Natural Resources and Civil Conflict: Evidence From a New, Georeferenced Dataset *

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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 183 resources that adds many resource types, locations, countries, and local price data from Africa, the Middle East, Asia and Latin America. 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 local price data, which is more relevant for conflict dynamics. Because local prices can be endogenous to conflict, we instrument local prices using U.S. and global 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 only for African countries.

1. Introduction

Over the last two decades, social scientists have investigated the "resource curse"—the proposition that an an abundance of non-renewable natural resources has negative political, social, and economic consequences (for a recent and thorough review, see Ross (2015)). Much of this work has focused on links between resources and violent conflict at the country level (De Soysa, 2002; Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Ross, 2004, 2012; Humphreys, 2005; Ross, 2006; Cotet and Tsui, 2013; Bazzi and Blattman, 2014; Lei and Michaels, 2014; Esteban, Morelli and Rohner, 2015; Paine, 2016; Menaldo, 2016). The role of petroleum wealth in fomenting conflict has received the most attention because it is the most valuable commodity at the global level (Ross, 2012) and because of the availability of data measuring national petroleum production and reserves at the national level. This has led some to conclude that the "resource curse" is, at the national level, really an oil curse (Ross, 2012), and studies of multiple resources have found few links between countries' overall resource wealth and conflict (Bazzi and Blattman, 2014) or that the link between resources and conflict is likely moderated by geographic and political factors (O'Brochta, 2019).

More recent research on the resource curse has taken a decidedly micro turn (Nillesen and Bulte, 2014). One reason for this shift is the recognition that while petroleum may be the most valuable and widely-traded commodity at the global level, some countries are rich in other types of resources, such as diamonds or other minerals, that may promote violent conflict. Another reason is that many conflicts are essentially local in nature, leading to violence in specific regions while the rest of the country experiences little violent contention. For these reasons, 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." That is especially relevant for understanding local conflict dynamics, the incentives for national leaders to tolerate conflict that does not threaten their control over resource revenues (Koubi et al., 2014), and how resources influence succesionist

conflicts (Ross, 2012; Asal et al., 2015). Some studies draw on local data from individual countries to analyze how differences in resource endowments influence violence across localities (Aragón and Rud, 2013; Dube and Vargas, 2013; Mähler and Pierskalla, 2015; Maystadt et al., 2014; Sanchez de la Sierra, 2019). Another strand of research examines how profiting from resources by rebel groups influences conflict dynamics (Asal et al., 2015; Fearon, 2004; Conrad et al., 2019; Walsh et al., 2018).

More recent work has analyzed how resource wealth influences violence at the local level in multiple countries (Berman and Couttenier, 2016; Berman et al., 2017; Christensen, 2019), which promises to yield more general findings. However, this last approach faces significant data limitations; there is no non-proprietary dataset that provides local information about resource wealth for a wide range of resources across many countries. Balestri, Lujala, and their colleagues have developed such data for gold, diamonds, gemstones, and petroleum (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), but their coverage of non-renewable resources is limited.[1] Table 1 compares the dataset introduced in this paper, the Global Resources Dataset (GRD), to other open sources of data that contain spatial, subnational information on non-renewable natural resources and are frequently employed by researchers. The GRD contains information on far more resources than do the other data sources, and it provides more detail across the relevant dimensions than do other data sources. The GRD includes information for all countries in Africa and most countries in Latin America and Asia.[2] The spatial unit in the GRD is the point location (i.e. latitude and longitude) of the extraction or production site. Other data sources also provide geolo-

[1] 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.

[2] See Appendix C for a list of countries currently included in the GRD. In future work, we plan to extend the GRD to cover all countries in Africa, Asia, and Latin America. Since a key advantage of the GRD is that it allows research on subnational variation in resource endowments, we view the 103 countries included in the current version as sufficient for many analyses.

cation at this level of resolution, but they provide information on fewer resources than the GRD. Berman et al. (2017) and Harari and La Ferrara (2018) provide data at the grid cell level, which may be too highly aggregated for some research purposes. The GRD data is also time-varying, documenting both when production starts in a location and when it ends, and provides annual data on output, world prices, and local prices. These variables should be of particular value to conflict researchers, as changes in production, output, and prices might both cause and be influenced by nearby violent events.

Other researchers have made important contributions to the literature using proprietary data that measures local resource endowments across countries (Berman and Couttenier, 2016; Berman et al., 2017; Christensen, 2019). But these data sources are not widely available to researchers and still include only a small number of resources or are limited in the number of countries for which they contain data. Berman et al. (2017), for example, include fourteen minerals in sub-Saharan Africa. While the replication data for Berman et al. (2017) is available, it aggregates across multiple resources at the grid-cell level. This means that other researchers cannot use the data to identify the specific locations of resource extraction sites or disaggregate details within a grid-cell. Furthermore, many existing data sources lack information about world or local prices of the non-renewable resources they document. While world prices for many commodities are now available (Bazzi and Blattman, 2014), the absence of local prices is a potentially important omission, as the local value of a resource likely exerts a more powerful influence on conflict dynamics.

Table 1: Spatial Natural Resource Datasets

Dataset	Countries	Spatial Unit	Time-Varing	Output	World Prices	Local Prices	Resources
Global Resources Dataset	103	Point	Yes	Yes	Yes	Yes	183 resources
Berman et al. (2017)	52	Grid cell	Yes	Yes	Yes	No	14 resources
Harari and La Ferrara (2018)	46	Grid cell	Start only	No	No	No	85 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

The GRD provides information on a much larger number of resources, the location of their extraction and production, their output, and their local prices. The GRD includes resources that are overlooked in extant data sources, such as iron ore, stone, and phosphates, and it also includes resources that involve downstream refining and production such as petrochemicals, steel, and cement. In total, we collected information on 183 unique resources, of which we are able to collect price information for 87% of the resource-location-years.[3] To obtain these data, we coded detailed country reports from the United States Geological Survey (USGS) for countries or independent territories in Africa, the Middle East, and parts of South America and Southeast Asia.[4] Overall, the new subnationally geo-referenced dataset contains $8,534$ unique country-resource-locations and $42,597$ country-resource-location-years.

To demonstrate the value of this new data source, we examine how the collective value of resources in a given location correlates with the incidence of conflict. 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 a given location. In conducting this main analysis, we find mixed results. When examining sub-Saharan African countries only and using the Armed Conflict Location and Event Dataset (ACLED) and Georeferenced Event Dataset (GED) measures for conflict, as natural resource values increase in a given location, the likelihood of conflict incidence tends to increase. This is consistent with much of the work on sub-national resources and conflict, which has focused primarily on sub-Saharan Africa (Berman et al., 2017).

We then extend our analysis by using local price data, which can differ for each country, rather than relying on world prices. Using local prices is an improvement in key ways, especially because local prices are more relevant to actors on the ground. With that said, local prices are also likely endogenous to conflict dynamics, and as such require an identification strategy. Accordingly, we instrument local prices using U.S. prices, which should not be heavily dependent on local prices, as well as with world prices, though they are less indepen-

[3] The list of resources included in the GRD can be found in the Appendix C.
[4] The list of countries included in the GRD can be found in the Appendix C.

dent given that world prices are defined through the aggregation of local prices. The use of U.S. prices is not without challenges, especially given that spillovers and interdependence are likely, and could therefore may make the instrument weak, something we discuss at length in the manuscript. In extending the analysis to use U.S. and world prices as instruments for local prices, we find strong evidence that higher natural resource values increase conflict incidence primarily in African countries, but like the base models that result does not hold in global perspective.

The paper proceeds as follows: we first discuss the GRD, including information about the resource locations as well as price information. We then carry out an investigation of the effects of natural resource values on civil conflict. As part of this, we implement an instrumental variables strategy that uses U.S. and world prices to instrument for local prices, which enables us to address concerns about endogeneity. 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.

2. The Global Resources Dataset

This section provides an overview of the GRD.[5] The unit of analysis is individual natural resource extraction and production facilites in each year from 1994 to 2014. For each site, the dataset records the location, type of resource produced, output, and local and global prices. The dataset is based on annual narratives of the the minerals industries of most countries in the world produced by the National Minerals Information Center of the United States Geological Survey (USGS).[6] These country reports contain exhaustive entries for natural resource sites and production facilities around the world, their locations, names of the facilities, types of resources present, and the capacity of the site. We had multiple

[5] The dataset and codebook will be made publicly available. The codebook, which provides further details on our methods for collecting these data, appears in Appendix C.

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

coders read each of these reports and extract information into a machine-readable format.[7] The USGS country reports most often simply give the name of the facility or the city/general vicinity in which it is located. These facility-years are the unit of analysis for the dataset. We took this information and used the Geonames, Google Maps, and Mindat databases to identify the most precise longitude/latitude possible. We applied a "precision code" to denote how close the latitude/longitude recorded is to the exact location of the facility. We recorded a "1" when the exact site was within the above databases itself, with accompanying satellite imagery of the facility. We recorded a "2" when the most precise we could be was the city in which/near which the site was located. The vast majority of sites were these two levels of precision. Less precise measures include a "3" or a "4," where we could be no more precise than the district or province in which the site is located, respectively. These levels of precision locate the site at the geographical center of the respective administrative division. Similarly, when we are unsure of the location of the site altogether, we recorded a "9," which places the site at the geographical center of the country. However, less than 10% of entries in the USGS data were so vague as to prevent subnational geolocation and warrant a precision code of "9".

The dataset identifies 183 unique natural resources at these extraction/production facilities, of which 87% of the resource-location-years have price data. The extraction/production sites includes both "natural" resources such as diamonds, oil, and gold, as well as the sites that refine them and those that produce downstream products such as steel or fuel. This comprehensive documentation of extraction and production facilities provides users of the data with the flexibility to address a wide range of research questions about the resource curse. For example, researchers interested in "lootable resources" can define the characteristics that make a resource lootable, and filter relevant data from the GRD. Similarly, those with an interest in particular resources that have been linked to conflict, such as petroleum or

[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.

diamonds, or specific types of minerals, such as metals, can draw on the location, output, and price data available for these resources. The GRD also includes information regarding downstream refining and processing facilities, such as petroleum refineries and mineral processing plants. We have observed recent examples of rebel groups capturing such capital-intensive resources and profiting from their extraction and sale, so that their inclusion is a potentially important contribution to understanding how production facilities relate to conflict. Foremost among them is the Islamic State's capturing and exporting fuel from Syrian and Iraqi oil facilities, which according to some estimates earned the organization up to $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. Although some resources might be more easily "looted," such as gold, diamonds, or drugs, these examples show that all types of resources may generate local grievances and produce incentives to capture them.

While our data are similar in intent and precision to Lujala (2010) and Berman et al. (2017), our data are more expansive and cover a broader set of countries. First, our data include information on 183 resources, including tin, copper, cobalt, uranium, iron ore, and phosphate. 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. As we can see in the political tumult around some of these resources (phosphate in Morocco/Western Sahara and uranium in the Democratic Republic of the Congo, for instance) non-gemstones and non-hydrocarbons can play a significant role in local incentives and the political-economic structure of countries in a way that warrants analysis.

The USGS country reports also include estimates of annual output for each facility, which we include the GRD. For most of our locations, we identified annual production capacities for the years 2002–2014. For some locations, the data extend back to 1994.

While the inclusion of output marks an advance over existing open source natural resource datasets, researchers often want to estimate the value of such output, which requires price data. The GRD provides up to three prices for each natural resource. The first is the price of the resource in the United States (Matos, 2015). The second is the world price, obtained from the World Bank Economic Monitor (World Bank, 2018) and Multicolour.[8] The third is local prices obtained from United Nations Statistics Division (2018), which reports the export price of the resource. It contains prices specific not only to resources and years but also to each respective country. All price data are expressed in each resource's standard measurement unit, for which we then create multipliers so as to ensure congruence between outputs and prices.[9]

The USGS country reports also document the ownership structure of each facility, which some research has found influences the intensity of resource curse effects (Jones Luong and Weinthal, 2010). The following ownership structures are available in the data: artisanal, artisanal/military, cooperative, cooperative/industrial, industrial, industrial/government, and government. Unfortunately, sometimes ownership information is not available. Mixed categories exist for when there is more than one type of 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.

The following maps depicted in Figures 1, 2, 3, and 4 illustrate the distribution of the natural resources globally, regionally, and then for Colombia and the Democratic Republic of the Congo. The maps illustrate the substantially broader coverage of our Global Resources Dataset. Recall that existing work focuses almost entirely on sub-Saharan Africa, especially recent in-depth sub-national analyses (Berman et al., 2017; Christensen, 2019). The maps also illustrates the greater variation in resource types. While the primary resources are what researchers typically imagine, such as oil or gold, we track a variety of other resources such

[8] Multicolour is a Hong Kong-based auction house that provides pricing information on many resources that are not available in other datasets. Those wishing for these data may contact its owner, David Weinberg, via email: info@multicolour.com

[9] Refer to the Codebook in Appendix C for more details.

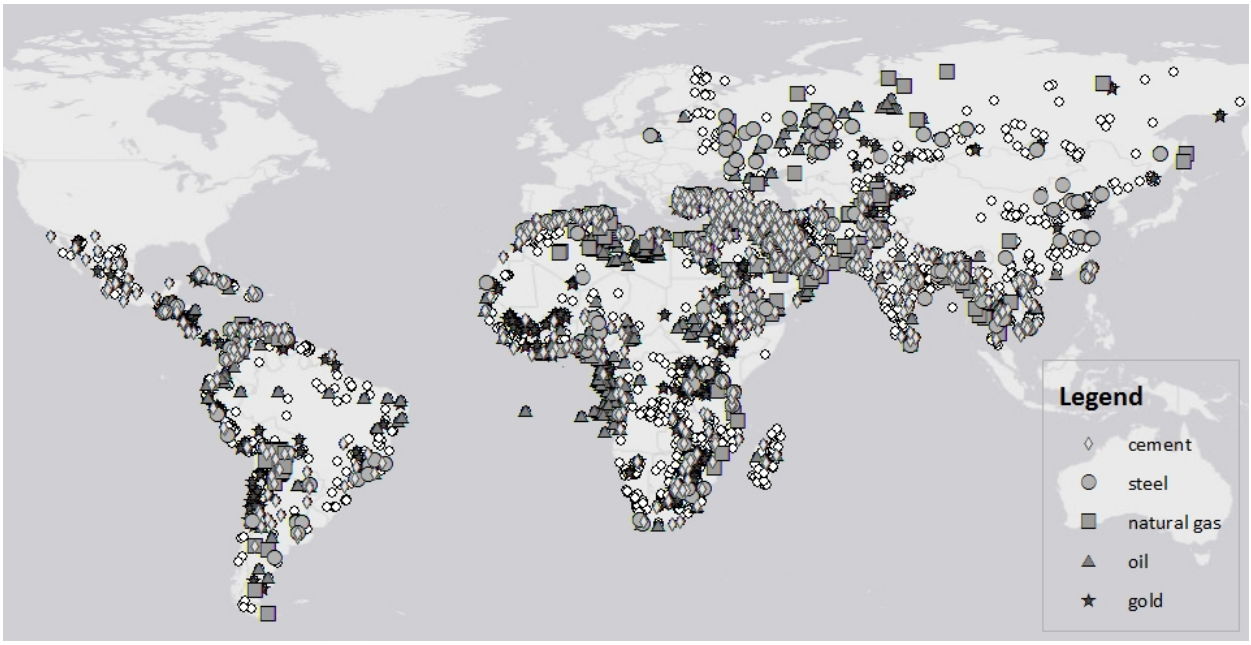

Figure 1: Natural Resource Locations Worldwide

as cement and steel, which involve downstream refining and production, but that have been tied to conflict dynamics in various ways.[10]

3. Research Design

We merged our new dataset based on spatial location in ArcGIS with the PRIO-GRID database (Tollefsen, Strand and Buhaug, 2012), which allows us to draw on that dataset's large number of covariates. 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."

We have coded all countries in sub-Saharan Africa as well as the Middle East and North Africa. Accordingly, we present the results for these two regions separately. We have coded an additional non-random set of Asian and Latin American countries. Because we do not

[10] We note again that the GRD covers all countries in sub-Saharan Africa, North Africa, and the Middle East. Although other areas may appear relatively complete, they are not yet finalized, although coding is in progress. Given the extensive coding protocols, other regions will not be complete for some time but will be made publicly available upon completion.

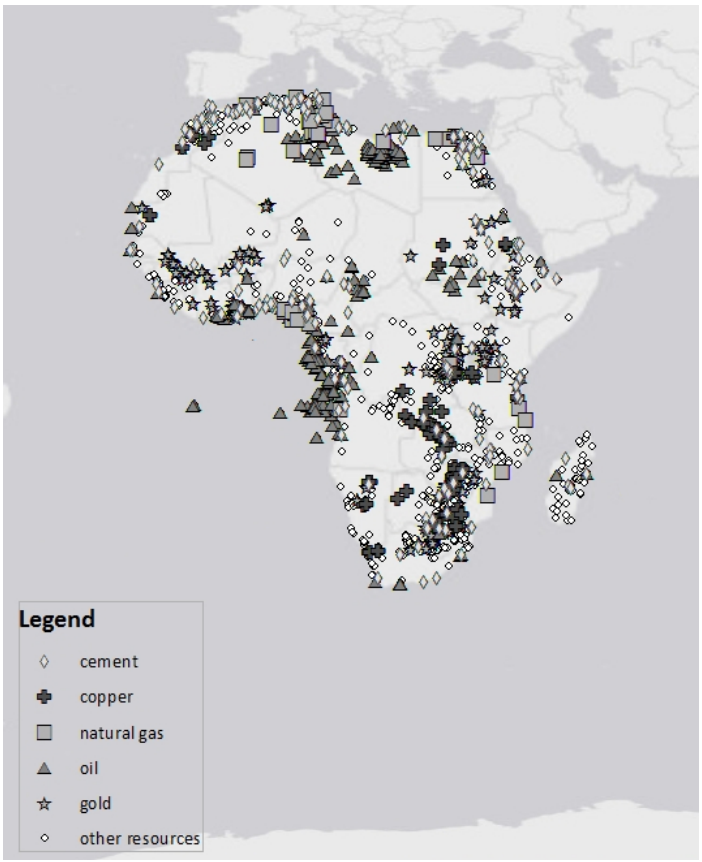

Figure 2: Natural Resource Locations Worldwide

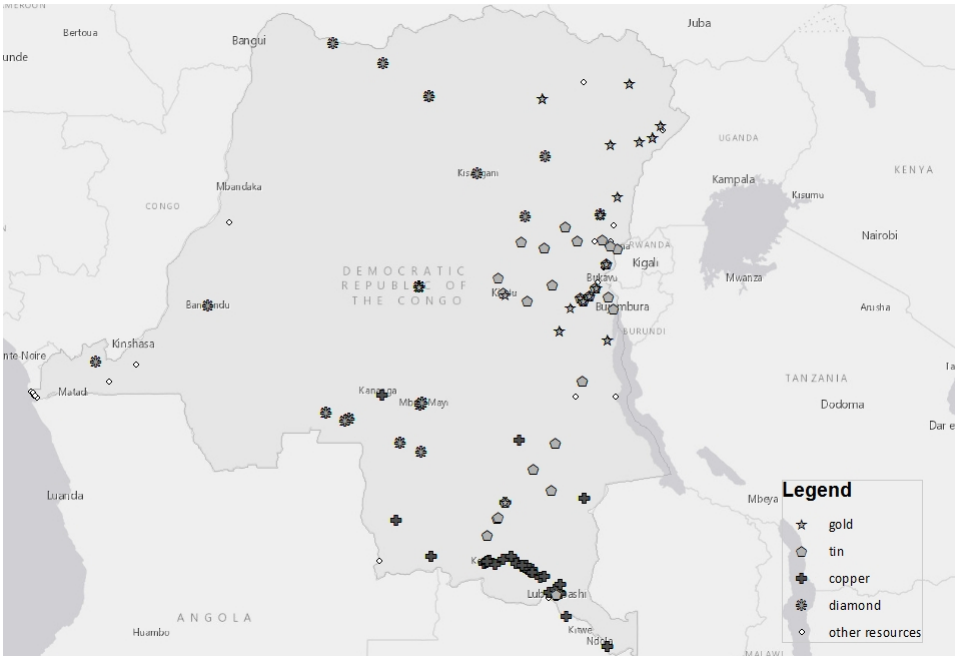

Figure 3: Natural Resource Locations in the DRC

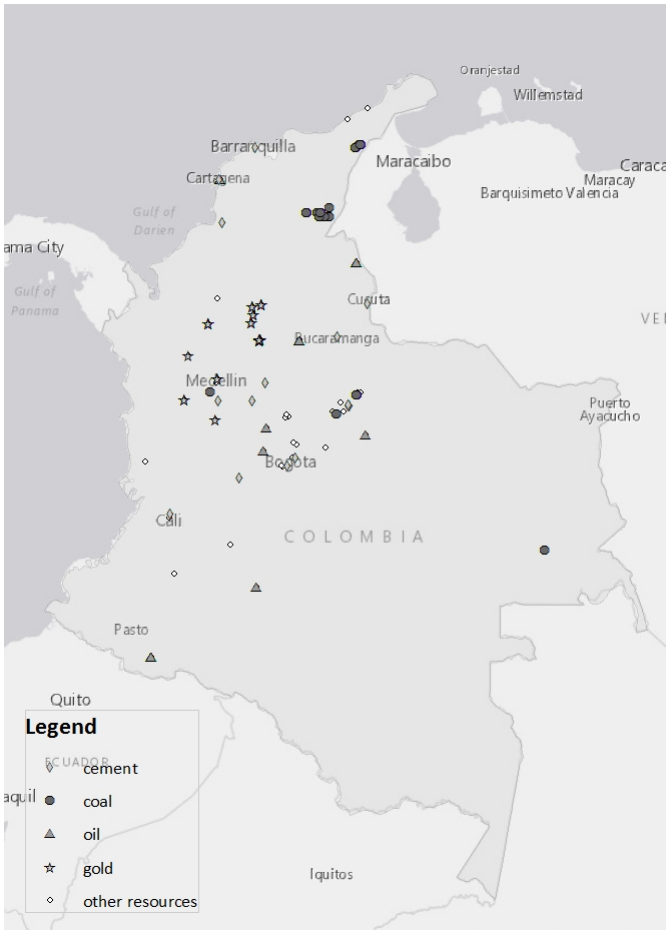

Figure 4: Natural Resource Locations in the Colombia

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 and Middle Eastern country models.

3.1. Variables: Response, Explanatory, and Controls

For our dependent variables, we employ measures of conflict from the Armed Conflict Location Events Dataset (ACLED), the dependent variable employed in Berman et al. (2017), and the Uppsala Conflict Data Program's Georeferenced Event Dataset (GED). In particular, we examine conflict incidence —a dummy capturing conflict incidence in a grid cell as recorded by each of these datasets (Raleigh et al., 2010; Sundberg and Melander, 2013).

Our primary explanatory variable is the overall value of the collective set of resources in a grid cell, represented in constant 2010 USD. One advantage of the GRD over many existing datasets is that it includes both output and price information for a wide range of resources, allowing us to calculate the total value of resources produced at a location in a year. This contrasts with existing studies that rely on dichotomous measures of the existence of a resource, or that include only price but not output information (Berman et al., 2017). Measuring the total value of resources produced at a location is important because existing theory would lead one to expect that changes in these values influence incentives for conflict.[11] 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. Given the dispersion in the resource values, we logged the data. And to address some of the challenges with contemporaneous

[11] 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.

measurement, we lagged the data by one year.[12]

We supplement this measure by using local values, which are likely more theoretically relevant for most theories of resources and conflict. The local 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 local 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 (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 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.

3.2. 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 similarly 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

[12] 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.

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 (Berman et al. (2017) use a similar approach).

3.3. Identification through Instrumental Variables

In our primary models, discussed above and reported below in Tables 2 and 3, we lag the natural resource price variable, which can be an important though not sufficient step towards avoiding endogeneity. As a next step, in this section we introduce an instrumental variables approach that allows us to include information on the local (export) prices of natural resources.[13] To do so, we use two-stage least squares to instrument local price values with U.S. price values and world price values.

3.3.1. Criteria to Satisfy for Instrument Validity

For any instrument to be valid, it must satisfy several criteria (Angrist, Imbens and Rubin, 1996). We first discuss the first-stage, monotonicity, and the stable unit treatment

[13] 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).

value (SUTVA) assumptions. Given that the ignorability/independence and the exclusion requirements require more explanations, we devote specific subsections to these topics.

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 (local values, D) and the instrument (U.S./world values, Z). In our case, log local values correlate with log World Bank values (used by Berman et al. (2017)) at 0.8, and log USGS values correlate with local values at 0.54.[14] Conventionally, instruments are thought to be strong if the F-statistic is above 12. In all of our models with control varaibles (other than for Asia), the F-statistic ranges from 29 to 225. In the Asia model, the F-statistic is 9. Accordingly, in most of the models the instrument is strong.[15]

Second, the instrument must satisfy the monotonicity assumption: $Pr(D_1 \geq D_0) = 1$ (Kern and Hainmueller, 2009). 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".[16] 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.

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)

[14] The figures in the footnoted sentence reflect grid-cell level correlations. At the spatial point level, log local values correlate with World Bank values at 0.88, and log USGS values correlate with log local values at 0.86.

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

[16] 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).

shows, natural resource extraction requires significant technology, capital, and investment.

3.3.2. Criterion 4: Exclusion Restriction

Fourth, the instrument needs to satify 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 U.S./world values (Z) are endogenous to local conflict (Y). On that score, 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 B). Rebels are generally thus not able to affect the global price at will. 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 local prices, so the exclusion restriction holds.

3.3.3. Criterion 5: Independence

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 local 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 local 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 an appropriate solution to the concerns about spatial interdependence.

4. 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 2.) We first report the results using the local resources values without and with controls (Models 1 and 2 respectively) and then using the instrumented local 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, including North Africa also using the ACLED dependent variable (Table 4). The results of all of these analyses are strong and show that natural resources

are positively associated with the incidence of conflict, a result that is consistent with past studies, especially the comprehensive Berman et al. (2017) study.

Table 2: Main Spatial HAC 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)	0.0046***	0.0029***		
	(0.0004)	(0.0004)		
Resources 1st Order Spatial Lag		0.0007***		0.0002
		(0.0002)		(0.0002)
Resources 2nd Order Spatial Lag		0.0001		0.0003**
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0191*		
		(0.0106)		
Number of Excluded Ethnic Groups		-0.0105***		-0.0065**
		(0.0036)		(0.0031)
Nighttime Lights		-0.8882***		0.6385***
		(0.1623)		(0.0666)
V-Dem Democracy Index		-0.4534		
		(181.3453)		
Spatially Lagged Conflict Measure		0.0417***		0.1021***
		(0.0023)		(0.0030)
Natural Resource Value w/ Instrumented Local Price			0.0178***	0.0093***
			(0.0013)	(0.0012)
Constant			0.0652***	0.0153***
			(0.0003)	(0.0028)
Observations	195128	170493	195128	170493
R^2	0.003	0.007		

Standard errors in parentheses

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

We are interested in the broader effects of natural resources on conflict, and because we have natural resource data for the entire Middle East as well as much of Asia and Latin America, we conduct a series of analyses slowly expanding out geographically. Unfortunately the ACLED data is 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 3 (compare to ACLED results in Table 2), and then extend out in successive analyses capturing Sub-Saharan Africa and North Africa (See Table 5 and compare to Table 4).

What is clear from these analyses using the UCDP measure is that the results found with the ACLED measure are no longer straightforward. In the main models, there are either null or negative relationships. And for the instrumented models, the results are inconsistent with the results negative in the models without controls, but positive for Sub-Saharan Africa using the instrumented local price model. Thus 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.

Everything about the setup of these models is identical to the earlier models save for the different operationalization of conflict, suggesting that natural resources may 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, such as ACLED capturing 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). In sum, 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 3).

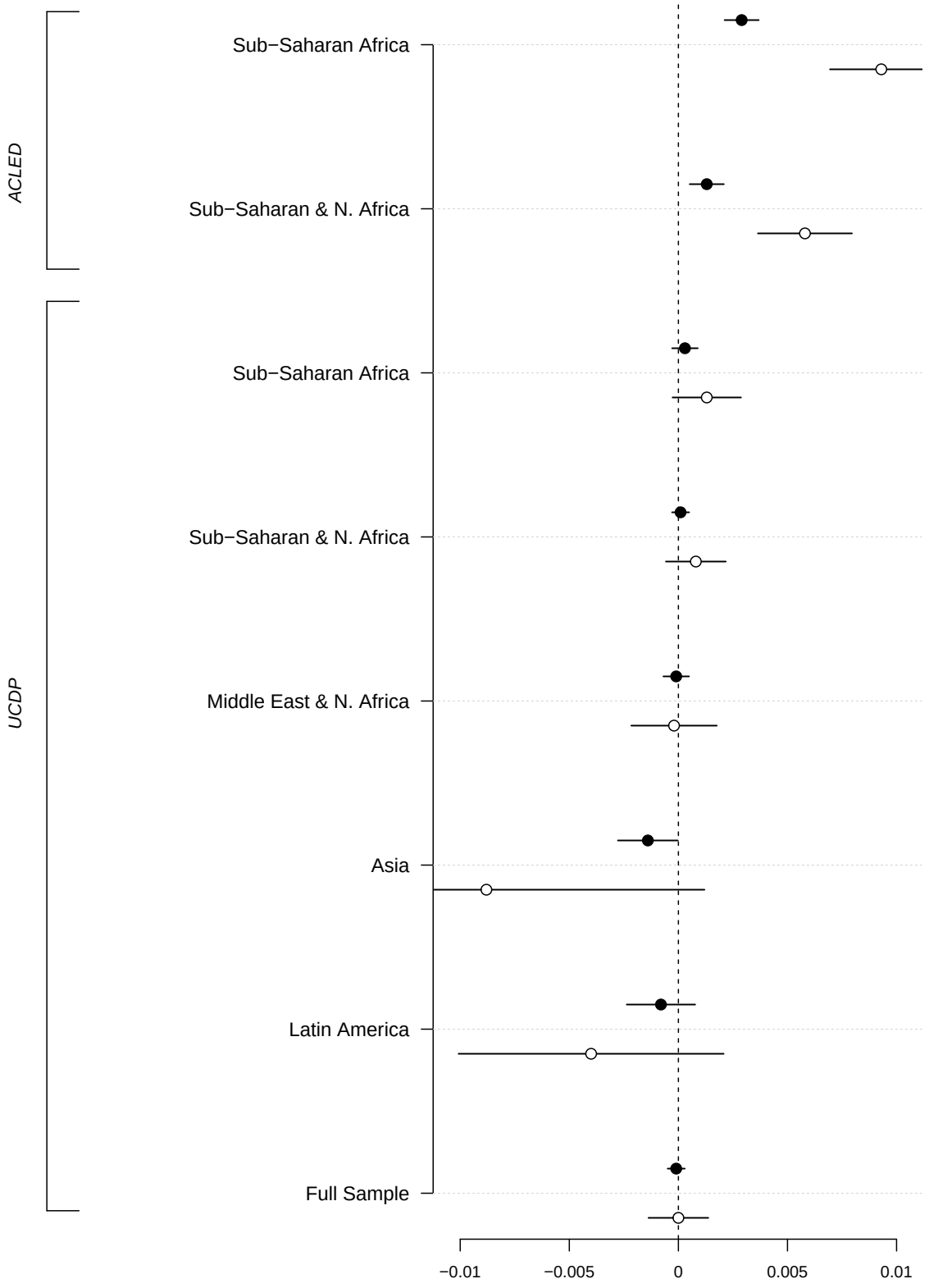

Figure 5: Results Across All Models. Solid dots represent base regression models with controls, but no instruments. The hollow dots represent the instrumental variable models.

Table 3: Main Spatial HAC 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)	-0.0004	0.0003		
	(0.0003)	(0.0003)		
Resources 1st Order Spatial Lag		0.0000		-0.0000
		(0.0001)		(0.0002)
Resources 2nd Order Spatial Lag		-0.0002		-0.0002*
		(0.0001)		(0.0001)
Presence of Lootable Resources		0.0103		
		(0.0083)		
Number of Excluded Ethnic Groups		0.0144***		0.0207***
		(0.0040)		(0.0034)
Nighttime Lights		0.1461		-0.0092
		(0.2217)		(0.0510)
V-Dem Democracy Index		-4.6966		
		(777.1070)		
Mean Population Density		0.0001		0.0000
		(0.0001)		(0.0001)
Spatially Lagged Conflict Measure		0.0163***		0.0279***
		(0.0019)		(0.0020)
Natural Resource Value w/ Instrumented Local Price			-0.0022***	0.0013*
			(0.0008)	(0.0008)
Constant			0.0410***	0.0237***
			(0.0002)	(0.0043)
Observations	195128	104380	195128	104380
R^2	0.000	0.002		

Standard errors in parentheses

Once we turn to the remaining UCDP models outside of the African context, the overall story becomes even more muddled. We now consider whether the results are similar (no effect) outside of Sub-Saharan African and North Africa when using the UCDP measure. Middle East and North Africa (See Table 6), Asia (See Table 7), Latin America (See Table 8), and then all countries globally that we have coded thus far (See Table 9). For purposes of interpretation, recall that we have coded the African continent and the Middle East in their entirety, but have only coded a non-random set of countries in Asia and Latin America.

Moving to the MENA region as well as the entire sample (also Table 6), all of which rely on the UCDP measure given ACLED is not available, resources are not significantly associated with conflict incidence, or in some cases are negatively associated. The story is similar for Asia and Latin America (Tables 7 and 8). 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 emerging narrative tying resources to conflict.

5. Conclusion

In this paper, we report on a new data set of 183 natural resources, geo-referenced across 103 countries. While the natural resource data could be used for many purposes, we used it here to examine its relationship to conflict. We carried out a basic set of models connecting natural resource value (using world prices) to conflict and show that in some cases, natural resources are positively correlated, though 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 local price data, instrumented with U.S. and world prices, in order to address endogeneity concerns. These results indicate for the ACLED outcome, but not the GED outcome, natural resources strongly and positively predict violence. The differences across these regions and measures of conflict suggest that

the relationship between local resource wealth and conflict is more complicated and heterogeneous than existing research, such as Berman et al. (2017), would suggest. Future research could profitably focus on developing more fine-grained explanations of the contextual factors that seem to lead to positive relationships between resource wealth and conflict at the local level.

While our empirical focus here has been 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 might be useful for understanding 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; the incidence of corruption; public goods provision (e.g. health, environmental protection); and voting behavior.

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