Concession Stands:
How Mining Investments Incite Protest in Africa*

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Abstract

Foreign investment in Africa's mineral resources has increased dramatically. This paper addresses three questions raised by this trend: do commercial mining investments increase the likelihood of social or armed conflict; if so, when are these disputes most prevalent; and, finally, what mechanisms help explain these conflicts? I show, first, that mining has contrasting effects on social and armed conflict: while the probability of protests or riots increases (roughly doubling) after mining starts, there is no increase in rebel activity. Second, I show that the probability of social conflict rises with plausibly exogenous increases in world commodity prices. Finally, I compile additional geo-spatial and survey data to explore potential mechanisms, including reporting bias, environmental harm, in-migration, inequality, and governance. Finding little evidence consistent with these accounts, I develop an explanation related to incomplete information — a common cause of conflict in industrial and international relations. This mechanism rationalizes why mining induces protest, why these conflicts are exacerbated by rising prices, and why transparency dampens the relationship between prices and protest.

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Foreign direct investment (FDI) to Africa now exceeds foreign aid flows, and much of that investment has been in extractive industries that aim to tap the region's mineral wealth (UNCTAD 2013b; The World Bank 2012). Whether this new investment represents a boon for, or impediment to, economic and political development is contested. On the one hand, Farole and Winkler (2014, 9) at the World Bank Group argue "that investment matters for economic growth ... [G]ains from FDI can materialize through increases in investment, employment, foreign exchange, and tax revenues." On the other, scholars working on the "resource curse" worry that heavy reliance on extractive industries handicaps manufacturing and other export-oriented sectors, undermines political accountability, and engenders civil conflict (see Ross 2015, for an recent review).

Motivated by this trend and ongoing debate, this paper addresses three questions: do commercial (non-oil) mining investments increase the likelihood of social or armed conflicts; if so, under what conditions do those disputes occur; and what mechanisms help to explain these conflicts?

Using geo-spatial, time-series data on the location of mines and incidence of conflict, I show that commercial mining investments have contrasting effects on social and armed conflict: the probability of a protest or riot more than doubles after mining (i.e., production) starts; yet, the probability of rebel events or deadly armed conflicts remains low and unchanged. Both my focus on protests and null finding with respect to armed conflict contrast with earlier work on the resource curse, which concentrates on how natural resources can motivate or sustain rebellions (e.g., Collier and Hoeffler 2002; Lujala et al. 2005; Dube and Vargas 2013; Berman et al. 2017).

Not all mining projects are met with protests, and the likelihood of social conflict varies over the life of a mine. I investigate what types of companies are more likely to face protests, and how this propensity changes with plausibly exogenous fluctuations in world commodity prices. Despite concerns about unscrupulous business practices among Chinese companies or corporations based in tax havens, I do not find that areas hosting investors from these countries experience a larger increase in the probability of protest. I do, however, find that projects partially owned by the host government do not face disputes. Second, I estimate the effect of changes in world commodity prices on the likelihood of protests or riots in mining areas. Consistent with recent empirical work (Berman et al. 2017), I find that these conflicts increase with prices.

Drawing on research into mining-related protests in Latin America (Bebbington et al. 2008; Bebbington and Williams 2008; Kopas and Urpaleinen 2016; Sexton 2017) and a more nascent literature in African politics

(Steinberg 2015), I explore a set of mechanisms that might explain these results. Compiling additional geospatial and survey data, I look for evidence that grievances related to environmental hazards, in-migration and displacement, economic inequality, or corruption drive the increased likelihood of protests around mining projects. Failing to find empirical support for these accounts, I develop an alternative explanation related to incomplete information — a well-known source of bargaining failures and common explanation for conflict in industrial and international relations (Kennan and Wilson 1993; Walter 2009). This explanation for conflict resonates with qualitative accounts from mining communities and can rationalize both why mining induces protest and why these conflicts are exacerbated by rising prices. In short, research by industry analysts indicates that mines' input costs increased alongside prices during the commodity boom, limiting the growth of profits. As these costs received less attention than sharply rising prices, host communities formed heightened expectations about what mines were worth and what they stood to gain. When companies refused to meet increased demands, protests resulted.[1] As further evidence in support of this explanation, I show that the positive relationship between prices and protest is dampened by policies, such as the Extractive Industries Transparency Initiative (EITI), that promote transparency and may help correct the informational problem that I argue generates protest.

This paper contributes to several debates in political economy. First, for the last twenty years, civil wars have rightfully topped the research agendas of scholars working on conflict in Africa (Fearon and Laitin 2003; Weinstein 2007; Roessler 2016). Yet, such wars have become less frequent: according to the Uppsala Conflict Data Program, the number of armed conflicts resulting in 100 or more battle-related deaths fell from over thirty in 1997 to five in 2007 and just two in 2010 (Melander and Sundberg 2012). While this is a positive development, it does not indicate an era of tranquility. The number of protests and riots doubled between 1997 and 2010 — what Branch and Mampilly (2015) dub a "third wave." This paper identifies one determinant of this increase in social conflict: mining areas make up just 0.3 percent of the rural population in Africa (localities with less than 100,000 people) but accounted for 22 percent of rural protests in 2009.

Second, research into the resource curse has similarly focused on whether and why natural resources, particularly oil and gas, provoke or sustain civil conflict (see Ross 2006; Brückner and Ciccone 2010; Bazzi

[1]This claim comports with several empirical studies of strike incidence in more developed countries, which find that industrial conflicts increase during high points in the business cycle (Harrison and Stewart 1994, 528).

and Blattman 2014, in addition to those cited earlier). I both qualify and extend this empirical literature. I find that commercial mines in Africa do not incite rebel activity in their immediate vicinity or in surrounding areas. While rebels may operate or extort small-scale and artisanal mines (e.g., de la Sierra 2014), the capital-intensive projects in my sample largely escape direct predation by armed groups. This result suggests that the scale at which natural resources are produced may condition their effects on conflict — a finding that echoes recent work arguing that production methods or ownership structures moderate the symptoms of the "resource curse" (e.g., Luong and Weinthal 2006; Andersen and Ross 2014). I show instead that these mining projects lead to social conflicts that have only recently started to garner academic attention (and primarily among Latin Americanists). While these protests are not as deadly as armed conflicts, they generate large economic losses: a widely-cited estimate from Davis and Franks (2014) claims that protests at major mining operations entail productivity losses of 20 million dollars per week and deter subsequent investment.

Third, much of the existing research on foreign investment focuses on its determinants, not its political or social consequences (e.g., Jensen 2008; Biglaiser et al. 2012). This literature emphasizes how hold-up problems deter investment to poorly institutionalized states. I make an empirical contribution by identifying the impact of one large set of foreign investment projects on conflict and a theoretical contribution by illustrating how informational asymmetries, like commitment problems, can strain investor-host relations.

Finally, by considering how communities use protests to bargain with firms, whether they target particular types of projects or owners, and the role of third-parties (like EITI) in preventing disputes, this paper addresses core questions from the "private politics" literature (Baron 2003; Baron and Diermeier 2007). This body of work examines how individuals, interest groups, and firms resolve value conflicts without reliance on the law. This is a salient question in many weakly institutionalized African countries, where commercial mining companies both outstrip the state's regulatory capacity and, at the same time, assume an out-sized societal role by providing infrastructure and public services in their host commununities. This study begins to correct the omission of these private politics, and the role of firms more generally, in studies of political and economic development in African countries.[2]

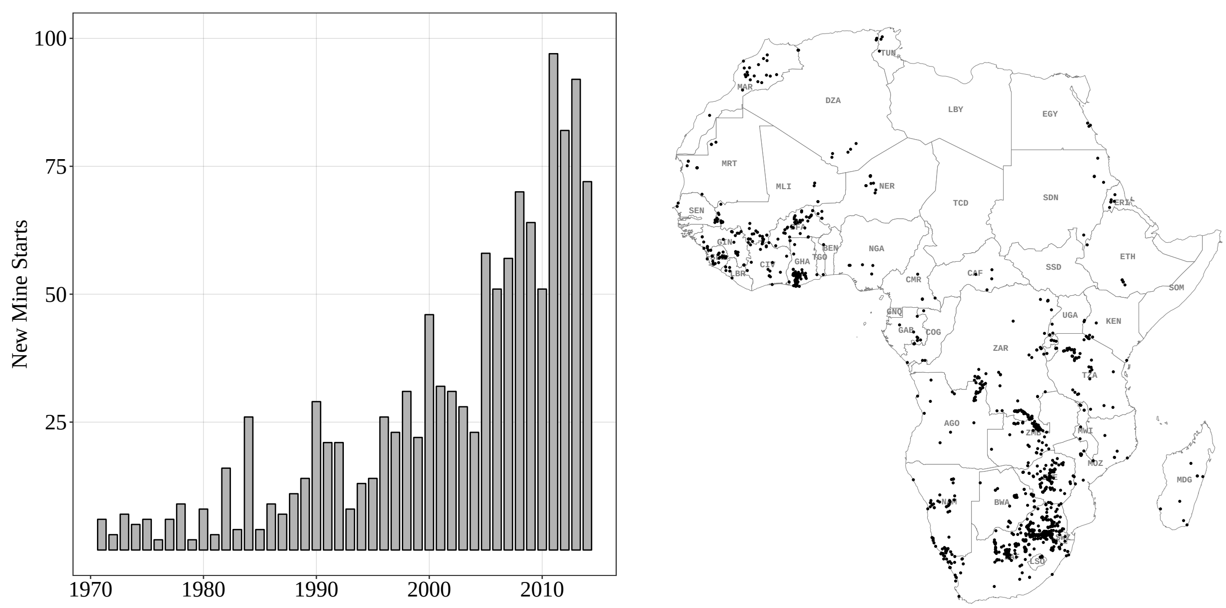
[2]A decade of reports on the Millennium Development Goals (2005-2015) use the words "firm", "company", "industry", and "corporation" (and their plurals) a total of 16 times; for comparison, "education" appears nearly 500 times. To my knowledge, Chris Blattman first noted this disparity.

1. Do mining projects cause conflict?

1.1 Is conflict around mines inevitable?

FDI in Africa has increased dramatically in the last three decades, going from almost nothing in 1980 to over 21 billion (in constant USD) in 2012 — 16 percent more than foreign aid from all countries and multilateral institutions to the region in that same year (UNCTAD 2013b; The World Bank 2012). Investments in extractive industries have propelled this upward trend (UNCTAD 2013a). As is apparent in figure 1, mining activity across the region has shot up: in 2011 alone more new mines were brought online than in the 1970s. Companies based in Australia, Canada, China, Switzerland, the UK, and the US own over half of all projects in Africa.

Figure 1: Frequency and Location of Mining Investments in Africa
Number of new mines opened annually triples between 1990 and 2010.



(a) Number of Annual Openings (b) Mine Locations

1(a) displays the number of mines opened (i.e., starting production) in every year from 1970-2014. 1(b) maps all unique mines with start dates. Data from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases.

These mining projects can benefit both investors and recipient communities. Companies receive access to exportable resources; communities, in return, enjoy increased development expenditure, employment, and land rents. Given the capital intensity of commercial mining, many communities — and even governments — in African states are unable to fully exploit their resource endowments. Allowing entry by foreign firms generates economic activity that would not otherwise occur (Farole and Winkler 2014, 9) — a win-win in theory if not in practice.

To establish and operate a mining concession, investors need to coordinate with governments to secure a mining license and deliver royalty or tax payments. Critically, they also need to negotiate with the community hosting their project. Goldstuck and Hughes (2010, 6) observe that "the most important and daunting challenge confronting any commercial mining operation is the securing of the support of local communities."[3] Between 2009-2013, the accounting firm Ernst & Young has included maintaining a "social license to operate" among the top risks facing the sector (Stevens et al. 2013, 23). To secure this social license, companies need to negotiate agreements with their host community, including how many workers will be employed and at what wage, compensation for resettlement, rents for land, or expenditure on infrastructure and public amenities (e.g., local clinics and schools).

Ideally, investors and their host communities amicably reach such agreements, and both parties share in any surplus generated by the project. Results from bargaining theory suggest that, if both the company and community know the project's surplus and each other's costs to delaying, then they should immediately settle on a mutually agreeable split of the pie (Osborne and Rubinstein 1990, 45). The community simply proposes a split that leaves the company indifferent between accepting today and counter-offering after some costly delay. This result holds even if the government first reduces the surplus through observable forms of taxation (e.g., license payments or royalties). Prior bargaining with the central government (and the payment of royalties and taxes) is not enough to induce conflict between the company and its host community.

In appendix E.1, I present a game of alternating offers played in continuous time between two informed parties: a community and a firm. The firm owns a mining project and is bargaining with its host community about how to split that project's profits. This complete-information game establishes the first-best outcome

[3]Community is a term of art in the sector: "[t]he *local* or *host* community is usually applied to those living in the immediate vicinity of an operation, being indigenous or non-indigenous people, who may have cultural affinity, claim, or direct ownership of an area in which a company has an interest" (qtd. in Evans and Kemp 2011, 1768).

— the deal that the firm and community conclude in the absence of any bargaining problems. In this idealized setting, firms and communities immediately agree on how to split the project's proceeds (with the more patient party retaining a larger share). Costly delays, such as protests, riots, or work stoppages, do not occur in equilibrium — firms and their host communities "bargain away" conflict (Fearon 1995).[4]

While this null hypothesis may strike some readers as pollyannish, it comports with earlier work, which found a null or negative relationship between foreign investment in mining and protest in poor countries (Rothgeb 1991).[5] For reasons specific to natural resource production, we might even expect to see fewer social conflicts in localities hosting mining projects. Rising mineral exports can increase exchange rates hurting other tradable sectors, a dynamic known as "Dutch Disease." If workers in the industries afflicted by Dutch Disease (e.g., manufacturing or agribusiness) protest in response to reduced employment or wage growth, then social conflict could increase outside of mining communities.

1.2 Do new mines raise the probability of social conflict?

Using a difference-in-differences design, I demonstrate that protests increase in localities receiving new investments, rejecting the hypotheses that mining has a null or negative effect on protest.

First, I combine information from three private repositories of mining data (IntierraRMG, SNL Metals and Mining, and Mining eTrack) to geo-locate unique commercial mining projects and determine their start years (Intierra RMG 2015; SNL Financial 2015; Global Data 2015). Second, I employ several datasets that geo-locate protests, riots, and other low-level social conflicts: the Armed Conflict, Location, and Event Project (ACLED); the Social Conflict in Africa Database (SCAD); the Global Database of Events, Language and Tone (GDELT); and the Integrated Crisis Early Warning System (ICEWS). I discuss the construction and limitations of these and other datasets in appendix F. To conserve space, I focus on results using the widely-cited ACLED data in the body of the paper (Raleigh et al. 2014). I replicate the paper's main results across the four datasets (appendix D).

[4] While I focus on mining, similar models have been used to characterize negotiations between labor and management across sectors and in more developed democracies (e.g., Kennan and Wilson 1993).

[5] Robertson and Teitelbaum (2011) find that FDI aggregated across sectors and industrial conflict positively covary across countries.

I merge data on mines and protests using a spatial grid with cells that measure 5 $\times$ 5 kilometers at the equator. Within relatively small grid cells (25 square kilometers is smaller than the median city size across Africa), I can more confidently attribute changes in social conflict to nearby mining activity. As a point of comparison, the commonly used PRIO grid uses cells that are 3,025 square kilometers at the equator; the entire US contains roughly 19,300 incorporated places (e.g., cities and towns) and 4,900 PRIO cells.

To recover the effect of mining activity on social conflict, I employ a difference-in-differences design. I compare the change in the probability of protest after mining in areas that receive projects to the change in areas that do not host new projects. I estimate this difference-in-differences using a panel model with cell (α_i) and year (δ_t) fixed effects, and a indicator (D_{it}) for whether a cell contains an active (i.e., producing) mine in a given year:

$$y_{it} = \alpha_i + \delta_t + \beta D_{it} + \varepsilon_{it} \tag{1}$$

I use an indicator for social conflict as the outcome: for the ACLED data, the dependent variable captures whether a protest or riot occurred in cell i in year t.[6] I cluster the standard errors on cell, but my inferences are robust to clustering on larger geographic units, including country.

In table 1, I find that the probability of protests or riots more than doubles after mining relative to the baseline probability of social conflict in those same cells. (The effect is orders of magnitude larger than the overall sample mean.) The levels alone are telling: in 2012 the probability of a protest across African cities with populations between 10,000 and 100,000 was 3.7 percent. By contrast, the median population in mining cells was less than 600 people; yet, the probability of protest was 4.2 percent.

In models 2-3, I modify equation 1 to demonstrate robustness. Model 2 includes country $\times$ year fixed effects, absorbing any country-specific shocks (e.g., national elections or currency fluctuations). Model 3 includes cell $\times$ period fixed effects, where periods are defined as the three six-year intervals in the study period. While I can not estimate unit-specific time trends for this many cells, this model flexibly accounts for cell-specific temporal variation. It should ameliorate concerns about cell-specific confounds that do not rapidly change within localities (e.g., slower-moving demographic variables).

[6] I sometimes refer to these events simply as protests; according to ACLED, riots are just a subset of protests involving violence.

Table 1: Effect of Mining Activity on the Pr(Protest or Riot)

	Dependent variable:						
	$\mathbb{1}$(Protest or Riot)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_{it}	0.01*	0.01*	0.005†	0.01*	0.01*		
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)		
P_{it} (Placebo)						0.001	0.001
						(0.001)	(0.002)
Cell FEs	1,500,538	1,500,538		66,014	18,771	1,500,189	18,422
Cell-Period FEs			4,501,614				
Year FEs	18		18				
Country-Year FEs		1,008				1,008	
Area-Year FEs				18,882	18,882		18,882
Mean(y_{it})	0.0003	0.0003	0.0003	0.0023	0.0035	0.0003	0.0025
Sample	Full	Full	Full	Border ≤ 5	Border ≤ 2	Full	Border ≤ 2
Observations	27,009,684	27,009,684	27,009,684	2,275,182	471,852	26,997,969	444,422

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-7: linear probability models per equation 1. The unit of analysis is the grid cell-year. Models 4-5, 7: see figure 3 for how border areas are defined. Models 6-7: P_{it} is a placebo indicator that turns on for a five-year period prior to mining. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from ACLED (see appendix F).

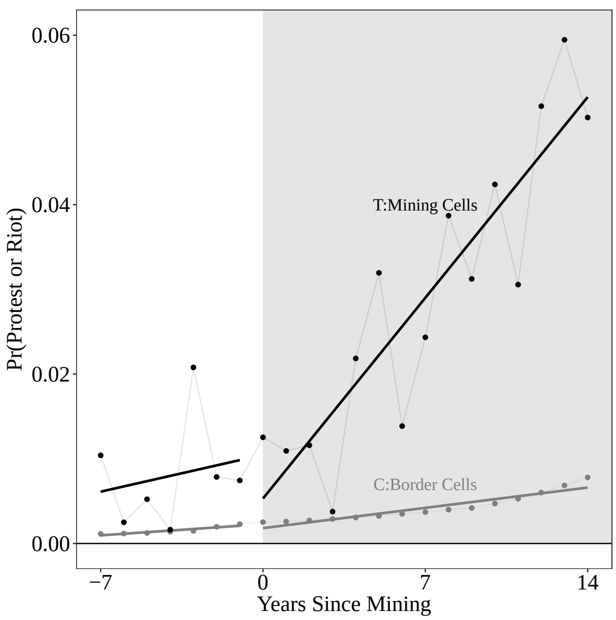
Models 4 and 5 restrict the control sample to areas that border mining cells (concentric squares as defined in figure 3) and, thus, likely contain ethnically similar populations exposed to common local economic trends (had mining never occurred). Model 5, for example, only contains cells that fall in the first two border regions, i.e., within 15 kilometers of a mine. These models include area $\times$ year fixed effects, which absorbs any shocks that affect a mine and its associated border area. Across these different model specifications, the difference-in-differences estimates remain consistent in magnitude and significant.

An identifying assumption for the difference-in-differences is that protest trends would have been parallel in mining and control cells absent mining.[7] While this assumption is untestable, it seems unlikely that companies are selecting into those communities experiencing escalating conflict. Rather, if companies try to

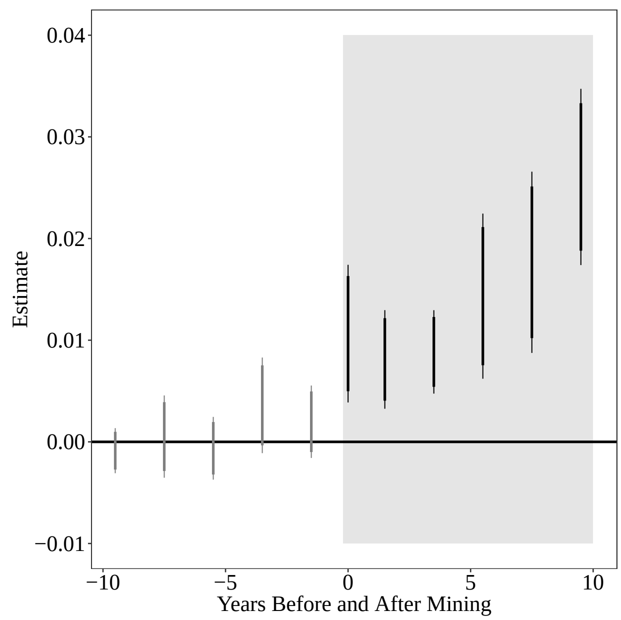
[7]I am not assuming the as-if random assignment of mines; mines are obviously endogenous to the presence and accessibility of minerals. However, these differences — and any other time-invariant characteristics of localities — will be absorbed by the cell fixed effects.

minimize political risk, they should seek out relatively docile communities, a selection process that pushes towards a null finding.

Figure 2: Social Conflict Trends in Mining and Control Areas
Protest increases after mining. Pre-trends bolster parallel-trends assumption.



(a) Parallel Trends



(b) Leads-Lags Plot

2(a) is an event-study plot that displays the probability of protest in the years before and after mining. The control group (grey) are cells in the first two border areas (i.e., within 15 kilometers of a mine). 2(b) displays the point estimates and 95% (and thicker 90%) confidence intervals for five two-year leads and lags of the treatment indicator.

A data-driven approach for assessing the parallel-trends assumption looks at pre-treatment trends. If treatment and control areas follow the same trajectory immediately prior to mines starting, this suggests that treated localities are not undergoing changes unrelated to mining (e.g., urbanization) that also increase their likelihood of protest. Figure 2 offers two ways of seeing that the likelihood of social conflict is not increasing at a greater rate in treated cells prior to mining. First, the event-study plot (left) shows that mining areas and their immediately bordering cells follow roughly similar linear trends in the seven years prior to mining. Only after mining starts do we see a large increase in the probability of protest in mining cells. Second, I estimate the change in the likelihood of protests or riots in mining and control areas in the ten years before and after mining starts. More technically, I plot (right) the 95 percent (and thicker 90 percent) confidence intervals for five (two-year) leads and lags of the treatment indicator (Autor 2003). Again, I find no evidence of anticipatory effects, bolstering the parallel trends assumption. Finally, in the last two columns of table 1, I report null results from "placebo tests" that recode treatment as the five-year period prior to the initiation of mining.[8] These checks all suggest that firms do not select into areas with escalating levels of social conflict.

1.3 Is the result due to reporting bias?

One concern with these results might be that mining invites more media attention, increasing the likelihood that conflicts receive coverage and, thus, appear in the ACLED data.[9] Four pieces of evidence cast doubt on reporting bias as an explanation for the findings presented above. First, using the GDELT data, another event dataset that records social conflicts, I calculate the average number of stories written about protests and the average number of media sources covering protests in each cell-year. Estimating equation 1 using these measures of media coverage as dependent variables, I find no increase in reporting resources with the start of mining (see table A.4). When protests occur they are not mentioned in more articles or covered by more sources if they occur in the vicinity of active projects. Second, it seems unlikely that media sources covering mining areas would not also report on events that occur in immediately surrounding border areas. In model 5 of table 1, I restrict the control sample to cells within 15 kilometers of mining cells and include area $\times$ year fixed effects. For reporting bias to confound this result, reporters would have to reallocate attention to protests in mining cells after production starts while simultaneously ignoring social conflicts that occur less than ten miles from those same places. Third, I find (below) no increase in armed conflicts recorded in ACLED. The upward bias implied by differential reporting is not apparent for other types of conflict in the ACLED data. Finally, the start of mining is typically proceeded by years of exploration activity (e.g., drilling and feasibility studies) and construction. If media attention increases with the announcement of a large investment, then that spike in interest occurs in the period prior to my treatment. Yet, figure 2(b) does not indicate the anticipation effects implied by such a story. While media-sourced event data always warrant caution, the ancillary data on reporting resources and the research design limit concerns about reporting bias.

[8] If a grid cell i receives a mine at time t, I code P_{it} as one for $t-6$ to $t-2$ (and missing thereafter). I then substitute P_{it} for D_{it} and reestimate the difference-in-differences.

[9] ACLED data is not only based on media, but incorporates three types of sources: "(1) more information from local, regional, national and continental media is reviewed daily; (2) consistent NGO reports are used to supplement media reporting in hard to access cases; (3) Africa-focused news reports and analyses are integrated to supplement daily media reporting" (Raleigh et al. 2014, 17).

1.4 Do new mines raise the probability of armed conflict?

Existing work on natural resources and conflict focuses not on protest or riots, but rather on armed conflict and rebellion (Collier and Hoeffler 2002; Dube and Vargas 2013; Berman et al. 2017). These papers offer a compelling logic: mines, particularly during periods of high prices, represent an attractive source of income for rebels and their campaigns.

Using a design and data similar to this paper, Berman et al. (2017) find that mineral price increases are associated with more conflict events in Africa between 1997 and 2010.[10] The authors do not insist on a particular mechanism, offering a more qualified conclusion: "It is likely that mineral extraction relaxes the financing constraints of rebels, because armed groups can sell minerals illicitly on the black market" (1601). In line with past research, they suggest that battles around mining sites likely represent attempts by rebel groups to seize or extort mines and use these operations to sustain or intensify their insurgencies (1566).

While Berman et al. (2017) focus on rebellion,[11] their dependent variable often includes different types of conflicts, involving actors that are not associated with rebel groups.[12] According to ACLED data, "rebel forces" are only involved in 26 percent of all events: 52 percent of battles, less than 20 percent of events involving violence against civilians, and less than 0.1 percent of protests and riots. Across all the cells with active mines in my data from 1997 to 2014, I count 67 events involving rebels forces and these take place in just 7 cells. A recent quote from the CEO of Randgold, a major mining company, echoes this descriptive finding: despite the civil war in Ivory Coast, coup in Mali, and rebellions in the Democratic Republic of Congo, he

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[10] The data used by Berman et al. (2017) differ in several respects: they rely on the IntierraRMG database, which includes only a subset of the projects in my sample; omit more recent years in the ACLED time-series; include prices for only 14 minerals; and perform their analysis at a much lower spatial resolution, cells that measure 55 x 55 km^2 at the equator.

[11] The authors reiterate the mechanisms reviewed in Bazzi and Blattman (2014), a paper concerned with civil wars and coups.

[12] ACLED event types include: (1) battle, no change of territory; (2) battle, non-state actors overtake territory; (3) battle, government regains territory; (4) headquarters or base established; (5) non-violent activity by a conflict actor; (6) riots/protests; (7) violence against civilians; (8) non-violent transfer of territory; (9) remote violence (Raleigh et al. 2014, 7-8).

says, "we've lived through them all. We've never — touch wood — had to stop operations" (Biesheuvel and Crowley 2015).

More systematically, when I estimate equation 1 using an indicator for events involving rebels, I find no effect of mining (see table A.1). I find a very small increase in the likelihood of battles in some models — considerably smaller than comparable panel results reported in Berman et al.'s (2017) table A.4 (model 4).[13] I also replicate these null findings using the Uppsala Conflict Data Program's (UCDP) Georeferenced Event Data (Melander and Sundberg 2012). An event in the UCDP data involves "the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death…" Whether I look at all events or just those involving at least 25 battle deaths, I estimate precise null results (see table A.2).

It could be that armed conflict events, as opposed to protests, occur slightly further from mining areas; by conducting my analysis at a finer spatial resolution, I could be missing battles slightly further from mine locations. To address this concern, I separately estimate the effects of mining on protests and riots, battles, and rebel events in the cell that contains the mine, as well as in the surrounding border areas. More technically, I estimate the difference-in-differences for six separate treatment groups, each defined by their proximity to an active mining project (see figure 3(a)). If $k \in \{0, 1, \ldots, 5\}$ indexes border areas (where $k = 0$ is the actual cell containing the mine), I define D_{it}^k as an indicator for whether cell i falls in area k and borders an *active* mine. I estimate:

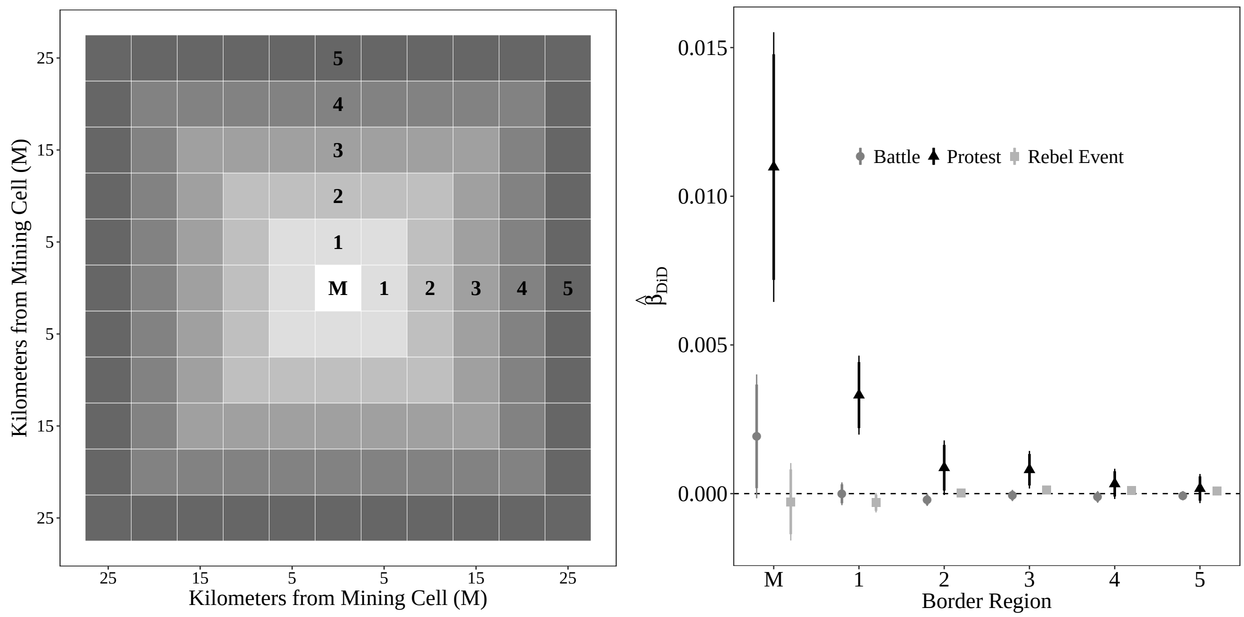
$$y_{it} = \alpha_i + \delta_t + \sum_{k=0}^{5} \beta_k D_{it}^k + \varepsilon_{it} \tag{2}$$

I then plot the estimates ($\widehat{\boldsymbol{\beta}}$) and associated confidence intervals for the three types of conflict in figure 3(b).

The start of mining does not increase the probability of rebel activity in the community hosting the mine or in border areas. There is a slight (insignificant) effect on the probability of a battle in the cell that contains

[13] These positive results shift with the exclusion of a few countries. Algeria, Côte d'Ivoire, and Tanzania collectively account for only 5 percent of cell-years with active mines. Dropping any two of these countries halves the result in table A.1 model 1, which loses significance; excluding all three attenuates the effect by an order of magnitude.

Figure 3: Contrasting Effects of Mining on Social and Armed Conflict
Mining investments increase social conflict locally, not battles or rebel attacks.



(a) Defining Border Areas (b) Effects of Mining on Social vs. Armed Conflict

3(a) defines border areas. 3(b) displays the estimates and 95% confidence intervals from equation 2 for different conflict outcomes: protests or riots (black), battles (medium gray), rebel events (lightest gray).

the mine, but no indication of such conflicts increasing in surrounding areas. In sharp contrast, we see a significant increase in protests and riots both in the cell that contains the mine, as well as in the immediately surrounding border area. This effect decays with distance: once we move 10 or more kilometers beyond the mining cell, the estimates approach zero, though they remain positively signed. This last finding suggests that geographic spillover attenuates my estimates in table 1; there is no indication that protesters are simply moving their demonstrations from nearby towns to mining sites.[14]

Separating rebel activity from protests clarifies the type of conflicts confronting commercial mines. I find no evidence that rebel groups attempt to forcibly seize these operations.[15] Yet, this does not imply that mining never contributes to armed conflict: work in Colombia on the FARC's illegal gold mining or on illegal

[14]This analysis also alleviates concerns about my choice of grid size; doubling the dimensions of the grid cells only increases the coefficient estimates.

[15]Dube and Vargas (2013) describe rebels in Colombia kidnapping politicians and attempting to raid government coffers. This violence could occur in provincial capitals, far from the mine site.

coltan mining by rebels in the Democratic Republic of the Congo demonstrate that some insurgent groups depend on revenues from small-scale mining (Jamasmie 2013; de la Sierra 2014). It may just be that how natural resources are produced conditions the extent to which mining generates armed conflict: while rebels fight for control of artisanal diamond pits, seizing and operating a commercial kimberlite mine may not represent a viable strategy for the same groups (see Ross 2004, on the "lootability" of different minerals). These contrasting findings call for research into variables, such as production scale, that condition the severity of the "resource curse."

2. When do mining projects cause social conflict?

This first set of results averages across sites and over the life of mines. Before considering why these conflicts occur, I first describe what types of companies are more likely to face protests and evaluate how this propensity changes with commodity prices. While this heterogeneity does not confirm a particular mechanism, it does help to winnow the set of plausible stories: if (as I find below) protests increase with commodity prices, then it seems unlikely that these conflicts reflect anger about layoffs and imminent mine closures.

2.1 Do owners' characteristics moderate the effect on social conflict?

Companies from Australia, Canada, South Africa, the UK, and US account for the bulk of mining investments. According to data from SNL Metals and Mining, companies from those five countries own over 75 percent of projects. Owners hailing from one of these countries are represented (i.e., own any share of a project) in over 65 percent of mining cell-years.[16]

While the Chinese own a comparatively small stake — less than two percent of all projects with ownership information in the SNL data — they have received special attention. Journalistic accounts have described a "clash of cultures" between Chinese investors and their employees, which have led to a proliferation of conflicts in Chinese mines (Okeowo 2013). Haglund's (2008) case study of Zambia articulates a concern that has motivated a burgeoning literature on Chinese investments in Africa: "certain corporate governance features prevalent among Chinese investors," he argues, "combined with the already weak regulatory frameworks of many African countries, risk undermining host country regulation and by extension sustainable development" (see Brautigam 2009, ch. 11 for a broader, more auspicious overview). These concerns are not confined

[16] Owners' country of origin is missing for 9 percent of treated observations.

to Chinese-owned mines: a number of owners are headquartered in countries like the British Virgin Islands and Bermuda, which are known less for their mining sectors than their lax business regulations.

Table A.5 first explores (models 1-2) whether we see a heightened probability of protest in mining cells where a project is partially owned by a Chinese company.[17] While the sign on the interaction term is positive, the coefficient is both substantively small and cannot be distinguished from zero. This is not a well-powered test given Chinese companies' relatively small stake in African mining operations. That said, this small share serves to qualify claims about the scope of potential problems related to Chinese mines. Second, I see no indication that mining cells with owners based in tax havens experience a larger uptick in social conflict (models 3-4).[18] If owners based in China or tax havens have distinct corporate governance practices, these do not seem to exacerbate the likelihood of protests after mining starts. This is not a well-identified test, and it could still be the case that such companies select into more conflictual business environments; even so, different risk profiles do not imply that their business practices exacerbate protest activity.

Finally, I find that partial government ownership within a mining cell (which occurs in under 20 percent of treated observations) eliminates the effect of mining starts on protest (models 5-6).[19] While it is tempting to conclude that exclusively foreign investment provokes conflict, this heterogeneity does not permit a clear interpretation: government may only invest in the most lucrative projects (and thus be able to buy off would-be protesters) or may be protected by the repressive capacity of the state.[20] Steinberg (2015), for example, develops a formal model where governments threaten repression to protect mines and, thus, maintain streams of royalty and tax revenues. It seems plausible that an ownership stake would only amplify governments' concerns about protests interrupting production.

[17] By construction, it is not possible for $\mathbb{1}(\text{China})_{it}$, $\mathbb{1}(\text{Tax Haven})_{it}$, or $\mathbb{1}(\text{Government})_{it}$ to be one when D_{it} is zero. Thus, this term is not separately estimated.

[18] I classify the following countries as tax havens: Bahamas, Barbados, Bermuda, British Virgin Islands, Cayman Islands, Cyprus, Ireland, Luxembourg, Netherlands, Netherlands Antilles, Singapore, Switzerland.

[19] Government ownership is coded using company names, which is available for a smaller number of mines than information on owners' country of origin. Hence, the smaller number of observations in models 5-6.

[20] This finding comports with Berman et al. (2017), who find that the impact of commodity prices on ACLED conflicts attenuates with the share of domestically owned public firms in an area.

2.2 Do changes in commodity prices affect social conflict?

In addition to bolstering the parallel-trends assumption, figure 2 indicates that the probability of protest varies over the life of a mine. Figure 2 suggests that exploration and construction activities (and the associated inflow of workers) that precede the start of actual mining do not increase the likelihood of protests. Moreover, conflict is not concentrated in the first years of production, suggesting that retrenchment to steady-state employment levels — mines typically require much larger workforces during their construction phases — is not the principal cause of disputes.

One measurable, and plausibly exogenous, variable that changes over the course of operations is the world price of the mineral being mined. To explore the relationship between price changes and protest, I compile real unit prices for over 90 unique minerals from the World Bank, US Geologic Survey, and US Energy Information Administration up to 2013. As is apparent in figure 4(a), the prices of several commodities increased dramatically between 1990 and 2013: iron and gold tripled, and platinum more than doubled. Yet, this commodity boom or "super cycle" was not uniform across commodities: bauxite, cobalt, gemstones, and zinc all declined in real value.

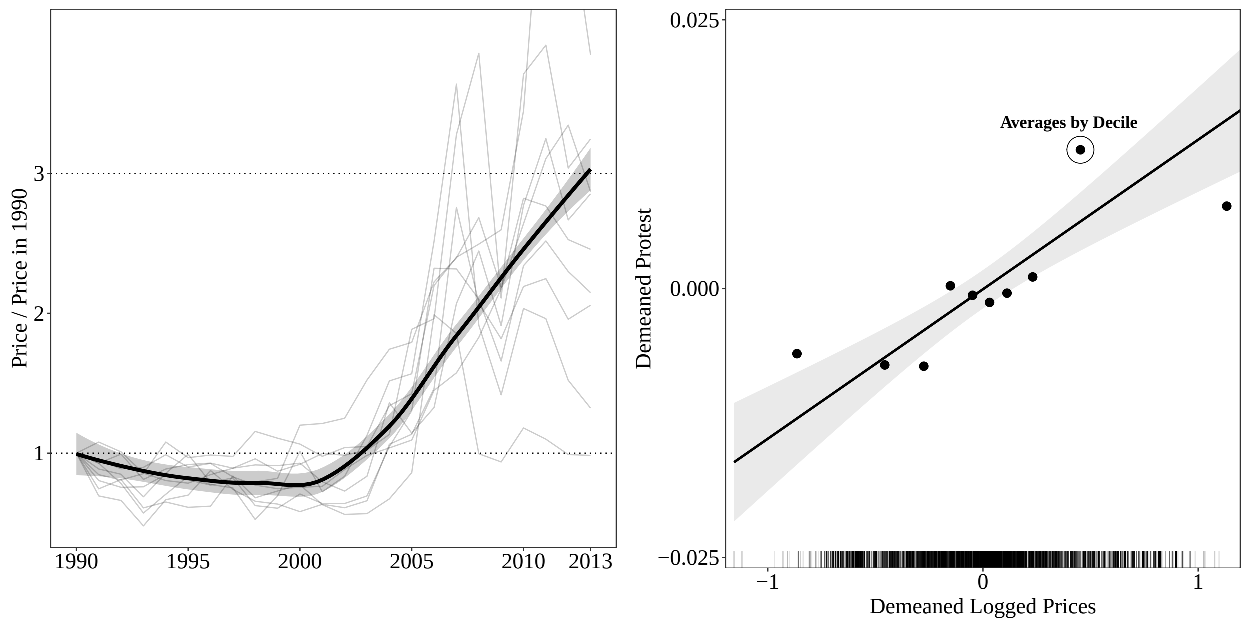
I exploit this variation, comparing changes in the likelihood of protest in mining areas differentially affected by price increases during the commodity boom. I start by simply plotting the relationship between prices and protests within mining areas after de-meaning both measures. Figure 4(b) displays both the bivariate linear relationship between de-meaned prices and protest, as well as the average change in protest (relative to the mean) for each decile of de-meaned prices. Above average commodity prices correspond to above average levels of protest.

While suggestive, this relationship could be confounded by unrelated upward trends in both prices and protest. To address this potential confound, I estimate the following difference-in-differences:

$$y_{it} = \alpha_i + \delta_t + \beta \log(\text{Price}_{it}) + \varepsilon_{it} \tag{3}$$

where i indexes cells and t year. While mines are regarded as price-takers, in robustness checks I also lag the price measure by a year to ameliorate concerns that the results are driven by protests affecting the world supply

Figure 4: Pr(Protest or Riot) Increases with Mineral Prices
Protest in mining areas increases during periods of above-average mineral prices.



(a) Commodity Price Series

(b) Increased Pr(Protest) as Prices Increase

4(a) displays mineral price series (indexed to 1990 values) from the World Bank from 1990-2013. The thicker loess smoother is weighted by the total number of cell-years producing each mineral. 4(b) estimates the bivariate, linear relationship between prices (logged) and protest after demeaning each variable at the cell-level. The raw data is also averaged by decile and plotted as points. The rug plot along the x-axis indicates the distribution of demeaned logged prices.

of a mineral (see table A.3). I cluster the standard errors on cell, but clustering on country or commodity does not affect my inferences.

I find in table 2 that rising commodity prices raise the likelihood of protest. Between 1997 and 2007, the price of gold increased by almost one log point; the coefficient in model 1 implies that would roughly double the average probability of protest in mining cells. The estimated effect is relatively stable using different specifications and samples: even-numbered models include country-year fixed effects; models 3-6 restrict attention to cells that see no change in their mining status (D_{it}) between 1997 and 2013; models 5-6 impute a price of zero to non-mining cells, which increases the precision of the estimates. These findings align with recent results from Berman et al. (2017) in Africa, as well as from Kopas and Urpaleinen (2016) in Brazil and Sexton (2017) in Peru.

Table 2: Effect of World Mineral Prices on the Pr(Protest or Riot)

	Dependent variable:					
	$\mathbb{1}$(Protest or Riot)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Price})_{it}$	$0.010^{\dagger}$	0.018^{*}	$0.008^{\dagger}$	0.011	0.012^{*}	0.011^{*}
	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.004)
Cell FEs	940	940	284	284	1,499,840	1,499,840
Year FEs	17		17		17	
Country-Year FEs		608		532		952
Mean(y_{it})	0.0133	0.0133	0.0099	0.0099	0.0002	0.0002
Mining Cell-Years Only	✓	✓	✓	✓		
Var(D_{it}) = 0			✓	✓	✓	✓
Observations	8,776	8,776	4,851	4,851	25,497,303	25,497,303

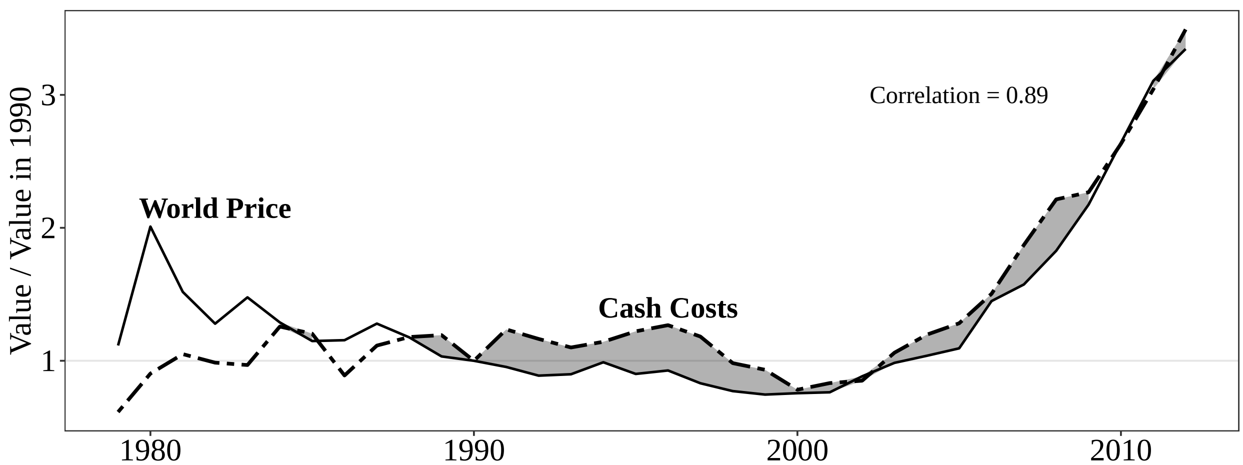
Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-6: linear probability models per equation 3. Models 1-4: sample only includes cell-years with active mines. Models 3-6: sample restricted to cells with no change in in mining status (D_{it}) from 1997-2013. Models 5-6: sample includes non-mining cells, imputing a price of zero to those areas. Commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from ACLED (see appendix F).

Looking at this finding, one is tempted to conclude that protesters strike when the iron is hot, holding up mining projects when they are most profitable. Yet, this intuition is misleading. If firms and communities bargain with complete information (as in the game from section 1.1), simply changing the size of the surplus has no effect on the likelihood of protest (i.e., costly delay). In fact, the parties should be especially keen to avoid work stoppages given the rising opportunity cost of shutting down a project as prices surge.

More surprising, it simply was not the case that companies' profits increased in lock-step with commodity prices during the boom. While headlines focused on record prices during the super cycle, industry analysts noted a "growing disconnect" between prices and mining projects' performance. In their 2011 annual report, PricewaterhouseCoopers (PwC 2012, 4) observed that "over the last five years mining stocks have underperformed the prices of the major mining commodities, a trend which accelerated in 2011." The 2012 report echoed this analysis: "in recent years, gold equities declined despite steady gold price increases ... [G]ross margins plummet[ed] from 49% [in 2010] to 29% [in 2012]. At the end of the day, while high gold prices are generally good news for gold miners, margins matter even more" (PwC 2013, 11).

Figure 5: Correlation between Prices and Cost in Gold Mining
The cash costs of gold mining grew at a rate similar to world prices during the commodity boom.



The time-series plot presents both the world price and cash costs of cold mining indexed to 1990 values. The price data come from the World Bank; data on cash costs was compiled by Christie (2013). The gray-shaded areas indicate periods when *indexed* cash costs exceeded the world price.

Why were profits not increasing at the same rate as commodity prices? First, shortages of skilled labor and specialized equipment raised input costs. According to Accenture, "the costs of mining operations have increased considerably faster than the Consumer Price Index over the last ten years. This is in large measure an outcome from the boom years when supply constraints resulted in increased input prices" (Accenture 2011, 15).[21] Figure 5 illustrates the striking correlation ($\rho = 0.89$) between the price of gold and the cash costs of gold mining (both indexed to their 1990 values). The World Gold Council actually proposed changing the industry convention for how they report costs, fearing that reporting cash costs "had aggravated matters by making the gold industry appear more profitable than was actually the case" (Humphreys 2015, 169).[22] Second, in an effort to meet rising demand (largely from China and India), companies drilled deeper and exploited less productive deposits. "When commodity prices picked up three years ago, the industry rushed to bring capacity online ... Head grades have fallen, mines have deepened, and new deposits are in riskier countries ... [M]oderate price increases will not be enough to claw back lost margin" (PwC 2012, 12). Cost increases and productivity declines in the sector placed downward pressure on profits — an accounting detail

[21]

[22] Cash costs exclude capital expenditure, exploration, corporate costs, and cash taxes.

that was rarely reported alongside news of steadily rising commodity prices, a common topic in communities that depend on mining.

For both theoretical and empirical reasons, rising profitability seems an unlikely explanation for protests. What then explains why mining sparks protest, and why the likelihood of such social conflicts increases with commodity prices?

3. What mechanisms help explain mining-related protests?

Many explanations of social conflict focus on grievances, a catch-all term that includes different sources of discontent: economic and status inequality, real or perceived injustices, or unsatisfied policy demands (see Shadmehr 2014, for a recent review and formal rationalization of grievance-based accounts).[23] In work focused on the relationship between natural resources and conflict, grievance-based accounts focus on environmental harm (Bebbington and Williams 2008; Kopas and Urpaleinen 2016; Sexton 2017) and, to a lesser extent, displacement (Bebbington et al. 2008), inequality (Collier and Hoeffler 2002), and governance (Bebbington, Anthony et al. 2008, 892). Much of the work to date has focused on Latin America (principally, Peru); I look for evidence that one or more of these sources of discontent account for the protests observed around new mining projects in Africa, especially during periods of high prices. This analysis is descriptive: the moderators used in this section do not exogenously vary; other (omitted) variables correlated with these moderators could account for the reported heterogeneity (or lack thereof).

Finding little empirical support for these grievance-based accounts, I develop an alternative explanation related to incomplete information — a well-known source of bargaining failures and common explanation for strikes in other industrial settings (Tracy 1987; Card 1990) and inter- and intra-state conflict (Fearon 1995; Walter 2009). Both qualitative accounts and evidence on the effects of transparency initiatives suggest that informational problems contribute to protest.

3.1 Environmental Hazards

Mining can degrade the environment of host communities, both by polluting water and soil or straining already scarce water resources. Several works have argued that these environmental harms motivate protest

[23] Shadmehr's (2014) model implies that protest does not monotonically increase with grievances as often argued. Rather, he predicts an U-shaped relationship between grievances and mobilization.

activity around mining sites. In the well-studied case of Peru, Sexton (2017) argues that protest results from the failure to mitigate pollution around commercial mines; Bebbington and Williams (2008) notes that communities worry about both the effects of mining on water quality and supply.[24] These arguments suggest that mining-related protests should be particularly likely in host communities with a heightened risk of environmental hazards.

I compile several additional datasets to evaluate this mechanism. First, I code whether or not active projects in a cell-year use surface mining methods, which are widely perceived to pose a greater environmental risk. Evans and Kemp (2011, 1771) observe that, "large-scale open-pit and strip mines can result in more visible manifestations of mining activity in the form of spoil piles and waste dumps and can be more disruptive to other land uses such as agriculture. Underground mines generally employ more selective mining methods and produce less waste…" Second, I measure the great-circle distance between each cell and the closest environmentally protected area according to the World Database on Protected Areas (WDPA).[25] According to the WDPA, African countries contain over 6,000 designated, terrestrial protected areas, covering over 370 million square kilometers.[26] Third, I spatially merge cross-sectional information from the World Resource Institute's Aqueduct Global Maps on "baseline water stress," which measures total annual water withdrawals as a percentage of the total available flow (Gassert et al. 2014, 8). Higher values indicate greater competition for water among users. Finally, I incorporate country-year indicators of environmental quality from the Environmental Performance Index (EPI) (Hsu 2016). I focus on environmental risk exposure, a summary measure of the health-burden of environmental risk factors (e.g., unsafe water, air pollution).[27]

[24] In Steinberg's (2015, 1513) model, environmental externalities affect the amount of compensation communities demand from firms; protest, however, results because of an informational problem. In a complete information game, environmental harms alone would not generate protest.

[25] Compiled by the United Nations' World Conservation Monitoring Centre, the WDPA is "the most comprehensive global database of marine and terrestrial protected areas" (UNEP-WCMC 2016, 6).

[26] This calculation subsets to designated protected areas that are state- or expert-verified. I do not subset when performing the minimum distance calculation, though doing so is inconsequential for the results.

[27] This measure is available in 1990, 1995, 2000, 2005, 2010, and 2013. I impute the most recent past measure of this variable for intervening country-years.

In table A.6, I interact these measures with my indicator for whether a cell-year contains an active mine (D_{it}).[28] Across all of these measures of environmental risk or scarcity, I do not find evidence to suggest that environmental concerns systematically increase the likelihood that mining generates protest. Surface mines, mines near protected areas, or in areas with high levels of water competition do not account for the first set of results. The only marginally significant interactions point in the wrong direction: the probability of protest increases *less* when mining occurs in country contexts with greater environmental health hazards.

Perhaps these environmental concerns are especially salient during periods of high prices, as mines look to enlarge their footprints. Yet, interacting commodity prices (logged) with these moderators tells the same story: these measures of environmental risk or scarcity do not amplify the effect of prices on social conflict in mining areas (see table A.7).

3.2 In-migration and Displacement

Migrants may flock to host communities, seeking jobs in the mine, and these inflows could be especially large during periods of high-prices. Long-time residents may resent these new arrivals, and such anger could boil over into protest.[29]

To assess this explanation, I combine over 800,000 household surveys from over 70 Demographic and Health Surveys (DHS) conducted in 30 sub-Saharan African countries that include geo-coordinates for the survey locations. I follow the approach of Kotsadam and Tolonen (2013) to spatially merge the DHS, mining, and protest data: first, I construct circular buffers around each active mine (using radii of 10 or 20 kilometers); second, if a survey location (or protest) falls within a mine's buffer, then I associate the respondents at that location (or protest) with that mine. This generates repeated cross-sections at the mine-level; I amend equations 1 and 3 to analyze this data, substituting mine fixed effects for the grid cell indicators.

In table A.8, I first estimate the effect of mining or rising prices on the proportion of households that report having ever moved.[30] I then look at whether this proportion appears to increase with mining or rising

[28]With the exception of environmental risk exposure (which varies by country-year), the measures are not time-varying; thus, the direct effects are absorbed by the cell fixed-effects.

[29]The mining sector in South Africa has been anecdotally linked to xenophobic violence (Jamasmie 2015). However, the prevailing narrative suggests that such violence has been exacerbated by *falling* commodity prices and cutbacks in employment, which generates more competition between local and foreign workers.

[30]This is the only measure of migration in the DHS and is only available for a subset of survey waves.

commodity prices. Using both the 10 and 20 kilometer buffers, I find no compelling evidence that more households report having moved after mining starts or as prices increase. Table A.9 then regresses an indicator for whether a protest or riot occurred near a mine (i.e., within its buffer) on the proportion of households that report having moved. Changes in mobility (as measured in the DHS) have no discernible effect on the likelihood of protest in areas around mines. Figure 2 foreshadowed this result: much of the migration to mining areas occurs prior to the start of mining when we see no uptick in protest.[31]

Why is there no relationship between in-migration and protest? First, anger and violence directed at migrants may take the form of targeted harassment (e.g., assaults and vandalism) rather than public protests. Of all riots and protests in the ACLED data, less than 0.1 percent mention the words xenophobia, immigrant, or migrant. Second, according to the DHS, there does not appear to be a material basis for such resentment: in areas with active mines, households that report having moved — or moved after mining starts — do not appear wealthier (based on their household assets) than permanent residents (see table A.9).

Bebbington et al.'s (2008, 2890) qualitative work focuses on grievances related to displacement and dispossession, "resistance is understood as a defense of livelihood." While these authors conceptualize dispossession quite broadly,[32] commercial mines can directly threaten the livelihoods of artisanal miners, who are unable to dig in concession areas. Protests or riots could then reflect discontent among these smaller scale miners. If true, we would expect the increase in protest to be concentrated around mines producing commodities that can also be mined artisanally. Across sub-Saharan Africa, gold and diamonds represent the largest sub-sectors of artisanal mining. Yet, dropping commercial gold and diamond mines from the sample does not affect the difference-in-differences estimates from table 1. The timing of protests over the life of the mine is also difficult to reconcile with this explanation: artisanal miners are typically displaced in advance of mining; companies establish and police the perimeters of their sites during earlier exploration or construction phases.

[31] Labor demand at mining sites peaks during the site design and construction phases that immediately precede production (International Council on Mining & Metals et al. 2014, 7).

[32] These authors write, "[movements] emerge to contest patterns of resource control and access, and to challenge the institutions, structures, and discourses that determine the social distribution of assets, as well as their relative productivity, security and reproducibility" (2890).

3.3 Inequality

Motivated by Gurr's (1971) notion of "relative deprivation", many scholars have used inequality as a measure of grievances. In seminal work on the topic of natural resources and armed conflict, Collier and Hoeffler (2002, 13) observe that "a high degree of economic inequality is therefore some indication that the poor are atypically marginalized." The onset of mining or rising prices may enrich some households (e.g., workers or local authorities) while delivering relatively little to others. This increased inequality could produce grievances related to inequality and, consequently, protests.

I use information on household assets from DHS surveys and the procedure outlined by McKenzie (2005, 7-8) to construct a measure of inequality for each mining area for every year in which DHS data is available.[33] McKenzie (2005) demonstrates that this provides a good proxy for inequality in living standards.

The results in tables A.11 and A.13 suggest that mining and rising commodity prices do not exacerbate economic inequality. And I cannot reject the null hypothesis that increased inequality has no effect on the likelihood of protest (see table A.12). This echoes a large set of null results, including that of Collier and Hoeffler (2002) (albeit for a different measure of conflict). Shadmehr (2014, 621) observes that "a decade-long academic debate concluded that higher grievances (in particular, more income inequality) do not translate into more violence…"[34] These results offer further support for that conclusion.

3.4 Governance

Citizens may believe that mining only enriches local officials, and anger about bribes or other forms of rent-seeking could boil over into protests.[35] A recent paper by Knutsen et al. (2016) geocodes data on perceptions of corruption from the Afrobarometer. Using an empirical design similar to my own analysis of the DHS data, they do not find that the onset of mining significantly increases reports of bribes for permits or

[33] I take the first principal component of household assets, compute the standard deviation for each mine and divided by the standard deviation for the full sample.

[34] Including the quadratic term suggested by Shadmehr's (2014) model does not confirm his prediction; if anything, the coefficients suggest an inverted-U relationship between inequality and protest.

[35] Recent work by Axbard et al. (2015) in South Africa finds that commercial mining and rising commodity prices do not exacerbate crime in mining areas — another governance problem that could mobilize residents.

perceptions of local corruption among respondents that live within 50 kilometers of a mine (see table 2, where these authors include mine fixed-effects).[36] The authors do find evidence that bribes to police increase; officers, they argue, take advantage of increased economic activity to extract more bribes. Given that perceptions of corruption do not increase after mining, it seems unlikely that anger about rent-seeking by local officials would motivate protests.[37]

4. Can informational problems help explain these conflicts?

In contrast to these grievance-based accounts, labor economists have argued that industrial conflicts — protests or strikes that result in work stoppages — can result from bargaining failure due to incomplete information (see Kennan and Wilson 1993, for a review). And this logic has been offered by political scientists as a rationale for inter-state and civil conflicts (Fearon 1995; Walter 2009). Extending the argument to this setting, if host communities are uncertain about the returns generated by mining projects, then we are no longer assured of the amicable, first-best solution described in section 1.1. Rather, protests that interrupt production (i.e., costly delays) can occur in equilibrium.[38] I present a formal argument and proof of this claim in appendix E.2.[39]

I focus here on the intuition for this theoretical result. Mining is often preceded by claims that a new project will both enrich investors and promote local economic development. Boosters hype a project's potential value both to raise capital and win entry from communities and governments. Yet, while most projects

[36] The Afrobarometer data used by Knutsen et al. (2016) cannot be released; hence, I am unable to reanalyze the data to look at whether perceived corruption increases with commodity prices changes.

[37] In their first table, Knutsen et al. (2016) report that perceptions of corruption significantly increase when they omit mine fixed-effects from their models. While significant, the magnitude of the effects on perceived corruption (model 3) remain quite small: 0.12 on a four-point scale or less than 10 percent of the mean of the dependent variable.

[38] Commitment problems have been the focus of research on the impediments to investment in states with weak property rights (Williamson 1979; Vernon 1971). Without denying that holdup problems deter investment, they do not help to rationalize protests. Firms, who are the party losing power due to the so-called "obsolescing bargain," cannot enlarge their stream of future profits by preemptively initiating conflicts.

[39] The formal model extends Admati and Perry (1987), who consider a bargaining game between an incompletely informed buyer and seller, whose valuations fall in a discrete type space.

begin with this optimistic outlook, actual profitability varies dramatically: expensive and prolonged exploration can fail to discover deposits; even productive mines differ in profitability due to ore amounts and quality, as well as production costs; global commodity prices and capital costs fluctuate. Entering negotiations, communities and workers cannot be certain where their local mine falls in this distribution of profitability. Boosters' optimistic initial claims can engender outsized and, ultimately, unmet expectations in some host communities.

How do these mismatched expectations lead to conflict? Suppose a community overestimates a project's value and makes a demand that the company is unwilling to meet. The company could trumpet their inability to pay, but this is cheap talk: if the community takes the company at its word, then even companies with the most profitable projects would have an incentive to plead poverty to retain a larger share of surplus. As communities cannot rely on firms to honestly disclose their margins, protests offer a strategy for separating firms with low-profit projects from those attempting to low-ball the community. This separating equilibrium exists, because projects with meager margins face low opportunity costs to pausing production and would, thus, rather shut down than immediately concede to the community. Firms with more profitable projects quickly capitulate, wanting to keep production humming.

Qualitative accounts provides numerous examples of this bargaining dynamic. First, in 2012, protests occurred in Bumbuna, Sierra Leone, a community hosting a large iron mine. Protesters were angry, believing that the project's profits had recently increased, but that this had not translated into better wages or improved living conditions for households resettled due to mining.[40] This frustration is echoed in interviews for a 2014 Human Rights Watch report on the protest: "After the exploration period was over, the company went into mining and production [in 2009-2010] and told the workers that they would get more and that everything would change for the better…We came into mining and it was no better" (Human Rights Watch 2014, 39). Later in the report, an employee at the mine states, "In 2011, management promised that 'when we start exporting, that's when things will change. We have to be patient; the investors don't have profits yet.' All the workers were fed up with this game" (47). Despite these beliefs among community members, the project's actual finances remained precarious: the mine's owner, African Minerals, posted an operating loss of over 225 million USD in 2012; in 2015, the company was put into receivership. The protest in Bumbuna arose, because the community held exaggerated expectations about the project's profits and did not feel that their wages or development expenditure reflected a "fair" split.

[40] Author's interviews, May 2014. IRB Protocol #28040.

Second, gold mines in Tanzania became sites of conflict, as skyrocketing prices generated high expectations about projects' profitability. Goldstuck and Hughes (2010, 13) write that, "the assumption that mining companies in Tanzania are making huge profits and are cash flush reinforces the public's perception that the mining sector's contribution to the economy should be greater." In interviews near Barrick Gold's conflict-ridden North Mara Mine, the authors discover "the community feels duped and deceived by the way in which the mine was established." The company that preceded Barrick made "a number of promises to community leaders, local government officials, and ministerial officials . . . Many of these reported promises and commitments failed to materialise" (61). Protests at the North Mara Mine, in part, reflect a belief that the community should be benefitting more given both the high price of gold and past promises about the mine's contribution to local development.

Finally, strikes in South Africa's platinum sector illustrate how rising prices can lead to conflicts over the scale of profits and how these should be split with workers. In 2014 seventy thousand workers halted production, demanding a more than doubling of entry-level wages. The action reflected resentment in the platinum belt about poor living conditions despite a massive increase in platinum prices. Workers cited research from Isaacs and Bowman (2014), which argued that workers' wage demands were reasonable given platinum mines' profits over the past decade. To the contrary, companies insisted that falling commodity prices and increased production costs made the proposed wage hikes unsustainable:

> "[N]one of the companies have said that the housing and living conditions or socio-economic opportunity of employees is what it could or should be . . . But the [union's] demand . . . is simply not affordable and it would be irresponsible of companies to agree . . . Rather than how can we better split the profits we are not making, . . . [let us] focus on how we can work together to . . . reward all our stakeholders" (Kings 2014).

Workers eventually settled for a twenty percent annual increase in wages. One way to interpret this prolonged social conflict is as costly signal by platinum companies that they could not afford workers' initial wage demands.

Disputes often center on how profits are split and whether host communities regard that as fair.[41] In their global study of prolonged instances of company-community conflicts surrounding mining projects, Davis

[41] See also Mensah and Okyere (2014), who argue that company-community conflicts in Ghana result from the failure of companies to meet communities' expectations regarding local development.

and Franks (2014, 14) find that "socio-economic issues, particularly the distribution of project benefits" were among the most common causes. These disagreements, I argue, can lead to protests when communities or workers do not know what a project is worth but have expectations that exceed what the company is currently able or willing to pay.[42] This insight is summarized in a recent report from Stevens et al. (2013, 98-99):

> "In practice, *parties have little choice other than to negotiate contractual arrangements with incomplete knowledge and with different expectations* about project risks and future prices. Under these conditions, information asymmetries and differences in bargaining power become key determinants of contractual outcomes. *With expectations and assumptions on both sides often far apart, this creates potential tensions and disputes as the project gets under way*" (emphasis added).

As communities' expectations increase about what they stand to gain from hosting a mine, so too do the demands that they put to firms. If profits fail to keep pace with these expectations, the probability of protest increases, as a larger proportion of projects would rather disrupt production than agree to more demanding terms.[43]

This explanation can not only account for protests around mining projects, but also helps to rationalize the positive relationship between commodity prices and protest.[44] As noted in section 2.2, profits did not move in lock-step with commodity prices. And yet, communities' expectations increased dramatically during the boom years. Stevens et al. (2013, 80) observe that "the phenomenon of higher mineral and oil prices in recent years (the price cycle) has increased . . . the expectations of societies in resource-producing countries."

[42] This mechanism underlies advice offered by management scholars working on extractive industries. Henisz (2014, 122) argues: "Stakeholders must understand not only your constraints but also how you ascertain what you can and cannot do on their behalf. Without transparency on this topic, people will doubt you."

[43] Appendix E.3 extends the model to incorporate inflated expectations on the part of communities, by allowing communities' prior beliefs about projects' profitability to diverge from the true distribution.

[44] The focus on bargaining might suggest that protests should proceed mining. Yet, as with other any investment, negotiations over corporate social responsibility, land rents, or wages are ongoing and frequently revisited (especially in contexts with weak contract enforcement). Moreover, qualitative accounts suggests that communities often defer their demands until production starts, recognizing that mining projects make only losses during exploration and construction phases. If, prior to export, communities believe projects have no surplus to share, then we should not expect them to protest demanding a larger cut.

Higher commodity prices generated more and louder "calls for the country to receive its 'fair share' of the profits" (47). While industry analysts lamented sharply increasing production costs, such concerns failed to pervade the public debate: gold companies in Tanzania, Goldstuck and Hughes (2010, 11) write, were thought to be immensely profitable "based on the assumption that companies' profits are calculated on the basis of gold production multiplied by the gold price." Booming prices outpaced profits, leading to heightened expectations and — this model would predict — the increased probability of protest we observe in the data.

Table 3: Mineral Prices, EITI, and Pr(Protest)

	Dependent variable:						
	$\mathbb{1}$(Protest)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Price)$_{it}$	$0.010^{\dagger}$	0.013^{*}	0.015^{*}	0.012^{*}	0.012^{*}	0.015^{*}	0.012^{*}
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\mathbb{1}$(Candidate)$_{c,t-1}$		0.020	0.013	0.020			
		(0.019)	(0.010)	(0.017)			
Corruption$_{c,t-1}$				0.002			-0.0003
				(0.015)			(0.014)
log(Price)$_{it}$ $\times$ $\mathbb{1}$(Candidate)$_{c,t-1}$		$-0.002^{\dagger}$	$-0.001^{\dagger}$	$-0.002^{\dagger}$			
		(0.001)	(0.001)	(0.001)			
log(Price)$_{it}$ $\times$ Corruption$_{c,t-1}$				-0.001			-0.0004
				(0.001)			(0.001)
$\mathbb{1}$(Compliant)$_{ct}$					0.056	0.027	0.053
					(0.040)	(0.023)	(0.035)
log(Price)$_{it}$ $\times$ $\mathbb{1}$(Compliant)$_{c,t-1}$					$-0.005^{\dagger}$	$-0.003^{\dagger}$	-0.004^{*}
					(0.003)	(0.002)	(0.002)
Cell FEs	940	927	927	925	927	927	925
Year FEs	17	16	16	16	16	16	16
Mean(y_{it})	0.0133	0.015	0.015	0.0152	0.015	0.015	0.0152
Mining Cell-Years Only	✓	✓	✓	✓	✓	✓	✓
Country-specific Trends			✓			✓	
Observations	8,776	7,450	7,450	7,236	7,450	7,450	7,236

Note: Robust standard errors clustered on country; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Model 1: linear probability model per equation 3. Model 2-7: price (logged) interacted with an indicator for whether a country was an EITI candidate (models 2-4) or compliant member (models 5-7) in the previous year. Models 3, 6: country-specific linear time-trends included. Models 4, 7: interaction of price (logged) with a measure of the control of corruption from the Worldwide Governance Indicators included. Commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from ACLED (see appendix F).

If protests result from an informational problem, then transparency should have a pacifying effect and mitigate the relationship between commodity prices and protest. Where communities have alternative sources of information about mining projects, they may be less dependent upon world prices as a noisy predictor of profitability. The adoption of the Extractive Industries Transparency Initiative (EITI) provides an opportunity to assess whether transparency has this effect. The EITI requires that companies in member countries "disclose information on tax payments, licenses, contracts, production and other key elements around resource extraction."[45] EITI claims that increased transparency "enhance[s] trust and stability in a volatile sector…Citizens and civil society benefit from receiving reliable information about the sector…" The first countries were admitted as candidates to EITI in 2007 and, as of 2014, there were 26 countries globally (16 African countries) considered compliant members of the EITI in good standing. A recent meta-study from Rustad et al. (2017, 156) finds that EITI has succeeded in garnering attention and increasing transparency around revenues. Roughly 7,000 articles were written about the initiative between 2003 and 2015; and, in one of the few nationwide polls, a 2008 survey in Liberia (a year after the country became a candidate) found that over 41 percent of respondents claimed to have heard or read about EITI. The authors continue, "overall, EITI seems to have increased timely reporting on revenues…many of the studies argue that the EITI has improved or at least partly improved transparency through the reporting" (159).

Table 3 reports the heterogeneous effects of commodity prices on the probability of protest, depending on whether a mining area falls in a country that is an EITI candidate (models 2-4) or compliant country (models 5-7) in a given year. I lag countries' EITI status, as reporting by EITI secretariats typically lags implementation. I find that EITI candidacy reduces the relationship between logged prices and protest by roughly 15 percent. As we would expect, this effect increases (roughly doubling) with full compliance.[46] This pacifying effect of transparency bolsters this theoretical account of protest. However, these results do not imply that EITI eliminates social conflict; EITI only dampens the effect of rising prices on protests in mining areas. These modest effects will not surprise critics of EITI, who rightfully note that the initiative has only partially succeeded in engaging the public and has had negligible effects on corruption (Rustad et al. 2017, 160).

The research design helps to rule out some sources of endogeneity. First, the cell fixed effects absorb any time-invariant features that might explain differences in social conflict across countries that do and do not become EITI candidates. Second, including country-specific, linear time trends (models 3 and 6) ameliorates

[45] Individual companies cannot select into or out of EITI.

[46] Berman et al. (2017, 1598) report results that point in the same direction; however, as they note, their sample ends in 2010 and, thus, includes very few EITI candidate or compliant country-years.

concerns that EITI adoption reflects differential trends in the likelihood of protest. Third, and most reassuringly, EITI does not track overall improvements in governance. In fact, existing studies point to "the lack of adoption by many of the most resource-rich (and corrupt) countries. They suggest that [EITI] adoption is mostly driven by incentives or external pressure — such as foreign aid dependence or the need for diplomatic and security support…" (Rustad et al. 2017, 156). Figure A.1 reports the pooled bivariate correlations — all of which are zero or negative — between EITI candidacy and measures from the Worldwide Governance Indicators (WGI) (Kaufmann et al. 2010).[47] Consistent with the earlier studies, candidacy is not associated with less corruption or more effective regulation. Models 4 and 7 of table 3 include the WGI's control of corruption variable (both directly and interacted with prices); the pacifying effect of EITI remains unchanged.[48]

Despite these robustness checks, this analysis suffers from the limitations that plague most efforts to gauge policy impacts. Even after accounting differences across mining areas and time-varying changes in governance, EITI candidacy or compliance could still coincide with unmeasured reforms to the regulation of extractive industries. If true, these heterogeneous effects would then reflect a bundle of interventions that improve transparency and, potentially, other aspects of oversight.

The relationship between prices and protests, I argue, is mitigated by policies that promote transparency and, thus, help correct the one-sided informational asymmetry that leads to mismatched expectations and, ultimately, social conflict. However, there could also be uncertainty on the part of companies, who are unsure whether communities can solve their collective action problem and mobilize (e.g., Steinberg 2015). While this alternative theory does not rationalize the relationship between prices or protest or account for the moderating effect of EITI, it remains an internally consistent account of social conflict in mining areas. Lacking a measure of communities' collective action potential or, better still, firms' prior beliefs about this potential, I leave an empirical exploration of this mechanism to future work.

[47]The WGI covers 1996-2013 and includes measures of voice and accountability, political stability, government effectiveness, regulatory quality, the rule of law, and control of corruption. Higher scores indicate higher quality governance.

[48]Control of corruption can be substituted with any of the other WGI indicators without changing the magnitude and significance of the interaction term of prices and EITI candidacy.

5. Conclusion

Foreign investment in sub-Saharan Africa, particularly in natural resources, has increased dramatically over the last three decades. This paper addresses three unanswered questions raised by this trend: do these investments increase the likelihood of social or armed conflict; if so, when are these disputes most prevalent; and, finally, what mechanisms help explain these conflicts?

Using fine-grained data on mining projects and protests across Africa, I show that the probability of a protest or riot more than doubles with mining. To bolster the credibility of my empirical design, I confirm that areas receiving investments do not have differential trends prior to mining. Moreover, the result is robust to limiting the control sample to areas that immediately border mining areas and, thus, would have experienced similar demographic or economic trends (absent mining).

My focus on social conflict departs from a resource curse literature that has concentrated on how natural resources can provoke or sustain armed conflicts and rebellion. I find, to the contrary, that areas hosting these commercial mining projects are largely immune from rebel attacks or deadly armed conflicts. Both in the vicinity of the mine and in surrounding areas, the likelihood of protests and riots increases, while the probability of battles or events involving rebels does not. This null finding with respect to armed conflict could, I speculate, relate to the scale of these investments: unlike panning for gold, large commercial mining projects may be difficult for rebel groups to seize and productively operate. This argument implies that the "resource curse" may only emerge under certain conditions (e.g., certain production scales). Enumerating those conditions represents a productive path forward (Ross 2015).

Not all mining projects are met with protests, and the likelihood of demonstrations varies over the life of a mine. I investigate, first, whether mine owners' characteristics moderate the likelihood of social conflicts. Despite concerns about labor practices or corporate governance at mines with Chinese owners or owners based in tax havens, I find no evidence that these owners' country of origin amplifies the increased probability of protests. I do, however, find that mining areas where the domestic government is a partial owner are largely immune from these disputes. Second, I look at how plausibly exogenous changes in world commodity prices affect the likelihood of social conflict over the life of mines. Consistent with other recent empirical work, I find that the likelihood of protest increases with prices.

I consider a set of mechanisms that might explain these results, looking for evidence that grievances related to environmental harm, in-migration and displacement, inequality, or corruption drive the increased likelihood of protest around mining projects. Compiling and merging additional datasets on, for example, protected areas, water stress, migration, and inequality, I do not find evidence to suggest that grievances associated with these measures drive the observed relationships between mining or commodity prices and protest. Finding little empirical support for these accounts, I develop an alternative explanation related to incomplete information — a well-known source of bargaining failures and common explanation for conflict in industrial and international relations. This mechanism is consistent with qualitative accounts and can rationalize both why mining induces protest and why these conflicts are exacerbated by rising prices: the price "super cycle" led to heightened and often unmet expectations among communities regarding their development dividend from the commodity boom. I also show that the relationship between prices and protests is mitigated by policies, such as EITI, that promote transparency and, thus, help correct the informational asymmetry that I argue generates conflict.

While the private sector has been largely omitted from recent research in African politics, firms play an important political role in research on more developed countries. The literature on private politics considers how individuals organize outside of the state to influence firms' activities. This question is particularly salient in weak states like Liberia or Angola, where central governments lack the capacity to regulate commercial operations, and where foreign mining companies often find themselves supplanting the state, building roads or schools. In these places, the politics of development — how societies foster growth and distribute its costs and benefits — center on firms' negotiations with their workers and host communities. This paper illustrates how conflicts can arise when this bargaining takes place in low-information environments.

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Supporting Information

Concession Stands:
How Mining Investments Incite Protest in Africa

Following text to be published online.

Contents

A. Mining's Effects on Armed Conflict

A.1 ACLED Data

Table A.1: Mining Activity and Pr(Armed Conflict) in ACLED

	Dependent variable:						
			$\mathbb{1}$(Battle)				
	Full	Full	Full	Border	Border≤2	Full	Border≤2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_{it}	0.003*	0.003*	−0.001	0.002	0.003†		
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)		
P_{it} (Placebo)						−0.001	−0.002
						(0.001)	(0.001)
Mean(y_{it})	0.0003	0.0003	0.0003	0.0005	0.0008	0.0003	0.0006
	Dependent variable:						
			$\mathbb{1}$(Rebel Event)				
D_{it}	−0.0001	−0.0000	−0.002	−0.001	−0.001		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
P_{it} (Placebo)						−0.001	−0.001
						(0.001)	(0.002)
Cell FEs	1,500,538	1,500,538		65,994	18,763	1,500,189	18,414
Cell-Period FEs			4,501,614				
Year FEs	18		18				
Country-Year FEs		1,008				1,008	
Area-Year FEs				18,864	18,864		18,864
Mean(y_{it})	0.0003	0.0003	0.0003	0.0003	0.0005	0.0003	0.0004
Observations	27,009,684	27,009,684	27,009,684	2,273,094	471,402	26,997,974	443,971

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-7: linear probability models per equation 1. The unit of analysis is the grid cell-year. Models 4-5, 7: see figure 3 for how border areas are defined. Models 6-7: P_{it} is a placebo indicator that turns on for a five-year period prior to mining. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from ACLED (see appendix F). Battles correspond to event types 1-3 in the ACLED data; rebel events are coded if ACLED codes either actor in a conflict as a rebel force.

A.2 UCDP Data

Table A.2: Mining Activity and Pr(Armed Conflict) in UCDP-GED

	Dependent variable:						
	$\mathbb{1}$(UCDP Event)						
	Full	Full	Full	Border	Border≤2	Full	Border≤2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_{it}	0.0002	0.0005	0.001	0.002	0.002		
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)		
P_{it} (Placebo)						-0.0000	0.001
						(0.001)	(0.002)
Mean(y_{it})	0.0002	0.0002	0.0002	0.001	0.0014	0.0002	0.0013
	Dependent variable:						
	$\mathbb{1}$(UCDP Event $>$ 25 Deaths)						
D_{it}	0.0002	0.0002	0.0000*	0.0003	0.0003		
	(0.0002)	(0.0002)	(0.0000)	(0.0002)	(0.0002)		
P_{it} (Placebo)						0.0000*	0.0001*
						(0.0000)	(0.0001)
Cell FEs	1,500,538	1,500,538		50,766	14,309	1,500,292	14,063
Cell-Period FEs			6,002,152				
Year FEs	22		22				
Country-Year FEs		1,232				1,232	
Area-Year FEs				17,490	17,490		17,490
Mean(y_{it})	0	0	0	0.0001	0.0001	0	0.0001
Observations	33,011,836	33,011,836	33,011,836	2,105,554	437,008	33,001,330	413,098

Note: Robust SEs clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-7: linear probability models per equation 1. The unit of analysis is the grid cell-year. Models 4-5, 7: see figure 3 for how border areas are defined. Models 6-7: P_{it} is a placebo indicator that turns on for a five-year period prior to mining. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from Uppsala Conflict Data Programfbs Georeferenced Event Data (UCDP-GED) (see appendix F).

B. Lagged Commodity Prices and Protest

Table A.3: Effect of World Mineral Prices (Lagged) on Pr(Protest or Riot)

	Dependent variable:					
	$\mathbb{1}$(Protest or Riot)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Price})_{i,t-1}$	$0.006^{\dagger}$	0.007^{*}	0.010^{*}	0.014^{*}	0.013^{*}	0.012^{*}
	(0.003)	(0.003)	(0.005)	(0.007)	(0.004)	(0.004)
Cell FEs	322	322	284	284	1,499,840	1,499,840
Year FEs	17		17		17	
Country-Year FEs		519		518		904
Mean(y_{it})	0.0105	0.0105	0.0104	0.0104	0.0002	0.0002
Mining Cell-Years Only	✓	✓	✓	✓		
Var(D_{it}) = 0			✓	✓	✓	✓
Observations	4,940	4,940	4,693	4,693	23,997,589	23,997,589

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-6: linear probability models per equation 3, where price has been lagged one year. Models 1-4: sample only includes cell-years with active mines. Models 3-6: sample restricted to cells with no change in mining status (D_{it}) from 1997-2013. Models 5-6: sample includes non-mining cells, imputing a price of zero to those areas. Commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from ACLED (see appendix F).

C. Evidence on Mechanisms

C.1 Reporting Bias

Table A.4: Mining Activity and Media Coverage

	Dependent variable:						
	Mean(Articles/Protest)						
	Full	Full	Full	Border	Border≤2	Full	Border≤2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_{it}	−0.46	−0.14	−0.32	0.49	−0.79		
	(0.81)	(0.73)	(1.15)	(1.14)	(4.16)		
P_{it} (Placebo)						−0.59	15.07**
						(0.78)	(6.07)
	Dependent variable:						
	Mean(Sources/Protest)						
D_{it}	−0.07	−0.04	−0.02	−0.11	−0.14		
	(0.06)	(0.07)	(0.04)	(0.07)	(0.23)		
P_{it} (Placebo)						0.10	−0.12
						(0.08)	(0.32)
Cell FEs	8,484	8,484		1,227	577	8,426	519
Cell-Period FEs			12,037				
Year FEs	36		36				
Country-Year FEs		1,479				1,479	
Area-Year FEs				6,893	3,079		2,400
Observations	20,427	20,427	20,427	11,619	3,760	20,122	2,922

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-7: OLS models per equation 1. The unit of analysis is the grid cell-year. Models 4-5, 7: see figure 3 for how border areas are defined. Models 6-7: P_{it} is a placebo indicator that turns on for a five-year period prior to mining. In the top panel, the outcome is the average number of articles written about each protest in a cell-year; the dependent variable in the bottom panel is the average number of sources covering each protest in a cell-year. These outcomes can only be coded for cell-years that involve at least one protest. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from GDELT (see appendix F).

C.2 Owners' Characteristics

Table A.5: Mining Activity, Pr(Protest), and Owners' Origins

	Dependent variable:					
	$\mathbb{1}$(Protest or Riot)					
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.005*	0.005*	0.005*	0.004*	0.006*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$D_{it} \times \mathbb{1}(\text{China})_{it}$	0.001	0.002				
	(0.015)	(0.015)				
$D_{it} \times \mathbb{1}(\text{Tax Haven})_{it}$			-0.001	-0.001		
			(0.003)	(0.003)		
$D_{it} \times \mathbb{1}(\text{Government})_{it}$					-0.006^{*}	-0.005^{*}
					(0.002)	(0.002)
Cell FEs	1,500,511	1,500,511	1,500,511	1,500,511	1,500,504	1,500,504
Year FEs	18		18		18	
Country-Year FEs		1,008		1,008		1,008
Mean(y_{it})	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
Observations	27,008,793	27,008,793	27,008,793	27,008,793	27,008,348	27,008,348

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-6: linear probability models per equation 1, where treatment is separated into two groups using indicators for whether companies from China (models 1-2), tax havens (models 3-4), or the domestic government (models 5-6) hold any ownership stake in an active mining area. The unit of analysis is the grid cell-year. Mining cells hosting projects without ownership information are dropped as missing. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from ACLED (see appendix F).

C.3 Environmental Hazards

Table A.6: Mining Activity, Environmental Hazards, and Pr(Protest or Riot)

	Dependent variable:							
	$\mathbb{1}$(Protest or Riot)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_{it}	0.02*	0.02*	0.01*	0.01*	0.01*	0.01*	0.03*	0.03*
	(0.01)	(0.01)	(0.003)	(0.003)	(0.002)	(0.002)	(0.01)	(0.01)
$D_{it} \times \mathbb{1}$(Surface Mine)$_i$	−0.01	−0.01						
	(0.01)	(0.01)						
$D_{it} \times$Min(Dist. Protected Area)$_i$			0.0000	0.0000				
			(0.0001)	(0.0001)				
$D_{it} \times$Avg. Water Stress$_i$					−0.0000*	−0.0000*		
					(0.0000)	(0.0000)		
Env. Risk Exposure$_{ct}$							−0.01*	
							(0.0004)	(0.00)
$D_{it} \times$Env. Risk Exposure$_{ct}$							−0.03*	−0.03*
							(0.01)	(0.01)
Cell FEs	1,500,470	1,500,470	1,500,530	1,500,530	1,476,989	1,476,989	1,485,590	1,485,590
Year FEs	18		18		18		18	
Country-Year FEs		1,008		1,008		1,008		954
Mean(y_{it})	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
Observations	27,006,816	27,006,816	27,009,540	27,009,540	26,585,802	26,585,802	26,740,620	26,740,620

Note: Robust standard errors clustered on cell; $^\dagger p < 0.1$, $^* p < 0.05$

Models 1-8: linear probability models per equation 1, where the indicator for an active mine (D_{it}) has been interacted with measures that vary cross-sectionally (surface mining, distance to a protected area, average water stress) or at the country-year level (environmental risk exposure). The unit of analysis is the grid cell-year. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from ACLED (see appendix F). Data on protected areas from UNEP-WCMC (2016); water stress, Gassert et al. (2014), and environmental risk exposure, Hsu (2016).

Table A.7: World Mineral Prices, Environmental Hazards, and Pr(Protest or Riot)

	Dependent variable:			
	$\mathbb{1}(\text{Protest})_{it}$			
	(1)	(2)	(3)	(4)
$\log(\text{Price}_{it})$	0.02^{*}	0.02^{*}	0.02^{*}	0.02^{*}
	(0.01)	(0.01)	(0.01)	(0.01)
$\log(\text{Price}_{it})\times\mathbb{1}(\text{Surface Mine})_{i}$	-0.002			
	(0.005)			
$\log(\text{Price}_{it})\times\text{Min(Dist. Protected Area)}_{i}$		-0.0001		
		(0.0001)		
$\log(\text{Price}_{it})\times\text{Avg. Water Stress}_{i}$			0.002	
			(0.003)	
Env. Risk Exposure_{ct}				-0.003
				(0.01)
Cell FEs	621	932	937	939
Country-Year FEs	540	608	608	592
Mean(y_{it})	0.0177	0.0134	0.0134	0.0134
Observations	6,256	8,703	8,748	8,760
Note:	Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$			

Models 1-4: linear probability models per equation 3, where price (logged) has been interacted with measures that vary cross-sectionally (surface mining, distance to a protected area, average water stress) or at the country-year level (environmental risk exposure). The unit of analysis is the grid cell-year. Commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from ACLED (see appendix F). Data on protected areas from UNEP-WCMC (2016); water stress, Gassert et al. (2014), and environmental risk exposure, Hsu (2016).

C.4 In-Migration and Displacement

Table A.8: Mining Activity or World Mineral Prices and Migration

	Dependent variable:							
	Prop. Moved							
	10km	10km	10km	10km	20km	20km	20km	20km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_{it}	-0.08	-0.06			-0.06	-0.05		
	(0.11)	(0.11)			(0.07)	(0.07)		
log(Price)$_{it}$			0.42	0.42			0.01	0.02
			(0.49)	(0.49)			(0.22)	(0.29)
Mine FEs	220	220	107	107	348	348	164	164
Year FEs	13		11		14		12	
Country-Year FEs		35		23		39		28
Mean(y_{it})	0.62	0.62	0.63	0.63	0.62	0.62	0.63	0.63
Mining Years Only			✓	✓			✓	✓
Observations	295	295	137	137	528	528	226	226

Note: Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-2, 5-6: OLS models per equation 1. Models 3-4, 7-8: OLS models per equation 3. The unit of analysis is the mine-year, where a mining area is defined by a 10 (models 1-4) or 20 (models 5-8) kilometer buffer centered on each mine's coordinates. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from DHS surveys (see appendix F).

Table A.9: Migration in Mining Areas and Pr(Protest or Riot)

	Dependent variable:			
	$\mathbb{1}$(Protest)			
	10km	20km	10km	20km
	(1)	(2)	(3)	(4)
Prop. Moved	0.08	0.04	0.03	0.01
	(0.18)	(0.14)	(0.07)	(0.02)
Mine FEs	219	348	107	164
Year FEs	12	13	11	12
Mean(y_{it})	0.1	0.09	0.11	0.11
Mining Years Only			✓	✓
Observations	294	527	138	227
Note:	Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$			

Models 1-6: linear probability models where an indicator for a protest or riot is regressed on the proportion of DHS respondents in a mining area that have ever moved. Mining areas are defined by a 10 (models 1, 3) or 20 (models 2, 4) kilometer buffer centered on each mine's coordinates. Models 3-4: sample restricted to years when the mine is active. Data on migration from DHS surveys; outcome data from ACLED (see appendix F).

Table A.10: Wealth Differences between Permanent Residents and Migrants

	Dependent variable:			
	HH Asset Index			
	10km	10km	20km	20km
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Moved)	0.003		0.01	
	(0.01)		(0.01)	
$\mathbb{1}$(Moved Post-Mining)		0.001		0.01
		(0.01)		(0.01)
Mine FEs	107	107	164	164
Year FEs	11	11	12	12
Mean(y_{it})	0.49	0.5	0.46	0.46
Mining Years Only	✓	✓	✓	✓
Observations	6,224	6,103	17,340	16,979
Note:	Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$			

Models 1-4: OLS models where a household's score on an asset index is regressed on whether they report having ever moved (models 1, 3) or moved after mining started (models 2, 4). The unit of analysis is the household. Mining areas are defined by a 10 (models 1-2) or 20 (models 3-4) kilometer buffer centered on each mine's coordinates. Models 1-4: sample restricted to years when the mine is active. Data on migration and household assets from DHS surveys (see appendix F).

C.5 Inequality

Table A.11: Mining Activity and Inequality or Wealth

	Dependent variable:							
	Inequality				Avg. HH Assets			
	10km	10km	20km	20km	10km	10km	20km	20km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_{it}	-0.001	-0.01	-0.01	-0.004	-0.003	0.0003	-0.003	-0.004
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mine FEs	402	402	549	549	404	404	550	550
Year FEs	22		22		23		23	
Country-Year FEs		97		110		102		114
Mean(y_{it})	0.52	0.52	0.51	0.51	0.44	0.44	0.42	0.42
Observations	909	909	1,877	1,877	937	937	1,937	1,937

Note: Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-8: OLS models per equation 1, where the outcome is either inequality (constructed per McKenzie (2005)) (models 1-4) or the average score on an asset index (models 5-8). The unit of analysis is the mine-year. Mining areas are defined by a 10 (models 1-2, 5-6) or 20 (models 3-4, 7-8) kilometer buffer centered on each mine's coordinates. Models 1-4: sample restricted to years when the mine is active. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; household assets from DHS surveys (see appendix F).

Table A.12: Inequality in Mining Areas and Pr(Protest or Riot)

	Dependent variable:			
	$\mathbb{1}$(Protest or Riot)			
	10km	10km	20km	20km
	(1)	(2)	(3)	(4)
Inequality_{it}	-0.03	-0.07	-0.01	-0.01
	(0.09)	(0.08)	(0.04)	(0.03)
Mine FEs	395	395	544	544
Year FEs	17		17	
Country-Year FEs		89		99
Mean(y_{it})	0.11	0.11	0.12	0.12
Observations	836	836	1,696	1,696

Note: Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-6: linear probability models where an indicator for a protest or riot is regressed on inequality in a mining area. Mining areas are defined by a 10 (models 1-2) or 20 (models 3-4) kilometer buffer centered on each mine's coordinates. Data on household assets from DHS surveys; outcome data from ACLED (see appendix F).

Table A.13: World Mineral Prices and Inequality or Wealth

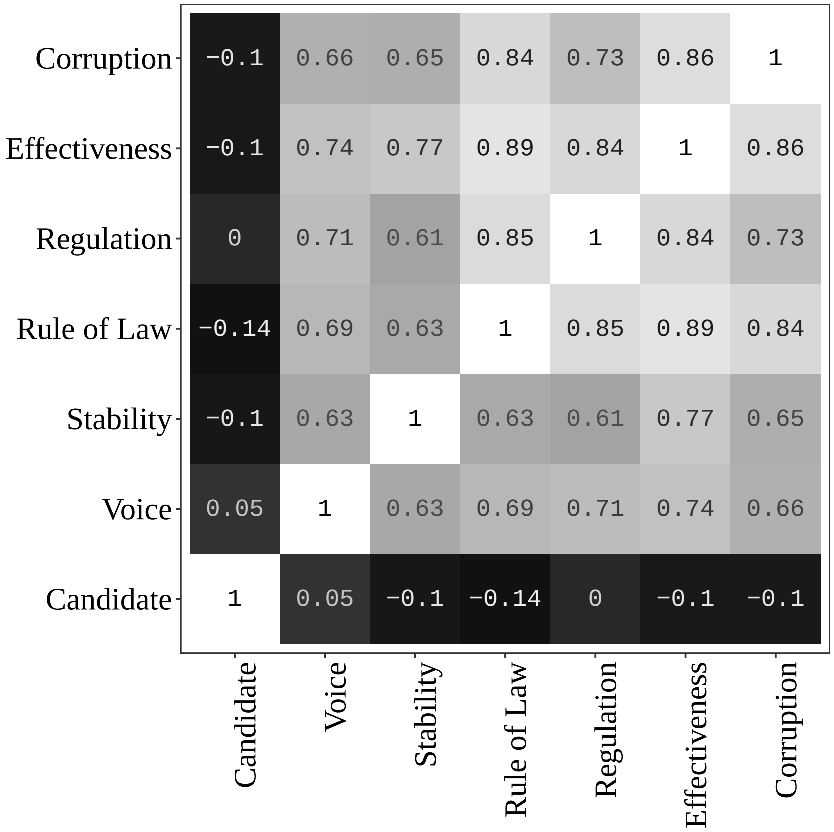
	Dependent variable:							
	Inequality				Avg. HH Assets			
	10km	10km	20km	20km	10km	10km	20km	20km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{Price})_{it}$	-0.05	-0.09	-0.03	-0.03	-0.03	0.03	-0.04	-0.06
	(0.09)	(0.16)	(0.04)	(0.07)	(0.05)	(0.09)	(0.03)	(0.04)
Mine FEs	239	239	339	339	245	245	340	340
Year FEs	17		19		18		20	
Country-Year FEs		66		83		70		87
Mean(y_{it})	0.57	0.57	0.55	0.55	0.47	0.47	0.44	0.44
Mining Years Only	✓	✓	✓	✓	✓	✓	✓	✓
Observations	407	407	785	785	422	422	813	813

Note: Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-8: OLS models per equation 3, where the outcome is either inequality (constructed per McKenzie (2005)) (models 1-4) or the average score on an asset index (models 5-8). The unit of analysis is the mine-year. Sample is restricted to years with active mines. Mining areas are defined by a 10 (models 1-2, 5-6) or 20 (models 3-4, 7-8) kilometer buffer centered on each mine's coordinates. Models 1-4: sample restricted to years when the mine is active. Commodity prices compiled from the World Bank, USGS, and US EIA; household assets from DHS surveys (see appendix F).

C.6 Correlation between EITI and the Worldwide Governance Indicators

Figure A.1: Pooled Bivariate Correlations between EITI Candidacy and WGI



The pooled bivariate correlation matrix between EITI candidacy and the Worldwide Governance Indicators. The unit of analysis is the country-year.

D. Other Event Datasets

Table A.14: Effect of Mining Activity on the Pr(Protest)

	Dependent variable:							
	𝟙(Protest or Riot)		𝟙(Protest)				𝟙(Social Conflict)	
	ACLED		ICEWS		GDELT		SCAD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_{it}	0.01*	0.01*	0.003†	0.003†	0.01*	0.01*	0.0004	0.0004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Cell FEs	1,500,538	1,500,538	1,500,538	1,500,538	1,500,538	1,500,538	1,500,538	1,500,538
Year FEs	18		20		36		25	
Country-Year FEs		1,008		1,120		2,016		1,400
Mean(y_{it})	0.0003	0.0003	0.0002	0.0002	0.0005	0.0005	0.0001	0.0001
Observations	27,009,684	27,009,684	30,010,760	30,010,760	54,019,368	54,019,368	37,513,450	37,513,450

Note: Robust standard errors clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-8: linear probability models per equation 1. The unit of analysis is the grid cell-year. Data on mining from IntierraRMG, SNL Metals and Mining, and Mining eTrack databases; outcome data from ACLED (models 1-2), ICEWS (models 3-4), GDELT (models 5-6), and SCAD (models 7-8) (see appendix F). In ICEWS and GDELT events are restricted to protests; in SCAD to social conflicts, more generally.

Table A.15: Effect of World Mineral Prices on the Pr(Protest)

	Dependent variable:							
	𝟙(Protest or Riot)		𝟙(Protest)				𝟙(Social Conflict)	
	ACLED		ICEWS		GDELT		SCAD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Price)$_{it}$	0.012*	0.011*	0.007†	0.007†	0.011*	0.010*	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)
Cell FEs	1,499,840	1,499,840	1,499,801	1,499,801	1,499,652	1,499,652	1,499,736	1,499,736
Year FEs	17		19		35		24	
Country-Year FEs		952		1,064		1,960		1,344
Mean(y_{it})	0.0002	0.0002	0.0002	0.0002	0.0004	0.0004	0.0001	0.0001
Var(D_{it}) = 0	✓	✓	✓	✓	✓	✓	✓	✓
Observations	25,497,303	25,497,303	28,496,281	28,496,281	52,487,950	52,487,950	35,993,749	35,993,749

Note: Robust SEs clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Models 1-8: linear probability models per equation 3. Sample restricted to cells with no change in mining status (D_{it}) from 1997-2013. A price of zero is imputed to non-mining areas. Commodity prices compiled from the World Bank, USGS, and US EIA; outcome data from ACLED, ICEWS, GDELT, SCAD (see appendix F).

E. Proofs

E.1 Complete-Information Game

Consider a game of complete information between a Community and a Firm that owns a project with non-negative profits ($\theta \in \mathbb{R}^1_+$). In each round of bargaining, one player proposes a split of the project's profits: $\{(x_i, x_{-i}) : x_i, x_{-i} \geq 0; x_i + x_{-i} \leq \theta\}$. The other player can accept, ending the game, or reject. If they reject, then they must choose a duration to delay ($t \in [\underline{t}, \infty)$). Proposal power alternates between players after each rejection. In all games presented below, the Community proposes first. Each player's payoff is simply their share of the surplus discounted by any delay required to reach agreement. Formally, $u(x_i, t; \delta_i) = x_i e^{-\delta_i t}$ for $i \in \{C, F\}$, where x_i is the share obtained by player i, $\delta_i > 0$ is player i's opportunity cost, and t is any delay prior to reaching the final bargain.

Definition 1. $\Gamma = \dfrac{\delta_F}{\delta_F + \delta_C}$

Proposition 1. *There exists a unique stationary sub-game perfect equilibrium in which the Firm immediately accepts the Community's offer. As the minimum time between offers approaches zero, the shares of the Community and Firm are given by* $(\theta\Gamma, \theta(1-\Gamma))$.

Proof. Stationarity implies that the each responder's value function is the same after each history: $V^i_R(h_t) = V^i_R$ for all h_t and $i \in \{C, F\}$. Suppose that the Firm is the responder without loss of generality.

It is straightforward to show that the Firm's unique optimal strategy when faced with an offer x is to reject if $x < V^F_R$ and accept when $x \geq V^F_R$. Obviously, the Firm has to accept if $x > V^F_R$, but it must also accept if $x = V^F_R$. Suppose it did not and rejected with some probability $\rho > 0$. The Community could then profitably deviate by offering just slightly more, $V^F_R + \varepsilon$ where $\varepsilon > 0$, which the Firm would certainly accept. To see how, note that $V^F_R + V^C_R \leq 1$. This implies that $V^F_R + V^C_R e^{-t_F \delta_C} < 1$, as $e^{-t_F \delta_C} < 1$ where $t_F \in [\underline{t}, \infty)$ is the equilibrium amount of delay by the Firm (and t_C is the equilibrium amount of delay by the Community) if they reject. (Note that stationarity implies $t_F(h_t) = t_F$ and $t_C = t_C(h_t)$ for all h_t.) This implies that we can find $\varepsilon \in (0, \rho(1 - V^F_R - V^C_R e^{-t_F \delta_C})$ that makes the deviation profitable.

Given the Firm's optimal unique strategy, the Community must offer V^F_R to the Firm. The Community does not want to offer more, as they could ensure acceptance and a larger share by offering exactly $x = V^F_R$. The Community also does not want to offer less, as rejection yields a lower payoff, since $1 - V^F_R > V^C_R e^{-t_F \delta_C}$, where t_F is the equilibrium delay by the Firm after rejecting.

It remains to derive the equilibrium offers. The Community's offer must leave the Firm indifferent between accepting now and rejecting, delaying, and counter-offering. This implies two indifference conditions that characterize V_R^F and V_R^C.

$$\begin{aligned}
(1 - V_R^F) &= V_R^C e^{-t_F \delta_C} \\
(1 - V_R^C) &= V_R^F e^{-t_C \delta_F} \\
1 > V_R^C &= \frac{1 - e^{-t_C \delta_F}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0 \\
1 > V_R^F &= \frac{1 - e^{-t_F \delta_C}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0
\end{aligned} \tag{4}$$

where t_C, t_F are equilibrium delay times for the Community and Firm, respectively. For all $t_C, t_F \geq \underline{t} > 0$, $V_R^F, V_R^C \in (0, 1)$.

Finally, it remains to be shown that neither party delays longer than they have to ($\underline{t}$) before making their offer. Consider a one-stage deviation in which the Community delays $\underline{t} + \varepsilon$ and then offers V_R^F. The Community's payoff from making this minimum acceptable offer after an additional ε delay is $(1 - V_R^F)e^{-(\underline{t}+\varepsilon)\delta_C}$, which is less than $(1 - V_R^F)e^{-\underline{t}\delta_C}$. So the deviation is not profitable.

Substituting $t_C = t_F = \underline{t}$, into the equilibrium offer (eqn. 4) and taking the limit as $\underline{t} \to 0$,

$$\lim_{\underline{t} \to 0} V_R^C = \frac{\delta_F}{\delta_C + \delta_F} \tag{5}$$

by L'Hopital's rule. Equation 5 is how Γ is defined. $\square$

E.2 One-sided Informational Asymmetry

In this modified game the Firm knows its project's profitability ($\theta \in \mathbb{R}^1_+$), but the Community only knows the range of profitability ($\theta \in [\underline{\theta}, \overline{\theta}]$; $\overline{\theta} > \underline{\theta}$) and holds a prior belief ($F(\cdot)$) about the distribution of projects over this range. In each round, the player making the offer proposes a payout to the Community of x_C with $x_F = \theta - x_C$ being retained by the Firm. The game is otherwise identical to the complete information game of alternating offers described in section E.1.[49]

To make the analysis tractable, I make three additional assumptions. First, as the primary concern is with the occurrence delays and not the final profit split, I assume for convenience that the Firm and Community share the same opportunity cost:

Assumption 1. *The Firm and Community have the same opportunity cost ($\delta_F = \delta_C = \delta$).*

Second, I also adopt the first assumption of Admati and Perry (1987, 349):

Assumption 2. *If a player can obtain the same payoff by making fewer offers, then they make fewer offers.*

Finally, I place a restriction on the Community's beliefs. I assume that the Community only pays attention to the Firm's delay strategy when updating their beliefs, and not the split (x_C) that the Firm proposes after that delay. This assumption is natural: while delaying is a costly signal for the Firm to send, shouting out a proposed split is not. Thus, the Community ignores the proposed split when attempting to infer the Firm's type.

Assumption 3. *The Community's beliefs about the project's type are based only on the time that the Firm delays.*

E.2.1 Lemmas

Definition 2. *Let $t : \Theta \to \mathbb{R}^1_+$ be a firm strategy. $t(\theta)$ is **locally incentive compatible** iff $\forall\ \theta \in \Theta$, there exists $\varepsilon > 0$ s.t. $u(t(\widetilde{\theta}) \mid \theta) \leq u(t(\theta) \mid \theta)\ \forall\ \widetilde{\theta} \in [\theta - \varepsilon, \theta + \varepsilon]$.*

Lemma 1. *In a stationary, differentiable fully separating pure strategy PBE, a firm's delay strategy ($t(\theta)$) must be locally incentive compatible. That is, a firm of type θ can not improve their payoff by delaying infinitesimally more or less to mimic a different type $\widetilde{\theta}$. Given this condition, a firm's strategy must be of the form $t(\theta) = k - log(\theta)/\delta$.*

Proof. Local incentive compatibility requires that no firm can profit by infinitesimally deviating to the equilibrium strategy of another firm (definition 2).

Let $u(t(\widetilde{\theta})|\theta)$ be the payoff that type θ gets when it mimics the delay strategy of type $\widetilde{\theta}$ and makes the offer that type $\widetilde{\theta}$ makes in equilibrium. This must be the offer that $\widetilde{\theta}$ makes in the complete information game, since we are conjecturing a fully separating equilibrium, stationarity, and assumptions 2 and 3.

[49] I continue to assume that the Community is a unitary actor, as collective action problems do not offer an explanation for why protests occur without further assuming that the Firm is uninformed about the Community's resolve — a questionable assumption given the firms' outlays for community relations officers.

Define $D(\widetilde{\theta} \mid \theta) := u(t(\widetilde{\theta}) \mid \theta) - u(t(\theta) \mid \theta)$, which is the payoff to type θ from mimicking type $\widetilde{\theta}$. Local incentive compatibility implies that the derivative of $D(\widetilde{\theta} \mid \theta)$ with respect to $\widetilde{\theta}$ must be zero at the firm's true type:

$$\frac{\partial}{\partial \widetilde{\theta}} D(\widetilde{\theta} \mid \theta)\bigg|_{\widetilde{\theta}=\theta} = 0$$

Plugging in $D(\widetilde{\theta} \mid \theta)$, this first order condition reduces to:

$$\begin{aligned} \delta\theta t'(\theta) + 1 = 0 \\ t'(\theta) = -\frac{1}{\delta\theta} \end{aligned}$$

Solving this differential equation,

$$t(\theta) = k - \frac{\log(\theta)}{\delta}$$

This strategy, $t(\theta)$, is, by construction, locally incentive compatible. □

Lemma 2. *In a stationary, differentiable fully separating pure strategy PBE, a firm's delay strategy must also be globally incentive compatible. That is, a firm of type θ can not improve their payoff by mimicking any other type. In this game, local incentive compatibility (IC) is sufficient to establish global incentive compatibility.*

Proof. Lemma 1 implies that $t(\theta) = k - \log(\theta)/\delta$. We can now rewrite $D(\widetilde{\theta} \mid \theta)$ as

$$D(\widetilde{\theta} \mid \theta) = \left(\theta - \frac{\widetilde{\theta}}{2}\right)\widetilde{\theta}e^{-\delta k} - \frac{\theta^2}{2}e^{-\delta k}$$

By construction, when the firm employs strategy $t(\theta)$, the first derivative of $D(\widetilde{\theta} \mid \theta)$ evaluated at the firm's true type is zero. As such, the prescribed equilibrium strategy is a local minimum or maximum of $D(\widetilde{\theta} \mid \theta)$. Taking the second derivative of $D(\widetilde{\theta} \mid \theta)$, we find that it is always negative:

$$\frac{\partial^2}{\partial \widetilde{\theta}^2} D(\widetilde{\theta} \mid \theta) = -e^{-\delta k} < 0$$

$D(\widetilde{\theta} \mid \theta)$ is globally concave in $\widetilde{\theta}$. As such, the firm attains the global maximum of $D(\widetilde{\theta} \mid \theta)$ by playing the prescribed equilibrium strategy and has no incentive to deviate and mimic another type. □

Lemma 3. *For any off-the-path beliefs by the Community that place a point mass on some $\theta' \in [\underline{\theta}, \overline{\theta}]$, no k strictly greater than $\log(\overline{\theta})/\delta$ can sustain the stationary, differentiable fully separating pure strategy PBE.*

Proof. Suppose that $k > \log(\overline{\theta})/\delta$. Lemma 1 implies that, in equilibrium, no firm chooses a period of delay in the interval $[0, t(\overline{\theta}))$. When k is this large, then even the most profitable firm chooses to delay.

If (off the equilibrium path) the Community observes $t' \in [0, t(\overline{\theta}))$, suppose that they form the posterior belief $\mu\left[\theta | t'; t(\theta)\right] = \theta'$. This is the Community's posterior belief after seeing a delay of t' given the conjectured firm strategy $t(\theta)$.

If $\theta' \leq \overline{\theta}$, then a firm with type equal to θ' can now profitably deviate: this firm can delay $t' < t(\theta')$, reveal their type, and propose the same counter-offer they would have after delaying $t(\theta')$. Given this profitable deviation, this cannot be an equilibrium. □

Lemma 4. *For any posterior beliefs by the Community that place a point mass on some* $\theta' \in [\underline{\theta}, \overline{\theta}]$ *after observing no delay, no* k *strictly less than* $\log(\overline{\theta})/\delta$ *can sustain the stationary, differentiable fully separating pure strategy PBE.*

Proof. Suppose that $k < \log(\overline{\theta})/\delta$. Let $\check{\theta}$ be the type that that now waits $t = 0$ given the strategy defined by lemma 1. Thus, all types in $[\check{\theta}, \overline{\theta}]$ do not delay, and there is a bunching of types at $t = 0$.

What does the Community infer after observing no delay? Suppose that $\mu\left[\theta | t = 0; t(\theta)\right] = \theta' \in [\underline{\theta}, \overline{\theta}]$.

We need to consider three cases:

(i) If $\theta' < \check{\theta}$, then a firm of type θ' can profitably deviate by not delaying, rather than waiting $t(\theta') > 0$.

(ii) If $\theta' > \check{\theta}$, then a firm of type $\check{\theta}$ can profitably deviate by infinitesimally delaying, separating, and offering $t^{-1}(\varepsilon)/2 < \theta'/2$, which the Community accepts.

(iii) Finally, if $\theta' = \check{\theta}$, then $\theta \in (\check{\theta}, \overline{\theta}]$ can profitably deviate by infinitesimally delaying and pooling on $t^{-1}(\varepsilon)$. That is, the most profitable types can, with virtually no cost, mimic a firm that is slightly less profitable than $\check{\theta}$ and, thus, retain a higher payoff.

Given these profitable deviations, this cannot be an equilibrium. □

Lemmas 1, 3, and 4 imply that $k = \log(\overline{\theta})/\delta$ and $t(\theta) = \dfrac{\log(\overline{\theta}) - \log(\theta)}{\delta}$.

E.2.2 Proof of Proposition 2

Let $t : \Theta \to \mathbb{R}^1_+$ be a firm strategy. A pure strategy, fully separating Perfect Bayesian equilibrium is "strongly pure" if for all $t \in \mathbb{R}^1_+$, the Community's posterior beliefs $\mu\big[\theta|t; t(\theta)\big]$ place probability 1 on some $\theta' \in \Theta$. This equilibrium concept does not permit posterior beliefs that are not a point mass. Also, I define a PBE in this model to be differentiable if the equilibrium function $t(\theta)$ is differentiable in θ. Finally, I require that the Community's posterior beliefs upon observing $t > t(\underline{\theta})$ are such that they believe they are facing $\underline{\theta}$ with probability 1.

Proposition 2. *Granting assumptions 1-3 and that the Community believes with probability 1 that they face $\underline{\theta}$ if $t > t(\underline{\theta})$, as the minimum time between offers approaches zero, there exists a unique stationary, differentiable pure strategy fully separating Perfect Bayesian Equilibrium that is strongly pure. In it, the following properties hold:*

(A) The Community makes an optimal initial offer (b^*).

(B) Firms with projects above a cutoff value ($\theta \geq \widehat{\theta}(b^*)$) immediately accept.

(C) Firms with projects below that cutoff value ($\theta < \widehat{\theta}(b^*)$) reject the initial offer, delay long enough ($t(\theta)$) to perfectly reveal their type, and then counter-offer. As the project's profitability has now been revealed, the Firm counters with the split from the complete-information game, which the Community accepts.

(D) Off the path, if the delay exceeds $t(\underline{\theta})$, then the Community assumes that they are facing the least profitable type ($\theta = \underline{\theta}$); otherwise (when $t \in [0, t(\underline{\theta})]$), the Community inverts the delay function to determine the type θ that they face after a delay of length t ($\theta = t^{-1}(t)$).

Proof. If the Firm rejects the Community's initial offer, then they choose to delay $t(\theta) = k - \log(\theta)/\delta$ (Lemma 1). This is globally incentive compatible (Lemma 2). If the Community believes that they face $\overline{\theta}$ after observing no delay (and places no positive probability on $\theta > \overline{\theta}$), then $k = \log \overline{\theta}/\delta$ (Lemmas 3 and 4).

After the Firm delays $t(\theta)$ and reveals its type, it counter-offers with the split from the complete information game (Proposition 1). By assumption 3, the Firm has no incentive to propose an alternative split, as the Community ignores this action in forming its posterior beliefs. By assumption 2, if proposing a different split does not change the Firm's payoff but does extend the game, then they prefer not to deviate.

How does the Community choose its initial offer? Let $\widehat{\theta}(b)$ be the type that is indifferent between accepting an initial offer of b and delaying $t(\widehat{\theta}(b))$. $\widehat{\theta}$ is then defined by the following indifference condition:

$$\widehat{\theta}(b) - \frac{b}{2} = \frac{\widehat{\theta}}{2} e^{-\delta t(\widehat{\theta}(b))}$$
$$\widehat{\theta}(b) = \overline{\theta} - \sqrt{\overline{\theta}(\overline{\theta} - b)}$$

(The second solution for $\widehat{\theta}(b)$ falls outside the support of θ.) All $\theta > \widehat{\theta}(b)$ will immediately accept an offer of b; all others will delay $t(\theta)$. The Community's optimal initial offer is then

$$b^* = \arg \max_{b \in [\underline{\theta}, \overline{\theta}]} \left\{ \underbrace{\left(1 - F[\widehat{\theta}(b)]\right)(b/2)}_{\text{Firm accepts } b} + \underbrace{F[\widehat{\theta}(b)]\ E_\theta \left[\frac{\theta}{2} e^{-\delta t(\theta)} \mid \theta < \widehat{\theta}(b)\right]}_{\text{Firm delays } t(\theta)} \right\}$$

□

E.3 Extension: Inflated Expectations

The probability of protest in the model with incomplete information is the probability the Firm would rather disrupt production than immediately accept the Community's initial offer (i.e., $\Pr(\theta < \widehat{\theta}(b^*) = F(\widehat{\theta}(b^*)))$. To compute this probability, I assume that project profitability is distributed uniformly between zero and some upper bound $\overline{\theta}$. We can now determine the community's optimal initial offer, $b^* = 3\overline{\theta}/4$. And, given this initial offer, all firms below $\widehat{\theta}(3\overline{\theta}/4) = \overline{\theta}/2$ would rather disrupt production than immediately concede; the probability that a given firm falls in this range is then $F(\overline{\theta}/2) = 1/2$.[50]

To extend the model, suppose that the true distribution of firms is $\theta \sim U[0, \overline{\theta} - \omega] = F(\cdot)$ where $\omega \in (0, \overline{\theta}/2)$. Yet, the Community continues to believe that $\theta \sim U[0, \overline{\theta}] = \widetilde{F}(\cdot)$ (and this prior belief is common knowledge). In such a setting, the Community expects to confront a firm that is more profitable (by $\omega/2$) than the population average type.

The equilibrium described in proposition 2 still exists (though not uniquely) with one modification: the Community's initial offer now reflects their inflated prior beliefs ($\widetilde{F}(\cdot)$) and not the true distribution of firm types. Changing the Community's prior in this way does not affect the Firm's behavior: while the Firm knows that the Community holds exaggerated beliefs, it can not exploit this information for its own gain and, thus, has no incentive to deviate from the strategy proposed in proposition 2.

Given their prior beliefs ($\widetilde{F}(\cdot)$), the Community's optimal initial offer remains $b^* = 3\overline{\theta}/4$, and all firms below $\overline{\theta}/2$ would rather disrupt production than concede. However, the probability that a firm actually falls in this range now a function of the Community's bias: $\Pr(\text{Protest}) = F(\overline{\theta}/2) = \frac{1}{2}\left(\frac{\overline{\theta}}{\overline{\theta} - \omega}\right)$. When the Community's beliefs match the true distribution of firms (i.e., $\omega = 0$), the probability of protest remains 1/2; however, this probability increases when the Community exaggerates the likelihood of hosting a highly profitable mine.

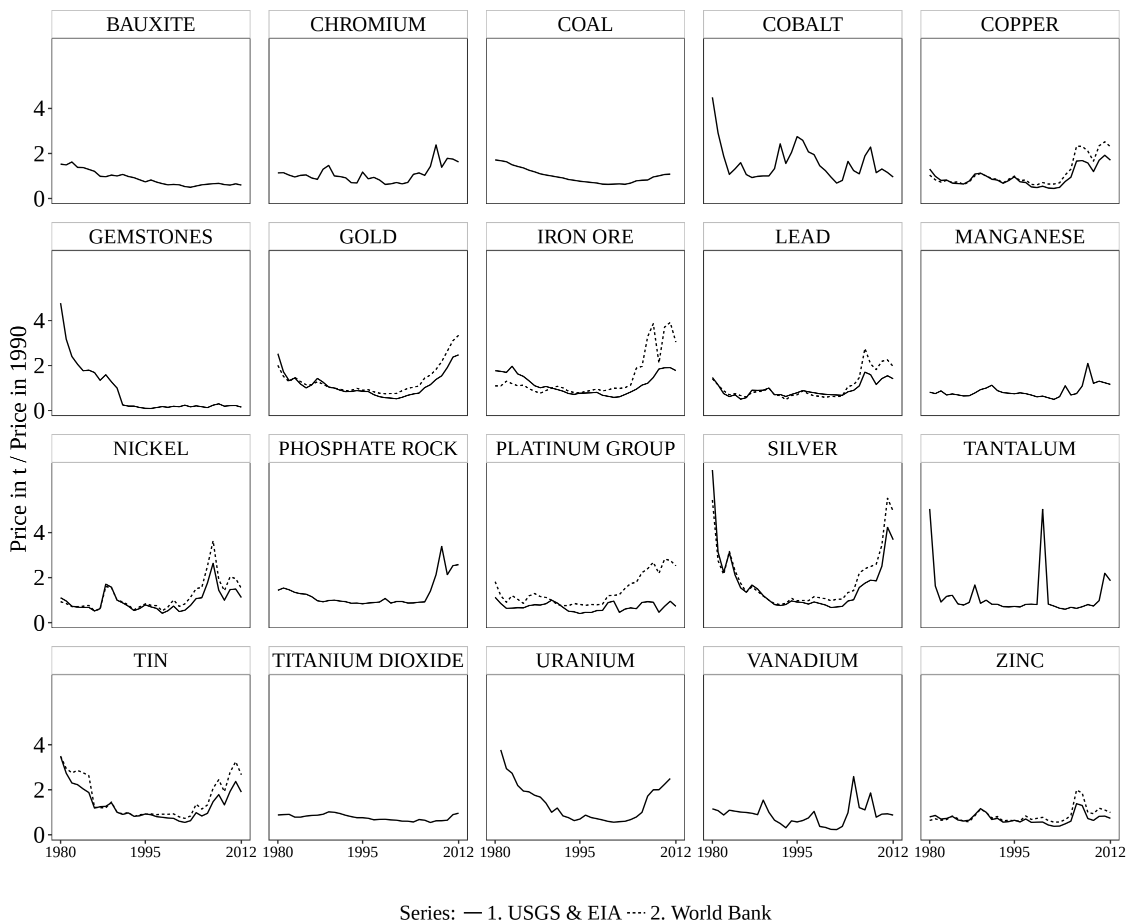
[50] Manipulating the upper bound on firms' profitability ($\overline{\theta}$) does not affect the probability of disruptions, because the community adjusts their offer as the upper bound of profits changes.

F. Data Sources

F.1 Commodity Prices

I employ World Bank (WB) commodity prices, the supply-demand statistics from the US Geological Survey (USGS), and coal and uranium prices from the US Energy Information Administration (EIA). WB prices are based on major commodity markets. The USGS uses a variety of trade journals and open market prices. Finally, the EIA bases its coal prices on open market prices, and its uranium series on the prices paid by civilian operators of US nuclear power reactors. I convert all units to USD per metric ton and deflate prices to real 1998 USD.[51] Where prices for the same commodity are available from both WB and USGS, I use WB prices. Figure A.2 graphs the price series for the twenty most common minerals (according to the number of cell-years for which the commodity is coded as the modal commodity).

Figure A.2: Commodity Price Series (Base Year = 1990)



[51] I choose 1998, because the USGS data provides real prices in 1998.

F.2 Demographic and Health Surveys

The Demographic and Health Surveys are nationally representative surveys of between 5,000 and 30,000 households that focus on outcomes related to population, health, and nutrition (http://www.dhsprogram.com/What-We-Do/Survey-Types/DHS.cfm). In many countries, multiple survey waves have been enumerated, allowing for comparisons over time. For this project, I compile the subset of surveys that also include approximate geo-coordinates. These allow researchers to locate over 99% of survey clusters to within 5km. The resulting dataset includes just under 760,000 household observations from 72 surveys.[52]

Table A.16: Included Survey Waves from DHS

	Country	Waves			
1	AO	2010	16	MD	1997, 2009, 2012
2	BF	1993, 1999, 2003, 2010	17	ML	1996, 2001, 2006, 2012
3	BJ	1996, 2001, 2012	18	MW	2002, 2010, 2012
4	BU	2011	19	MZ	2009, 2011
5	CD	2007, 2013	20	NG	1990, 2003, 2008, 2013
6	CF	1994	21	NI	1992, 1998
7	CI	1995, 2012	22	NM	2000, 2007, 2013
8	CM	1991, 2004, 2011	23	RW	2005, 2008, 2010
9	ET	1994, 2003	24	SL	2008, 2013
10	GA	2012	25	SN	1995, 2005, 2008, 2011
11	GH	1993, 1998, 2003, 2008	26	TG	1998
12	GN	1999, 2005, 2012	27	TZ	1999, 2007, 2012
13	KE	2003, 2009	28	UG	2001, 2007, 2011
14	LB	2008, 2012	29	ZM	2007
15	LS	2004, 2009	30	ZW	1999, 2005, 2010

Migration

The DHS asks how long households have lived in their place of residence. Respondents can answer "always," which I use to code households that have never moved (i.e., permanent residents).

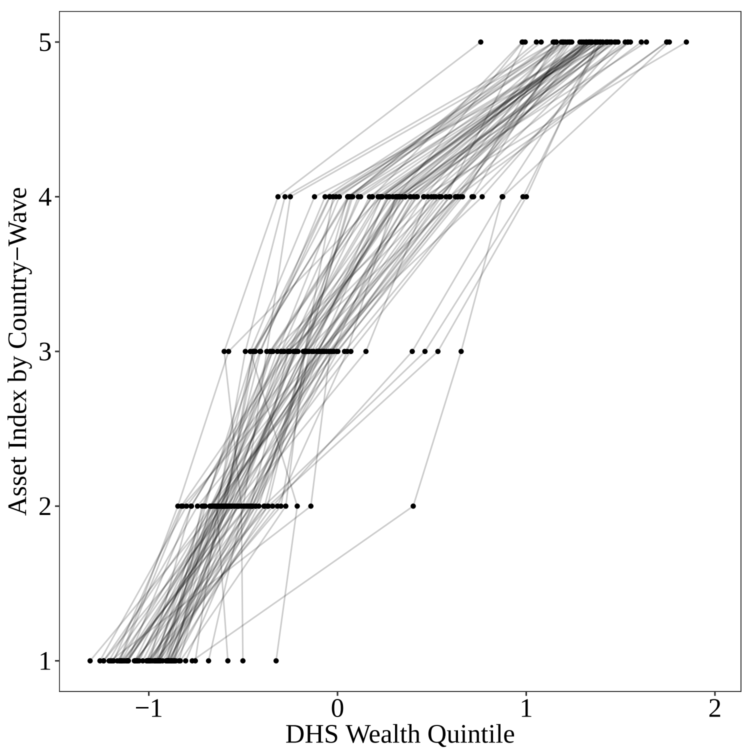
Knowing both the year of the survey wave and how long a household has lived in their current residence, I can also determine whether they moved before or after mining started, which I use in table A.10.

[52]The DHS documentation notes that each row in the household recode datasets correspond to a unique household. There are, however, some instances of repeated household IDs within the same survey wave. In the analysis presented above, I retain all rows.

Assets and Inequality

Across most surveys, the DHS collects a common set of variables related to households' access to drinking water and toilet facilities, what the respondents' homes are constructed of and the number of rooms used for sleeping, and the ownership of common consumer items. I use the recode maps from the DHS to generate standard codes for the drinking water (piped, well, surface, tanker/bottled, or other), toilet facilities (flush, pit, none, other), and home construction variables (natural, rudimentary, finished, other). The variables related to consumer items are yes or no questions. The asset index I employ is the mean of the following non-missing indicator variables: does not rely on surface water, has some toilet facility, does not have a floor made of natural materials, does not have walls made of natural materials, does not have a roof made of natural materials, has electricity, owns a radio, owns a telephone, owns a television, owns a refrigerator, owns a bicycle, owns a motorcycle, and owns a car.

Figure A.3: Asset Index vs. DHS's (Relative) Wealth Classifications



Households' scores on the asset index are first demeaned by survey. I then take the average of these demeaned scores for each wealth quintile. Finally, these averages are connected by a line, with one line for each unique survey.

The DHS does not report an asset index. It does, however, classify households into wealth quintiles based on how they compare to other households surveyed in the same country and year (i.e., within the same wave). This DHS classification incorporates respondents' answers to additional country-specific questions. Unfortunately, the relative classification does not permit comparisons across countries or over time. Nonetheless, I can use it to assess the validity of my own asset index: are households that score relatively high on my index (for a given survey wave) more likely to be classified as richer? Figure A.3 presents this comparison. I normalize my asset index by survey (to remove variation due to cross-country or over-time variation) and then plot the normalized value of my asset index against the DHS's wealth classification. I connect these values with a line; there is, thus, one line for each unique DHS survey in the data. As is apparent from the figure, knowing where a household falls on my asset index (relative to other respondents in their same country and year) provides a good indication for where they fall in the DHS's wealth distribution.

F.3 Environmental Hazards

World Database of Protected Areas

According to UNEP-WCMC (2016), "The World Database on Protected Areas (WDPA) is the only global database of protected areas. It is a joint effort between IUCN and UNEP, managed by UNEP-WCMC, to compile protected area information for all countries in the world from governments and other authoritative organizations which are referred to as data providers."

The WDPA includes areas designated by national governments, regional and international conventions, and indigenous or community groups. The WDPA defines protected areas per the International Union for Conservation of Nature (IUCN) and Convention on Biological Diversity. The IUCN considers a protected area "a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long term conservation of nature…" (9). Areas only enter the WDPA if they meet this definition, include an associated list of attributes, provide source information, and sign a contributor agreement (12). In the analysis I use all sites included in the WDPA and measure the minimum (great circle) distance between these sites and each mine.

Water Stress

The World Resource's Institute produces the Aqueduct Water Risk Atlas Global Maps (Gassert et al. 2014). In this paper, I use their measure of baseline water stress, which "measures total annual water withdrawals (municipal, industrial, agricultural) expressed as a percent of the total annual available flow. Higher values indicate more competition among users" (8). This is calculated by dividing water withdrawals by total available blue water. The baseline water stress data are only available cross-sectionally and could be measured post-treatment.

Environmental Risk Exposure

Environmental Risk Exposure is one of the indicators included in the Environmental Performance Index from Hsu (2016). The authors describe it as a summary measure of "how much of the burden of disease observed in a given year can be attributed to past exposure to environmental risk factors, which include: unsafe water (unsafe sanitation); air pollution (ambient particulate matter pollution, household air pollution, and ozone pollution)" (2). The measure runs from 0-1, with higher values indicating greater risk, and is available as a panel with observations in 1990, 1995, 2000, 2005, 2010, and 2013. For intervening years, I impute the most recent past observation.

F.4 Governance

The Worldwide Governance Indicators from Kaufmann et al. (2010) include six measures:

(1) Voice and Accountability: "Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media."

(2) Political Stability and Absence of Violence: "Reflects perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism."

(3) Government Effectiveness: "Reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies."

(4) Regulatory Quality: "Reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development."

(5) Rule of Law: "Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."

(6) Control of Corruption: "Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests."

The WGI are a country-year panel that runs from 1996-2016. Each of the six measures range from roughly -2.5 to 2.5 and are an index constructed using an unobserved components model.

F.5 Mining Projects

This paper draws on three sources of project-level data on global mining activity: SNL Metals and Mining, IntierraRMG, and Mining eTrack.[53] These data are only available to subscribers and primarily serve clients within the mining and financial sectors, though recent research by Knutsen et al. (2016) and Berman et al. (2017) draws upon the IntierraRMG data. These providers compete on their completeness and accuracy and rely on press releases, corporate and government reports, and local and international news to compile and update their databases.

[53] In 2014, IntierraRMG was acquired by SNL Metals and Mining. However, the respective databases had not been fully merged when some of the data used in this paper was accessed.

Completeness

These databases do not include artisanal or illegal mines. Given the composition of source materials, they are also more likely to miss two types of mines: (a) small-scale operations and (b) mines operated by private companies, especially in cases where neither the company nor the government disclose information about the project. This second group could include mines operated by private or state-backed companies in less transparent contexts. As noted in the main text, the empirical claims made in this paper are restricted to commercial investments. The omission of artisanal, illegal, and small-scale miners is, thus, appropriate.

Duplicate Mines

One challenge of working with partially overlapping databases is how to exclude duplicate observations. As most of the analysis employs an indicator for mining activity (and not counts of mines), duplicate projects are less of a concern. Nonetheless, I take a number of steps to identify and exclude duplicates. In particular, I identify duplicate mines using (a) the names of mining projects (and approximate string matching), (b) the commodities mined, and (c) the geo-coordinates of the mining projects (rounded to one decimal place to allow for approximate matches). This results in a dataset of mining projects sourced from one or more databases.

Table A.17: Number of Mining Projects by Data Source

Source	N
SNL	673
SNL, IntierraRMG	202
SNL, Mining eTrack	148
SNL, IntierraRMG, Mining eTrack	146
Mining eTrack	105
IntierraRMG, etrack	104
IntierraRMG	72

This includes projects for which geo-coordinates and start years are available.

Assigning Start and End Dates

All three databases include a variable for when a project starts. The SNL Metals and Mining and IntierraRMG glossaries claim that this corresponds to the first year of actual mining (i.e., production) and not the year in which exploration commenced. Among the projects labeled as operational by SNL Metals and Mining or IntierraRMG or included in the Mining e-Track database, a start year is included for 84% of projects (or can be coded from the earliest year in which production data is available). A start year is also included for 535 other projects in the SNL Metals and Mining or IntierraRMG data. Most of these are classified into the following stages: closed, expansion, feasibility, reserves development, satellite, or various stages of production. I err on the side of inclusiveness and use all projects with start years and geo-coordinates to code cells with active mines. If a project is labeled as active in 2014, then I code the end year as 2014, the last year in the panel.

F.6 Social Conflict

The Armed Conflict Location and Event Data Project (**ACLED**) covers all countries on the African continent from 1997 to 2014 (Raleigh et al. 2014). ACLED data is based on three types of sources: "(1) more information from local, regional, national and continental media is reviewed daily; (2) consistent NGO reports are used to supplement media reporting in hard to access cases; (3) Africa-focused news reports and analyses are integrated to supplement daily media reporting" (Raleigh et al. 2014, 17). The providers of the data claim that "the result is the most comprehensive and wide-reaching source material presently used in disaggregated conflict event coding" (17). This information is used to code what type of event occurred, the type of actor that participated (government, rebel force, political militia, ethnic militia, rioters, protesters, civilians, or outside/external force), and where the event took place. I only retain events coded as a "protest or riot" (a protest becomes a "riot" if the event turns violent) that have a precise geo-coding, i.e., a particular town is noted and geo-coordinates are available for that town. ACLED has enjoyed widespread use in both political science and economics: Raleigh et al. (2010), the article introducing the dataset, has been cited over 330 times according to Google scholar.

The Global Database of Events, Location, and Tone (**GDELT**) machine codes events from a wide array of news sources (Leetaru and Schrodt 2013). GDELT includes a number of different types of events, but I only include protests, which can be geo-located based on the name of specific city or landmark. The dataset covers all countries over the period from 1979 to 2014. If an event is reported on in multiple stories or by multiple sources, these reports are aggregated (to avoid double-counting) and information is recorded about the number of news sources and stories covering each event.

GDELT errs on the side of inclusion and, thus, contains more false positives than other event databases. However, head-to-head comparisons suggest that the dataset captures important *changes* in protest activity (Ward et al. 2013). Ward et al. (2013) look at events in Egypt, Syria, and Turkey as reported in GDELT and ICEWS, a warning system used by the US government. They find that "the volume of GDELT data is very much larger than the corresponding ICEWS data, but they both pick up the same basic protests in Egypt and Turkey, and the same fighting in Syria" (10). Two aspects of the research design that make me more comfortable about employing GDELT: first, my empirical strategy focuses on trends in protest activity and not levels; and second, I include both cell and year (or country-year) fixed effects in our regressions, which helps to account for differential rates of reporting in different places and over time.

The Integrated Crisis Early Warning System (**ICEWS**) is a product of Lockheed Martin that draws on commercially available news sources from approximately 300 publishers, including both international and national publishers (Boschee et al. 2015). Like GDELT, ICEWS machine codes events from this corpus of news stories using the Conflict and Mediation Event Observations (CAMEO) system, which includes a top-level category for protest (Schrodt and Yilmaz 2007). The dataset covers all countries over the period from 1995 to 2014. To exclude events with imprecise geo-codes, I limit my sample to events that include the name of a specific city or town.

A recent evaluation of the ICEWS data asked human coders to evaluate a sample of events (from 2011 to 2013) and determine (a) whether protest events were, in fact, protests, (b) whether the correct source actor was coded, and (c) whether the correct target actor was coded. The report found that 84.5% of protest events in the sample met these three criteria (Raytheon BBN Technologies 2015, 8).

I use the Uppsala Conflict Data Program's Geo-referenced Event Dataset (**UCDP-GED**) to evaluate whether the onset of mining increases the probability of armed conflict (Melander and Sundberg 2012). An event in the UCDP-GED data is defined as: "The incidence of the use of armed force by an organised (sic) actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration" (Melander and Sundberg 2012, 3). I only use events that can be related to an exact location (i.e., a city or landmark). The dataset covers the African continent from 1989-2010.