	**Heat Content (MMBtu/bbl)**
liquified natural gas	3.735
natural gas	3.735
oil/petroleum	5.8
petrochemicals	5.976
petroleum products	5.976

D.4.16. specific_surface_area

This variable corresponds to the specific surface area of stone, sandstone, granite, and marble in meters^2/grams. This variable is necessary for these minerals because USGS annual allocation capacity figures are expressed in square meters. We obtained data from the following resources:

- Keppert, Martin, Jaromir Zumar, Monika Cachova, Dana Konakova, Petr Svora, Zbysek Pavlik, Eva Vejmelkova, and Robert Cerny. 2016. "Water Vapor Diffusion and Adsorption of Sandstones." *Advances in Materials Science and Engineering* (2016). DOI:10.1155/2016/8039748
- Ticknor, Kenneth V., and Preet P.S. Saluja. 1990. "Determination of Surface Areas of Mineral Powders By Adsorption Capacity" *Clays and Clay Minerals* (38)4: 437-441.

D.4.17. locationname

This information is taken from United States Geological Survey (USGS). The location information describes the closest available city, town, or point of interest to the mine or resource extraction site.

D.4.18. mineownership

This information comes from United States Geological Survey (USGS). The following different types of mines are available in the data: artisanal, artisanal/military, cooperative, cooperative/industrial, industrial, industrial/government, and government. When ownership information is not available, it has been listed as "n/a". The mixed categories with more than one type of owner are for instances in which there is more than one owner and neither owns a majority stake (i.e. greater than 50%). When any one of the above owns more than a 50% stake, it is classified as only one of the above categories.

D.4.19. minetype

This variable denotes whether the site is a mine, other extraction site, refinery, or downstream plant/processing facility. Coders consulted a variety of sources to determine the minetype, including the USGS country reports, Internet searches, specialized publications, and remote sensing images of the location.

We define these values as follows:

1. Mines are generally related to ores and minerals. They can be underground, or aboveground in the case of strip-mining.

2. Extraction sites cover a broader scope, and includes gas and oil. This minetype value also river deposits of commodities such as diamonds or gold.

3. Production facilities are locations which smelt or produce a commodity, rather than

extract it. Cement and steel are examples, as well as anything specified as a "metal" or a product of some process.

4. Refineries are generally only put as a minetype if it is specifically referred to as such in the USGS .pdf. An example of this would be "Petroleum: Refined", rather than the usual "Petroleum" or "Petroleum: Crude". We apply the same process to metals.

5. The Unknown minetype exists in the event that no minetype can be identified.

D.4.20. admin1

This information is taken from GeoNames (www.geonames.org) or Google Maps on the basis of the location name from USGS. This information corresponds to the administrative level 1 precision code. Generally, it corresponds to a province/department/state.

D.4.21. admin2

This information is taken from GeoNames (www.geonames.org) or Google Maps on the basis of the location name from USGS. This information corresponds to the administrative level 2 precision code. Generally, it corresponds to a district/municipality.

D.4.22. latitude

This information is taken from GeoNames (www.geonames.org) or Google Maps on the basis of the location name from USGS. In instances where there are multiple location names that match the USGS description, the coder arbitrates between the locations given clues on the USGS document, such as province information given by USGS. Further, geonames provides aerial shots of the location, which can be used to pinpoint a probable mine location.

D.4.23. longtitude

This information is taken from GeoNames (www.geonames.org) or Google Maps on the basis of the location name from USGS. In instances where there are multiple location names that match the USGS description, the coder arbitrates between the locations given clues on the USGS document, such as province information given by USGS. Further, geonames provides aerial shots of the location, which can be used to pinpoint a probable mine location.

D.4.24. precisioncode

This information is derived from GeoNames (www.geonames.org) or Google Maps on the basis of the location name from USGS. We use the following precision codes:

- 1: Mine/production facility itself
- 2: Nearby city
- 3: District level
- 4: Province
- 9: Unsure if location is correct

D.4.25. comtrade_price_mult

This variables corresponds to the UN Comtrade export price of the resource, expressed in its standard measure output unit (see above). Thus, prices are available for specific resources and years but also each respective country. All prices are deflated to represent their 2010 United States dollar value. To access the deflators, refer to the World Bank's World Development Indicators.

D.4.26. wb_price_mult

This variables corresponds to the World Bank price for the resource, expressed in its standard measure unit (see above). All prices, which are world prices, are deflated to represent their 2010 United States dollar value. To access the deflators, refer to the World Bank's World Development Indicators.

D.4.27. usgs_price_mult

This variables corresponds to the USGS for the resource, expressed in its standard measure unit (see above). All prices, which are world prices, are deflated to represent their 2010 United States dollar value. To access the deflators, refer to the World Bank's World Development Indicators.

Kindly also note the following:

1. We merge antimony and antimony ore into one antimony price variable. There are few antimony ore observations in our dataset, and pure antimony is a very rare in occurrence. So, it is logical to use one price for antimony.
2. We merge boron and boron refined concentrates into one boron price. There are few boron observations in the dataset.

D.4.28. multicolour_price_mult

This variable corresponds to the Multicolour price for the resource, expressed in its standard measure unit. All prices, which are world prices, are deflated to represent their 2010 United States dollar value. To access the deflators, refer to the World Bank's World Development Indicators. For all information regarding Multicolour, please contact David Weinberg: info@multicolour.com

Kindly also note the following:

1. We merge bi-color tourmaline with chrome tourmaline into one tourmaline price. Often, it is possible to find tourmalines of different colors in the same mines.

2. We merge color change sapphire, fancy sapphire, and sapphire into one sapphire price. It is possible to find sapphires of different colors in the same mine.

3. We merge grossular garnet, tsavorite, color change garnet, and garnet into one garnet price. Garnets of different colors can be found in the same mine.

4. We merge chrysocolla quartz, rose quartz, rutilated quartz, and quartz into one quartz price.

D.4.29. multiplier_comtrade

This variable corresponds to the multiplier used for the conversion of the UN Comtrade price unit conversion into the standard measure unit.

D.4.30. multiplier_wb

This variable corresponds to the multiplier used for the conversion of the World Bank price unit conversion into the standard measure unit.

D.4.31. multiplier_usgs

This variable corresponds to the multiplier used for the conversion of the United States Geological Service (USGS) price unit conversion into the standard measure unit.

D.4.32. multiplier_multicolour

This variable corresponds to the multiplier used for the conversion of the USGS or World Bank price unit conversion into the standard measure unit.

D.4.33. annualallocationcapacity

This information is taken from United States Geological Survey (USGS). It measures yearly output of the mine or resource extraction site in the standard measure unit.

D.4.34. exp_annual_value_location1

This variable accounts for annual value of the location in 2010 United States Dollars (USD). This measure of the annual value of the location prioritizes UN Comtrade export prices first. Then, it incorporates prices from the World Bank, followed by those of the USGS. The variable excludes prices from Multicolour.

A few reasons underpin our rationale provide one set of prices without Multicolour values. First, not each resource-year in the Multicolour dataset has a high number of observations. Second, Multicolour sales tend to be a on a very small scale, with typical prices being at the gram or carat level. Accordingly, small fluctuations in the Multicolour prices per carat, which is normal given factors such as gem quality size, clarity, and color, can make a significant difference in the price. By contrast, the prices for most minerals from UN Comtrade, USGS, the World Bank tend to be aggregated at the kilogram, metric ton, or thousand metric ton levels, making them less prone changes from small fluctuations.

D.4.35. exp_annual_value_location2

This variable accounts for annual value of the location in 2010 United States Dollars (USD). This measure of the annual value of the location prioritizes UN Comtrade export prices first. Then, it incorporates world prices from World Bank, USGS, and Multicolour (in that order). The variable is calculated by multiplying the annual allocation capacity of the mine/resource extraction site by `export_price_first_mult2`.

D.4.36. wd_annual_value_location1

This variable accounts for annual value of the location in 2010 United States Dollars (USD). This measure of the annual value of the location prioritizes world prices from World Bank. Then, it incorporates US prices from USGS, followed by country-specific export prices from UN Comtrade. The variable excludes prices from Multicolour. The variable is calculated by multiplying the annual allocation capacity of the mine/resource extraction site by `world_price_first_mult1`.

A few reasons underpin our rationale provide one set of prices without Multicolour values. First, not each resource-year in the Multicolour dataset has a high number of observations. Second, Multicolour sales tend to be a on a very small scale, with typical prices being at the gram or carat level. Accordingly, small fluctuations in the Multicolour prices per gram or carat, which is normal given factors such as gem quality size, clarity, and color, can make a significant difference in the price. By contrast, the prices for most minerals from UN Comtrade, USGS, the World Bank tend to be aggregated at the kilogram, metric ton, or thousand metric ton levels, making them less prone to changes from small fluctuations.

D.4.37. wd_annual_value_location2

This variable accounts for annual value of the location in 2010 United States Dollars (USD). This measure of the annual value of the location prioritizes world prices from World Bank and US prices from USGS. Then, it incorporates export prices from UN Comtrade. The variables excludes prices from Multicolour. The variable is calculated by multiplying the annual allocation capacity of the mine/resource extraction site by `world_price_first_mult2`.

D.4.38. comtrade_value

This variable corresponds to the annual value of the location using only export prices from UN comtrade.

D.4.39. wb_value

This variable corresponds to the annual value of the location using only world prices from the World Bank's Global Economic Monitor Commodities Pink Sheet.

D.4.40. usgs_value

This variable corresponds to the annual value of the location using only US prices from the United States Geological Survey (USGS).

D.4.41. world_val_nomc

This variable corresponds to the the annual value of the location using world prices from the World Bank or US prices from USGS (in that order), excluding world prices from Multicolour. We include USGS prices alongside World Bank ones since, based our data,`wb_value` and `usgs_value` correlate at 0.99. That is even before logging the data, too.

D.4.42. world_val_withmc

This variable corresponds to the the annual value of the location using world prices from the World Bank, US prices from USGS or world prices from Multicolour (in that order). We include USGS prices alongside World Bank ones since, based our data, `wb_value` and `usgs_value` correlate at 0.99. That is even before logging the data, too.

D.4.43. lootable

This is a dummy variable indicating, based on our research, that the resource is potentially lootable. To be lootable, a resource must have high value and low barriers to entry/extraction. We say "potentially" lootable because certain types of resources can be found in different extraction sites, and some of these extraction sites make it easier to extract than others. For example, gold may be mined through placer techniques, which can be done by most anyone. By the same token, gold can also be mined through the use of expensive dredging or digging machinery. Even though not everyone has access to the expensive machinery, the fact that almost anyone can mine gold through placer techniques makes the resource "lootable" for the purposes of this dataset.

D.5. Resource Price Data Availability

Table D6 provides the availability of prices used in this dataset by resource. In cases when there are prices from more than one source by variable, refer to Section D.3 for how we calculate the respective prices.

Table D6: Source of Resource Prices

Resource	UN Comtrade	World Bank	USGS	Multicolour
alumina	X		X	
aluminum	X	X	X	
aluminum floride	X			
amazonite				
amber				
amethyst				X
ametrine				X
ammonia	X			
ammonium nitrate				
andalusite	X			X
anhydrite	X			
antimony	X		X	
antimony trioxide	X			

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	UN Comtrade	World Bank	USGS	Multicolour
apatite				X
aquamarine				X
arsenic	X			
arsenic trioxide				
asbestos	X		X	
asphalt	X			
attapulgite				.
barite	X		X	
basalt	X			
bauxite	X		X	
bentonite	X		X	
beryl				X
beryl and emerald				
beryllium	.		X	
bismuth	X		X	
black carbon	X			
borax				
boron	X		X	
bromine	X		X	
cadmium	X		X	
calcite				
calcium carbonate	X			
calcium oxide				
carbon dioxide	X			

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	**UN Comtrade**	**World Bank**	**USGS**	**Multicolour**
caustic soda	X			
celestite				
cement			X	
chlorine				
chromite	X			
chromite ferrochomium				
chromium	X		X	
citrine				X
clay	X		X	
coal	X	X		
cobalt	X		X	
coke				
copper	X	X	X	
copper sulfate				
diamond	X		X	X
diatomite	X		X	
diesel				
dolomite	X			
emerald	X			X
feldspar	X		X	X
ferro-chromium	X			
ferro-manganese	X			
ferro-molybdenum	X			
ferro-nickel	X			

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	**UN Comtrade**	**World Bank**	**USGS**	**Multicolour**
ferro-silicon	X			
ferro-vanadium				
ferroalloys	X			
fertilizer				
fluorspar	X		X	
gallium	X		X	
garnet	X		X	X
gasoline	X			
gemstones	X		X	
germanium			X	
glass				
gold	X	X	X	
granite	X			
graphite			X	
guano				
gypsum	X		X	
helium			X	
indium	X		X	
iodine	X		X	
iron	X	X		
iron and steel			X	
iron oxides		.	X	
iron pyrites	X			
kaolin	X		X	

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	**UN Comtrade**	**World Bank**	**USGS**	**Multicolour**
kerosene				
kyanite	X		X	X
labradorite				X
lapis	.			X
lead	X	X	X	
lignite	X			
lime	X		X	
limestone	X			
liquefied natural gas	X	X		
liquefied petroleum gas	X			
lithium			X	
lithium carbonate				
lithium chloride				
lithium hydroxide	X			
magnesite	X			
magnesium	X		X	
manganese	X		X	
marble	X			
mercury	X		X	
methane				
methanol	X			
mica	X		X	
molybdenum oxide	X			
morganite	.			X

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	UN Comtrade	World Bank	USGS	Multicolour
naphtha				
natural gas	X			
nickel	X	X	X	
niobium	X		X	
niobium and tant	X			
nitrates	X			
nitrogen	X		X	
nitrogen ammonia				
nitrogen urea				
oil	X	X		
onyx				
opal				X
palladium	X			
peat	X		X	
perlite	X		X	
petroleum products	X			
phosphate	X	X	X	
phosphoric acid	X			
phosphorite				
platinum	X	X	X	
potash				
potassium				
potassium chlorite				
potassium nitrate				

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	**UN Comtrade**	**World Bank**	**USGS**	**Multicolour**
potassium sulfate	X			
pozzolan				
pozzolana				
pumice			X	
pyrophyllite			X	
quartz	X		X	X
quartzite				
rare earths			X	
rebar				
rhenium	X		X	
rhodium	X			
rhyolite				
ruby	X			X
ruthenium	X			
salt	X		X	
sand	X			
sand and gravel	X		X	
sandstone	X			
sapphire	X			X
scoria				
selenium	X		X	
sepiolite				
silica	X			
silicomanganese				

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	UN Comtrade	World Bank	USGS	Multicolour
silicon	X		X	
silver	X	X	X	
soapstone				
soda ash	X		X	
sodium				
sodium nitrate	X			
sodium silicate				
sodium sulfate			X	
sodium tripolyphite	X			
steel			X	
stone	X		X	
strontium	X		X	
sulfur	X		X	
sulfuric acid	X			
synthetic fuels				
talc	X		X	
tantalite				
tantalum	X		X	
tanzanite				X
tellurium	X		X	
tin	X	X	X	
titanium			X	
titanium oxide				
tourmaline				X

Continued on next page

Table D6 : Source of Resource Prices – *continued*

Resource	**UN Comtrade**	**World Bank**	**USGS**	**Multicolour**
travertine				
tuff				
tungsten	X		X	
tungsten anhydrite				
turquoise				X
uranium	X			
urea	X	X		
vanadium	X		X	
vanadium pentoxide	X			
vermiculite	X			
wolframite				
wollastonite			X	
zeolite				
zinc	X	X	X	
zircon				X
zirconium	X		X	