Concession Stands:
How Foreign Investment in Mining Incites Protest in Africa [*]

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April 6, 2017

Abstract

Why do foreign investments that can improve economic welfare also induce protest? Using newly compiled data on commercial mining, commodity prices, and protest in Africa, I establish that foreign mining investments double the probability of protest. I argue that communities have to strike a bargain with companies but have limited information about the value of these projects. When communities' expectations exceed what companies can pay, protests result. I marshal two pieces of evidence consistent with this theory: first, elevated mineral prices can inflate communities' expectations and exacerbate protest; and second, policies that increase transparency mitigate this relationship between prices and protest by helping correct the informational asymmetry that generates conflict. I do not find support for alternative explanations related to environmental risks, in-migration, inequality, corruption, or reporting bias. Despite claims that resource extraction fuels armed conflict, I also do not find that these projects increase rebel activity.

Foreign direct investment (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 2013*b*; The World Bank 2012). Investments in extractive industries have propelled this upward trend (UNCTAD 2013*a*).

These investments can contribute to local development: "There is no debate," according to Farole and Winkler (2014, 9), "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 hand, scholars working on the "resource curse" worry that heavy reliance on extractive industries can hamper the development of other export-oriented sectors, undermine political accountability, and even engender civil conflict (see Ross 2015, for an recent review).

This paper evaluates the effects of foreign investments in natural resources on conflict in Africa. Earlier work has argued that mines and other primary commodities represent an attractive source of income for rebel groups (e.g., Collier and Hoeffler 2002; Lujala, Gleditsch and Gilmore 2005; Berman et al. 2014). Despite these claims, I find no evidence that commercial mining increases the likelihood of rebel activity or armed conflict. Yet, the communities hosting these mines are not pacific. I demonstrate that these projects amplify the probability of protests or riots. My difference-in-differences estimates imply that mining more than doubles the probability of these social conflicts. While these protests are not as deadly as armed conflicts, they generate large economic losses: Davis and Franks (2014) estimate that protests at major mining operations entail productivity losses of 20 million dollars per week and impose larger long-run costs by deterring subsequent investment.

This first finding contrasts with earlier research by Rothgeb (1990, 266), who claims that foreign investments in mining in poor countries ameliorate deprivation and, thus, reduce protests. While I can reject this rosy view, my findings raise the question of why investments that can improve economic welfare induce conflict? In a search for mechanisms that can help explain this empirical finding, I explore several common explanations for these protests but find little support in the available data. First, if protests reflect concerns about environmental harm, then we would expect these conflicts to target surface mines, which pose a greater environmental risk. I uncover no evidence of

such targeting, even as prices rise and these mines may be expanding their footprints. Second, new mining jobs attract migrants, which could anger existing residents. Yet, after compiling over seventy geo-coded Demographic and Health Surveys from thirty sub-Saharan countries, I do not find that increasing the proportion of migrant households in a mining community raises the likelihood of protest. Third, the rents from mining may be captured by a small group, and this inequality could generate resentment. However, mining does not appear to exacerbate wealth inequality; moreover, raising inequality in mining areas does not increase the likelihood of protest. Fourth, these new, commercial projects may displace artisanal miners, who protest their eviction. But protests not only afflict gold or diamond mines, but also projects producing commodities that do not commonly overlap with artisanal claims. Finally, recent works by Axbard, Poulsen and Tolonen (2015) and Knutsen et al. (2016) report that commercial mining does not amplify crime in South Africa or perceptions of local corruption across sub-Saharan Africa (though police bribes increase modestly) respectively, suggesting that protesters are not incensed by social decay or increased rent-seeking.

I argue instead that many protests can be understood as conflicts over the distribution of project benefits between mining companies and their host communities. Drawing on earlier research into strikes in more developed contexts (e.g., Tracy 1987), I argue that an informational asymmetry sometimes prevents companies and communities from amicably reaching a deal about how to distribute profits from the mine. Communities often have limited information about the value of these projects. Nevertheless, they have high expectations for what they stand to gain, especially when mineral prices are high. This can lead communities to make large demands of companies. As all companies are wont to claim that they cannot meet such demands, protests provide a tactic for separating the mining firms that really cannot pay from those attempting to low-ball their hosts.

Beyond qualitative accounts that suggest this model of protests, I marshal two additional pieces of empirical evidence. First, high world prices during the recent commodity boom exacerbated protest in mining areas. I argue that high prices generated inflated expectations within communities about mining projects' profits, exacerbating the informational problem described above. Second, I show that this relationship between prices and protests declines with candidacy in the Extractive Industries Transparency Initiative (EITI), a policy that promotes transparency and could help correct

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the informational asymmetry that I argue generates conflict. Moreover, the effect of EITI is greater in mining areas covered by cell phone networks, suggesting that information transmission rather than changes in local governance accounts for the effect.

Some readers may question the relevance of protests in remote mining towns in Sierra Leone or Tanzania. For the last thirty years, civil wars rightfully garnered the attention of political economists studying Africa. Yet, such conflicts have become increasingly rare: according to UCDP data, 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. While this is a positive development, it does not indicate an era tranquility. The number of protests and riots doubled between 1997 and 2010, what Branch and Mampilly (2015) dub a "third wave." This rise reflects an increasing number of mining and land-related protests. If we look outside of major cities (i.e,. localities with fewer than 100,000 people), mining areas make up less than one tenth of one percent of populated land area and just 0.3 percent of the population. Yet, these mining localities account for 17.6 percent of protests in 2002 and 22 percent of protests in 2009. Moreover, these protests in response to large foreign investments are not unique to Africa or mining: Protests crippled Peru's mining sector in 2015, and new agribusiness companies operating in Africa have been accused of "land grabbing" and met with similar forms of resistance (Cotula et al. 2009). Understanding why these conflicts occur indicates policies, such credible transparency regimes, that can help prevent these inefficient and increasingly prevalent confrontations without resorting to repression.

In addition to its policy relevance, this paper contributes to three academic literatures. First, existing research in international political economy focuses on the determinants of foreign investment, not its political or social consequences (e.g., Jensen 2008; Biglaiser et al. 2012). The literature emphasizes how hold-up problems deter investment to poorly institutionalized states. This paper makes both an empirical advance by identifying the consequences of foreign investment projects for conflict, as well as a theoretical contribution by illustrating how informational asymmetries, like commitment problems, strain investor-host relations. Second, I find that these commercial mines generate social, but not armed, conflict. While labor-intensive, artisanal mines may be easily operated or taxed by rebels, the capital-intensive projects in my sample largely escape predation by

armed groups (Ross 2004). This result suggests that how natural resources are produced may condition their effects on conflict — a finding that echoes recent work arguing that production methods or ownership structures can amplify or moderate the symptoms of the "resource curse" (e.g., de la Sierra 2014; Andersen and Ross 2014). 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 in preventing disputes, this paper addresses several core questions from the "private politics" literature (Baron 2003). 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. 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.[1]

1.   Do Foreign Investment Projects Provoke Protest?

1.1   Bargaining with Complete Information: The Null Hypothesis

Foreign mining investments could 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 countries 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).

To establish and operate a mining concession, investors need to coordinate with government 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."[2] Since 2009, Ernst & Young has included maintaining a "social

[1]Reports from Millennium Development Goals from 2005 to 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.

[2]Community is actually a term of art in the sector: "[t]he *local* or *host* community is usually applied to

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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. This can include how many workers will be employed and at what wage, compensation for resettlement, rents for land, or expenditure on infrastructure and public facilities (e.g., local clinics and schools).

In the ideal scenario, investors and their host communities amicably reach such agreements, and both parties share in any surplus generated by the project. When can we expect these parties to frictionlessly decide how to divide the returns generated by a new investment? 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).[3] The logic is straightforward: the community proposes a split that leaves the company indifferent between accepting today and counter-offering after some costly delay.

In appendix A.1, I present a game of alternating offers played in continuous time between two informed parties: a community and a firm.[4] 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, i.e., the deal that the firm and community can conclude in the absence of any informational problems.

In the complete information setting, firms and communities immediately agree on how to split the project's proceeds (with the more patient party retaining a larger share). In this model, costly

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" (emphasis original; qtd. in Evans and Kemp 2011, 1768).

[3]This is true even if the government reduces the surplus through observable forms of taxation (e.g., license payments or royalties). That a mining company bargains with, and makes payments to, the central government is not enough to induce conflict between that company and its host community.

[4]Well-known results from games of alternating offers with discrete time periods do not prove the first proposition. In this model, actors can choose how long to delay. The proof establishes both the optimal initial offer and that the party receiving that offer has no desire to delay before accepting.

delays, such as protests or work stoppages, do not occur in equilibrium — firms and their host communities "bargain away" conflict. While I focus attention on the mining sector, the model is more general and has been used to characterize negotiations between labor and management across sectors with different production functions (e.g., Kennan and Wilson 1993).

While this null hypothesis will 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] Moreover, there is a second reason, specific to natural resource production, that we might 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 industries afflicted by Dutch Disease (e.g., manufacturing or agribusiness) protest in response to reduced employment or wage growth, then social conflict would likely increase *outside* of mining communities.

1.2 Investments Generate Protest: Evidence of Bargaining Failure

Employing panel data on mining activity and social conflict, I demonstrate that protests increase in localities receiving new investments. This leads me to reject the null hypothesis that mining has a null or negative effect (due to Dutch Disease) on protest.

First, I use information from three repositories of mining data (IntierraLive, SNL Metals and Mining, and Mining eTrack) to geo-locate unique commercial mining projects and determine their start years. Figure 1 displays the location of these projects, as well as the number of new projects in each year from 1960 to 2014. Since the mid-1980s, mine starts have increased dramatically: in 2011 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.[6]

Second, I employ four separate datasets that geo-locate the occurrence of protests, riots, and other low-level social conflicts: the Armed Conflict, Location, and Event Project (ACLED, only protests and riots), the Social Conflict in Africa Database (SCAD), the Global Database of Events, Language and Tone (GDELT, only protests), and the Integrated Crisis Early Warning System (ICEWS,

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

[6]Chinese companies own less than three percent of projects in Africa (SNL Financial 2015).

Figure 1: Mine Locations and Start Years.
Mining investments in Africa have increased dramatically.
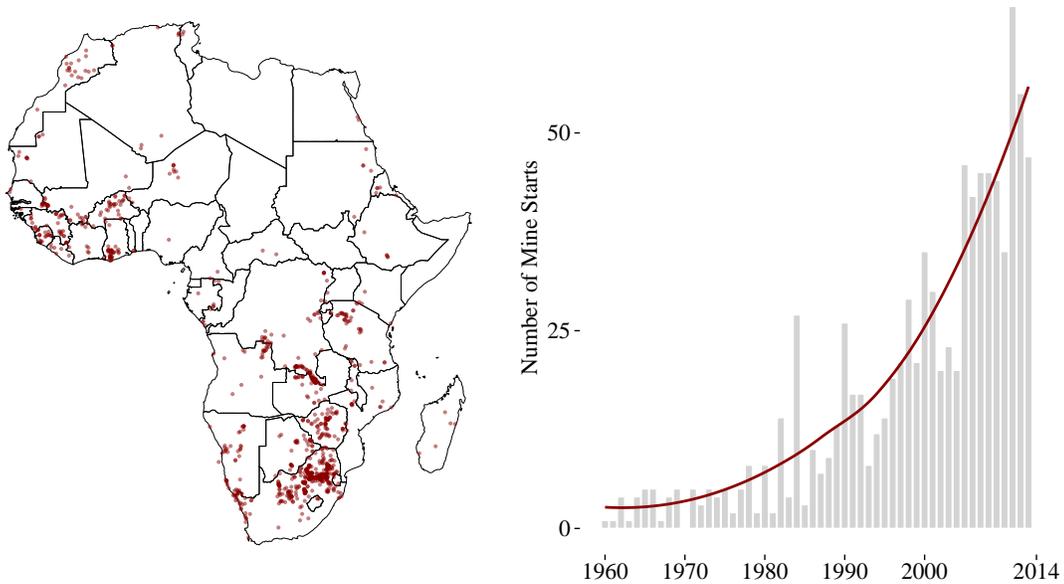
The map includes all unique mining projects in Africa with geo-coordinates and information regarding their start year compiled from three databases, SNL Metals and Mining, IntierraLive, and Mining eTrack. The time-series plot displays how many of these projects were started in each year since 1960 and a loess fit (span = 0.75) of this trend.

only protests). These datasets all provide information on the location and timing of social conflicts, as well as some information regarding the actors involved in each event. I discuss the composition and limitations of these and all other datasets employed in this paper in appendix D. To conserve space, I focus on results using the ACLED data in the body of the paper. I show in the appendix that the paper's results hold across all four datasets.

I spatially merge data on mines and protests using a grid comprising cells that measure 5 × 5 kilometers at the equator. As most conflict events are geo-coded using the names of towns, I chose grid cells roughly equivalent in area to the median city size in the region.[7] I exclude cells with no inhabitants based on the 2012 LandScan data (Oak Ridge National Laboratory 2012).

With this data, to recover the effect of mining activity on social conflict, I employ a difference-in-differences design. In short, I compare the change in the probability of protest after mining in areas that receive investments, relative to the change in the likelihood of protest observed in popu-

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[7]The PRIO grid uses cells that are 3,025 sq. km., an area 84 times larger than the median city.

lated areas that do not host new projects. I estimate this difference-in-differences using a regression with cell (α_i) and year (δ_t) fixed effects, and a indicator (D_{it}) for an active mining project:

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

I use an indicator for social conflict as the outcome, i.e., the dependent variable captures whether a protest or riot occurred in cell i in year t.

Table 1: Mining Activity and Pr(Protest)

	*Dependent variable:*				
	$\mathbb{1}$(Protest or Riot)				
	1	2	3	4 (Border $\leq$ 2)	5 (Placebo)
$\mathbb{1}$(Mine) (D_{it})	0.011*	0.011*	0.006*	0.009*	
	(0.003)	(0.003)	(0.003)	(0.003)	
$\mathbb{1}$(Placebo) (P_{it})					0.0003
					(0.002)
Cell FEs	764,361	764,361	764,361	13,612	764,016
Year FEs	18				
Country×Year FEs		900		702	900
Cell×Period FEs			2,293,083		
Observations	13,758,498	13,758,498	13,758,498	245,016	13,748,253

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

Columns 1-6: linear probability model regressions (see equation 1). All models include cell fixed effects and year (1), country×year (2, 4-5), or cell×period fixed effects (3). The unit of analysis is the cell-year. Cells with no population are excluded. Data on mining is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; outcome data comes from ACLED (see appendix D). See figure 3 regarding the definition of border cells for model 4. Model 5 presents a placebo test, which recodes treatment as a five-year period prior to mining in treated cells.

In table 1, I find that the probability of protest more than doubles after mining starts relative to the baseline probability in treated cells. (The effect is an order of magnitude larger than the overall sample mean reported in table 4.) I cluster the standard errors on grid cell, but the inferences do not change if I cluster on larger geographies including country. In models 2-4, I modify equation 1 and the composition of the control group to demonstrate robustness. First, models 2 and 4

**Table 2:** Summary Statistics: Mining Activity and Pr(Protest)

Statistic	N	Mean	St. Dev.	Min	Max
D_{it}	13,758,498	0.00063	0.02514	0	1
P_{it}	13,748,253	0.00017	0.01300	0	1
$\mathbb{1}$(Protest or Riot)	13,758,498	0.00037	0.01915	0	1

substitute the year dummies for country×year fixed effects. This larger set of indicators absorbs any shocks that affect a country in a given year (e.g., national elections or currency fluctuations). Second, model 3 includes cell×period fixed effects instead of the year dummies, 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 some cell-specific temporal variation. It should ameliorate concerns about confounds that do not rapidly change within localities (e.g., slower-moving demographic variables). Finally, I restrict the sample used in model 4 to cells with centroids that fall within 15 kilometers of a mining area (i.e., cells within the first two border regions of a mine, as defined in figure 3). Even when comparing mining cells to bordering areas (which likely contain ethnically similar populations experiencing the same local economic trends), I find that new investments generate a large increase in the probability of protest. To help put these effect sizes in some perspective, in 2012 the probability of a protest in 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.

An identifying assumption for the difference-in-differences is that protest trends would have been parallel in mining and control cells absent mining.[8] While this assumption is untestable, it is plausible: if companies seek to minimize political risk, they should not choose sites experiencing escalating conflict. Rather, investors should seek out relatively docile host communities, a selection process that pushes towards a null finding.

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[8]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 all other time-invariant characteristics of localities — will be absorbed by the cell fixed effects.

Figure 2: Visualizing the Difference-in-Differences
Protest increases after mining. Pre-trends bolster parallel-trends assumption.

(a) Event-Study Plot

Pr(Protest or Riot) — Years Since Mining

T:Mining Cells

C:Border Cells

(b) Leads and Lags Model

Estimate — Years Before and After Mining
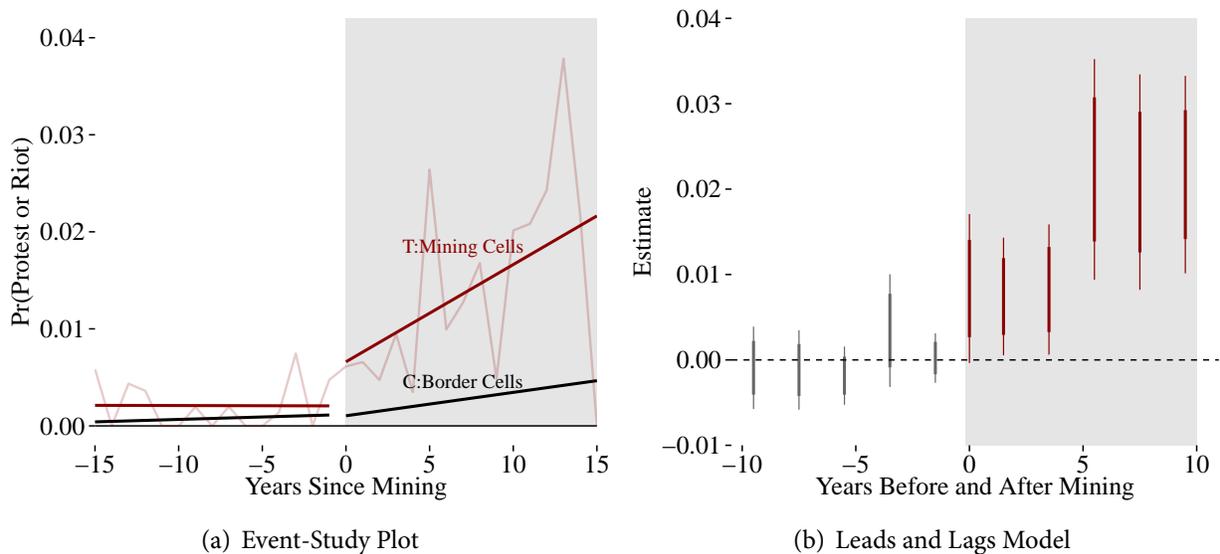
The **left** figure plots the probability of protest in the years before and after mining. The control group (black) here are cells within 15 km of mining cells. The **right** figure displays the point estimates and 95% (and thicker 80%) confidence intervals for five two-year leads and lags of the treatment 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 protest is not increasing at a greater rate in treated cells prior to mining. First, the event-study plot (figure 2a) shows that mining areas and their immediately bordering cells follow roughly identical linear trends in the fifteen years prior to mining. It is only after mining starts that we see a large increase in the probability of protest in mining cells. Second, I estimate the change in the likelihood of protest in mining and control areas in the ten years before and after mining starts. More technically, I plot (in figure 2b) the 95 percent (and thicker 80 percent) confidence intervals for five (two-year) leads and lags of the treatment indicator (see Autor 2003, for an early implementation of this strategy). Again, I find no evidence of anticipatory effects, bolstering the parallel trends assumption.[9] Finally, in the last column of table 1, I report null results from a "placebo test"

[9]The leads and lags plot shows, first, that exploration and construction activities (and any associated

that recodes treatment as the five-year period prior to the initiation of mining.[10] These checks all suggest that firms do not select into areas with escalating levels of social conflict.

Readers may be concerned that mining invites more media attention. If true, I could be conflating changes in the likelihood of social conflict with changes in the probability that protests garner press attention. However, I find no evidence that the onset of mining activity affects the intensity of media coverage.[11] When protests occur they are not mentioned in more articles or covered by more sources if they occur in the vicinity of new projects (table A.7).

The results presented above average across mines owned by different types of firms, located in countries that vary in their quality of government. Do these differences across projects generate heterogeneity in the extent to which investments induce protest? First, despite anecdotes suggesting that Chinese-owned mines generate more conflict, I do not find that localities hosting Chinese-owned projects (coded based on the address of each project's primary owner) see larger increases in the probability of protest. This is true when we compare Chinese-owned projects to all other projects or only to those owned by firms based in Australia, North America, and Western Europe (see table A.6 and figure A.1). It could still be that Chinese companies select into more unstable environments, but these results do not suggest that Chinese business or labor practices exacerbate protest. Second, projects where the host government is a partial owner (roughly 10 percent of the sample) generate a much smaller increase in the likelihood of protest. While it is tempting to conclude that exclusively *foreign* investment provokes conflict, this heterogeneous effect does not permit a clear

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inflows of workers) that precede production do not increase the likelihood of protest in mining areas. Second, the increase in protest is not concentrated in the first years of production, suggesting that retrenchment to steady state employment levels is not the principal cause of protests.

[10] 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.

[11] I use the GDELT data to estimate equation 1, using the average number of articles or sources per protest as outcome variables. I find no increase in reporting resources following mining. I also find no evidence that mining amplifies armed conflict. This further alleviates concerns about reporting bias, as the armed conflict data is derived from the same media sources.

interpretation: government-owned mines may be more lucrative (and, thus, better able to buy off would-be protesters) or better protected from protest given the state's repressive capacity. Finally, governance does not appear to moderate the effect: mining provokes protest in post-conflict Sierra Leone, as well as in South Africa. Using the Worldwide Governance Indicators (Kaufmann, Kraay and Mastruzzi 2010), there is no indication that investment proceeds more peacefully in African states with greater government effectiveness or regulatory quality. The low incidence of protest near government owned projects and the absence of heterogeneous effects related to governance quality both suggest that central governments — even low capacity or corrupt regimes — are not the primary target for these protests.[12]

1.3   Contrasting Effects of Investments on Armed and Social Conflict

Existing work on natural resources and conflict focuses not on protest, but rather on armed conflict and rebellion (Collier and Hoeffler 2002; Dube and Vargas 2013).[13] These papers offer a compelling logic: mines, particularly during periods of high prices, represent attractive sources of income and, thus, tempting targets for rebels.

Recent empirical work by Berman et al. (2014) finds that new mining activity and commodity prices are associated with more conflict events in Africa.[14] The authors interpret these results as evidence that rebel groups are battling for control of mining areas, because seized mines provide funds

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[12] Figure A.4 uses GDELT and ICEWS data to show that government actors participate in a smaller share of protests in mining cells (relative to their participation in non-mining areas); labor and business, on the other hand, are involved in a larger share of these social conflicts.

[13] Fearon (2005) demonstrates the fragility of early results from Collier and Hoeffler (2002). More recent work by Bazzi and Blattman (2014) finds that "[commodity] price shocks have no effect on new conflict, even large shocks in high-risk nations."

[14] Berman et al. (2014) use ACLED data from 1997-2010, employ a subset of the mining projects in my sample, and only include price data for 10 commodities. They also perform their analysis at a lower resolution; their grid comprises 55×55 km grid cells. In an effort to more faithfully replicate their analysis, I aggregate my own data to PRIO's 55×55 km grid (see appendix C.3). I still find no evidence in the ACLED or UCD datasets that mine starts increase armed conflict.

to sustain and intensify rebellion (19). However, while Berman et al.'s theoretical account focuses on predation by rebels, their dependent variable often includes many different types of conflicts, involving actors that are not associated with rebel groups. When I estimate the difference-in-differences (equation 1) using an indicator for any battle, any event involving rebels, or any armed conflict that involves rebels, I find no evidence that new commercial mines are associated with an increase in armed conflict or rebel activity (see table A.8).[15]

Figure 3: Effect of Mining on Local Armed and Social Conflict
Mining investments increase protest locally, not rebel attacks or armed conflict.

(a) Defining Border Regions (b) Effects of Mining on Protest vs. Rebel Activity
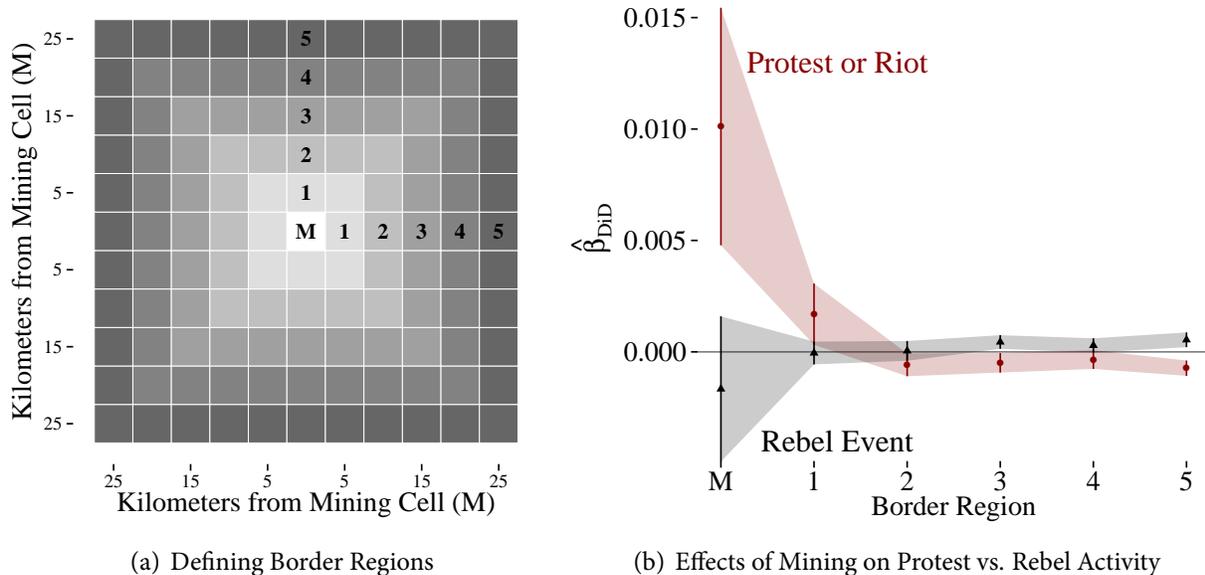
The **left** figure illustrates how border regions are defined. The **right** figure displays the difference-in-differences estimates for cells that fall in each of these border regions (specification in footnote 16).

Figure 3 contrasts the effects of mining on armed and social conflict in the locality that contains the mine, as well as in the surrounding areas. This figure helps make several points. First, these projects do not increase the probability of rebel activity in the community hosting the mine or in bordering areas.[16] A recent quote from the CEO of Randgold, a major mining company, echoes

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[15] Armed conflict is operationalized as battles, the establishment of a rebel headquarters or base, or violence against civilians (see Raleigh, Linke and Dowd 2014, 9).

[16] Let $k \in \{0, 1, \ldots, 5\}$ index our border regions, where $k = 0$ is the actual cell containing the mine.

this finding: despite the civil war in Ivory Coast, coup in Mali, and rebellions in the Democratic Republic of Congo, he says, "We've lived through them all. We've never — touch wood — had to stop operations" (Biesheuvel and Crowley 2015). Second, while we see an increase in the probability of protest in the cell that contains the mining project, this effect quickly decays: once we move beyond 10 kilometers, the effect of these projects on social conflict is a precisely estimated zero. This suggests that, if anything, geographic spillover attenuates my estimates in table 1.[17] Protesters are not simply relocating their demonstrations from nearby towns to mining communities.

Separating insurgent activity from protests and riots clarifies the type of conflicts confronting mining companies. Mining areas and their surroundings are not more likely to experience rebel activity, undermining claims that rebel groups in Africa *directly* predate on investments.[18] The point here is not to dispute the existence of a relationship between natural resources and rebellion. Reports from Colombia about the FARC's increasing reliance on illegal gold mining or illegal coltan mining by rebels in the Democratic Republic of the Congo suggest that some insurgents depend on resource revenues (Jamasmie 2013; de la Sierra 2014). Rather, these contrasting findings suggest that how natural resources are produced may condition the extent to which mining generates armed conflict: while rebels fight for control of labor-intensive artisanal diamond mines, seizing and managing a capital-intensive Kimberlite diamond mine may not represent a viable funding strategy for these same groups. These findings help answer the call by Ross (2015) for more research into variables, such as production scale, that condition emergence of the "resource curse."

2. Why Do Foreign Investment Projects Provoke Protest?

The first result indicates that mining more than double the probability of protest. This raises the question: why do communities and firms fail to bargain away conflict?

I define D_{it}^k as an indicator for whether cell i falls in region k and borders an *active* mine. I then run: $y_{it} = \alpha_i + \delta_t + \sum_{k=0}^{5} \beta_k D_{it}^k + \varepsilon_{it}$. This is simply the difference-in-differences for six separate treatment groups, each defined by its proximity to a mining project.

[17] If I use a 10×10 kilometer cell size, my estimate in model 1 of table 1 increases by 30 percent.

[18] Dube and Vargas (2013) describe rebels in oil-producing areas kidnapping politicians and attempting to raid government coffers. This violence occurs in provincial capitals, far from the mine site.

I argue that these protests are, in part, caused by uncertainty among host communities regarding the returns generated by mining projects. 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 over communities or governments, who may be persuaded to grant entry by promises of development expenditure or increased employment. Yet, while most projects begin with this optimistic outlook, actual profitability varies dramatically: expensive and prolonged exploration can fail to discover deposits; even productive mines differ due to ore amounts and quality, as well as production and transportation costs. Entering negotiations, communities and workers cannot be certain where their local mine falls in this distribution of profitability. Boosters' optimistic initial claims may engender unreasonable expectations.

What happens if a community overestimates a project's value and makes a demand that the company cannot afford? The company could trumpet their inability to pay, but this falls on deaf ears. If the community takes the company at its word, then even the most profitable firms would have an incentive to plead poverty to retain a larger share of profits. As communities cannot rely on firms to honestly report their earnings, protests that threaten production offer a strategy for separating firms with low-profit projects from those attempting to low-ball the community.[19]

One can find examples of this bargaining dynamic across mining projects in Africa. First, in 2012, protests occurred in Bumbuna, Sierra Leone, a community hosting a large iron mine. Protesters were angry, believing that the project's revenues had recently increased, but that this had not translated into better wages or improved living conditions for households resettled due to mining.[20] 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 export-

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[19]This logic builds upon work by labor economists, such as Tracy (1987) or Card (1990), who model strikes as a consequence of incomplete information among workers.

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

ing, 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.

Second, South Africa's platinum sector experienced large and prolonged strikes in 2014, when 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 (though still historically elevated) 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. If they had trusted companies' pronouncements, they could have saved five months of stoppages that strained the local economy and cost the industry an estimated 2.25 billion dollars (Stoddard 2014). One way to interpret these prolonged conflicts is as costly and, thus, credible signals by the companies that they could not afford workers' initial demands.

Third, a 2010 report on mining in Tanzania argues that maintaining a social license to operate is difficult where communities hold unreasonable 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." As part of the report, the authors visited Barrick

Gold Corporation's North Mara Mine. They report widespread claims that "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 in Dar es Salaam to the effect that community development projects would be established as part of granting of the mining license. Many of these reported promises and commitments failed to materialise (sic)" (61). One source of conflict at the North Mara Mine is lingering anger that the community has not received its promised share of the proceeds.

These are not isolated cases: disputes often center on how profits are split and whether host communities regard that as fair.[21] In their recent study of prolonged instances of company-community conflicts surrounding mining projects around the world from 1967-2012, Davis and Franks (2014, 14) find that "socio-economic issues, particularly the distribution of project benefits" were among the most common causes.

These cases suggest that protests occur when communities or workers do not know what the project is worth but have expectations that exceed what the company is currently able or willing to disburse. This insight is reflected 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).

These accounts suggest that conflicts arise, because companies and communities do not agree on the value of the project. As everyone recognizes the company's incentive to understate the project's true profitability, the company cannot credibly communicate its financial situation and, thus, resolve the community's uncertainty. Protests and strikes provide a tactic for separating projects that really cannot payout from those attempting to short-change the community.

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[21]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.

2.1 Protests as Bargaining Failures: A Model of Incomplete Information

The qualitative work summarized above suggests that an informational asymmetry prevents firms and communities from bargaining away conflict. And I show formally that conflict can arise when the community does not know the profits generated by mining projects. Introducing this one-side informational asymmetry leads to the possibility of protests in equilibrium.[22]

Leaving the formalism and proof to appendix A.2, I focus here on the intuition for this result.[23] The community living next to a mine does not see the project's balance sheet. It, nonetheless, holds some prior belief about the range of profitability and, based on that belief, puts a demand to the firm (e.g., a level of development expenditure or jobs and wages). Firms know that rejecting the community jeopardizes their social license to operate and invites work stoppages. If their mine turns a large profit, the firm prefers to accept the community's offer and avoid strife — large margins imply a large opportunity cost to production stoppages. Yet, if the mine is barely breaking even, the firm cannot agree to the community's initial terms; when profits are already meager, large development or infrastructure expenditures could push a project into the red.

Firms with less profitable projects reject the community's demands. But obstinance is not enough to convince the community of their project's smaller margin. If rejecting and pleading poverty could persuade the community to lower their expectations, then even firms with lucrative projects would take this approach. After rejecting, firms with less profitable projects hold out and endure industrial and social conflict to signal that they cannot meet the community's initial demands. Protests and strikes persuade the community to lower their expectations, as they infer that only firms with meager margins and, thus, low opportunity costs would rather shut down production than immediately concede. Conflict and the resulting work stoppages, thus, serve to separate

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[22]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 can deter investment, none of this earlier work suggests that firms can retain power (i.e., slow the "obsolescing bargain") by preemptively initiating conflicts.

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

firms that cannot meet large demands from those that, absent the threat of protest, might be tempted to short-change their hosts.[24]

Uncertainty generates protests in equilibrium. Communities sometimes put sizable demands to struggling projects, and firms cannot be trusted to honestly disclose their projects' margins. Work stoppages provide a costly and, thus, credible signal of projects' profitability.

Yet, qualitative accounts suggest that communities are not just uncertain but also optimistic, holding inflated expectations about projects' margins. Communities simply overestimate the likelihood that they are hosting a lucrative mine.[25] One way to formally incorporate these inflated expectations is to allow communities' prior beliefs to diverge from the true distribution of firms (see appendix A.3). As communities' expectations become inflated, so too do the demands that they put to firms. This, in turn, raises the likelihood that protests result, as a larger proportion of firms would rather disrupt production than agree to the communities' exaggerated terms.

2.2 Explaining Variation in Protest Across Investments

This theory predicts that protests are more likely when communities are uncertain but hopeful about the project they are hosting. Believing that they face a firm with a more profitable project, communities ratchet up their demands and, thereby, the likelihood that the firm would rather disrupt production than concede. This claim comports with several empirical studies of strike inci-

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[24]One might think that lucrative projects can afford to endure protests, and that struggling projects should quickly concede. However, this conjectured separation is not an equilibrium of the model. Unless we assume that new investors can wait out long-standing communities, firms with lucrative projects will not forego profits only to reveal their deep pockets; such firms would immediately defect and concede, hoping the community will mistake them for those with less profitable projects.

[25]One could micro-found this claim in different ways. Below, I argue that communities observe large increases in commodity prices, but do not see simultaneous increases in the cost of mining. This drives a wedge between the perceived and actual profitability of mining projects. Communities need not be exuberant; rather they hear more about booming commodity prices than rising input costs. Alternatively, findings from psychology suggest that individuals suffer from "optimism bias," overestimating the likelihood of positive events (Sharot et al. 2007).

dence in more developed countries, which find that industrial conflicts increase during high points in the business cycle (Harrison and Stewart 1994, 528).

The question is when should we expect communities to be bullish about projects' returns?[26] Goldstuck and Hughes (2010, 11) argue that mining companies in Tanzania are believed to be immensely profitable "based on the assumption that companies' profits are calculated on the basis of gold production multiplied by the gold price." If this is how communities reckon projects' surplus, then rising commodity prices should raise expectations. Stevens et al. (2013, 80) advance this claim, observing 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." Higher commodity prices are accompanied by "calls for the country to receive its 'fair share' of the profits" (47). This research suggests that price increases during the recent commodity boom (see figure 4a for mineral price trends) raised communities' expectations.

Communities seem to be making a reasonable inference: projects' profits increase in proportion to commodity prices, expanding the size of the pie to be split. While this may be intuitive, it overstates the extent to which rising commodity prices during the recent boom increased projects' margins. In fact, during this period, industry analysts noted a "growing disconnect" between prices and mining companies' 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." PwC's 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).

Why are projects' margins not increasing at the same rate as commodity prices? First, shortages

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[26]While my empirical strategy leverages price changes, price is not the only factor shaping communities' expectations about projects. The development team charged with establishing the mine often makes grand promises about how the mine will foster rapid economic growth and how the company will pump proceeds back into local development projects. These promises also leave a community optimistic about what it stands to gain once the mine starts producing.

Figure 4: Trends in the Mineral Prices and Mining Costs
Several minerals increased dramatically in price. Yet, mining costs also increased.

(a) Mineral Price Series

(b) Price and Cash Cost of Gold Mining
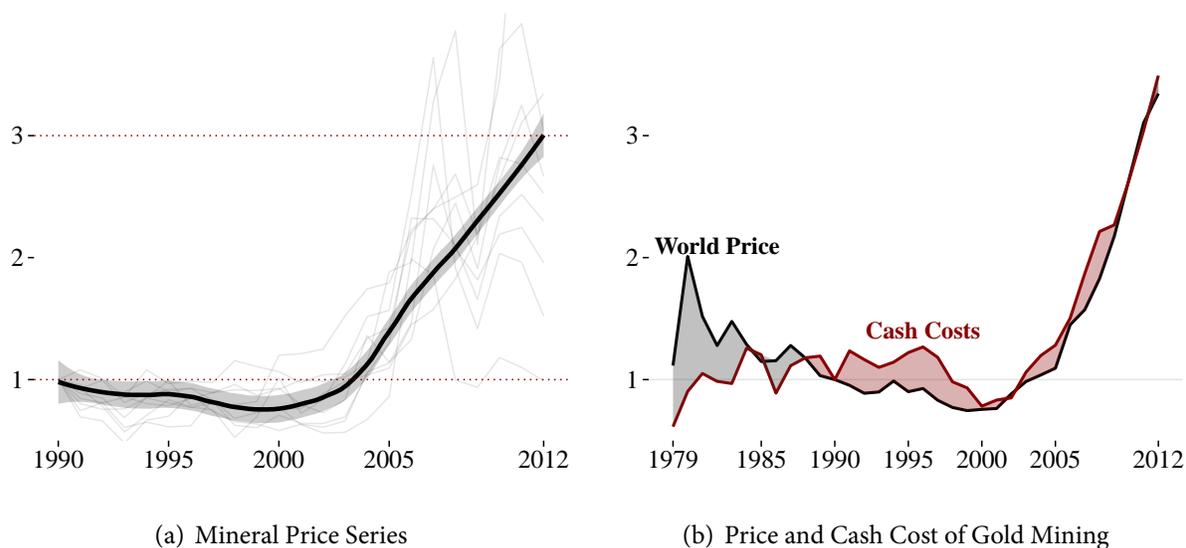
The **left** figure displays mineral prices (indexed to 1990 values) from the World Bank as grey lines. The thicker loess curve is weighted by the number of projects producing a given mineral in my sample of mining projects. The **right** figure displays the price and cash cost of gold mining indexed to 1990 values. The price data come from the World Bank; data on cash costs was compiled by Christie (2013) from Scotiabank GBM and Thomson Reuters GFMS.

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). Figure 4b illustrates the roughly parallel trends in the price of gold and the cash costs of gold mining (which exclude capital expenditure, exploration, corporate costs, and cash taxes). Second, in an effort to meet rising demand (largely from China and India), companies drilled deeper and exploited deposits with lower head grades, reducing productivity. "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).

I am not claiming that mining companies do not benefit from higher prices, all else equal. Rather, I am arguing that all else was not equal: cost increases and productivity declines in the sector placed downward pressure on projects' margins. Yet, these developments were buried in reports

by accounting firms and did not receive the same attention as rising commodity prices, which are frequently front-page news in Sierra Leone or South Africa. As such, booming prices engendered inflated expectations among host communities.

The model predicts that, if rising prices inflate expectations, then they should also increase the likelihood of protest. In Tanzania, rising gold prices raised expectations and generated "palpable anger and resentment towards mining companies [which] has resulted in a confrontational relationship …" (Goldstuck and Hughes 2010, 6). More broadly, the data indicate that what was true of gold in Tanzania holds across projects producing different minerals. I find that above average commodity prices correspond to above average levels of protest (figure 5).[27]

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:

$$y_{it} = \alpha_i + \delta_t + \beta \log(\text{Price}_{it}) + \varepsilon_{it} \tag{2}$$

where i indexes cells and t year.[28] This analysis compares changes in the likelihood of protest in mining areas differentially affected by price increases during the commodity boom. The "control" group in these regressions comprises mining areas producing commodities with more stable world prices, such as coal, manganese, or nickel.

One of the challenges in performing this analysis is selecting the correct sample. In the first model in table 3, I run the analysis using those cells with at least one mine in 1997. In this model, prices could affect bargaining with existing mines, as well as the entry of new mines. To enable a sharper interpretation and ensure that the composition of mines remains fixed, I can restrict the sample to cells with a single mine throughout the period (model 2) or with no change in the num-

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[27]I compile real unit prices for over 90 unique minerals, with nearly complete coverage over the study period (see appendix D). On the rare occasion that a cell contains multiple mines producing different commodities, I use the price of the modal commodity.

[28]The results are similar if I substitute country×year for the year fixed effects.

Figure 5: High Prices Increase Pr(Protest)
Protest in mining areas increases during periods of above-average mineral prices.
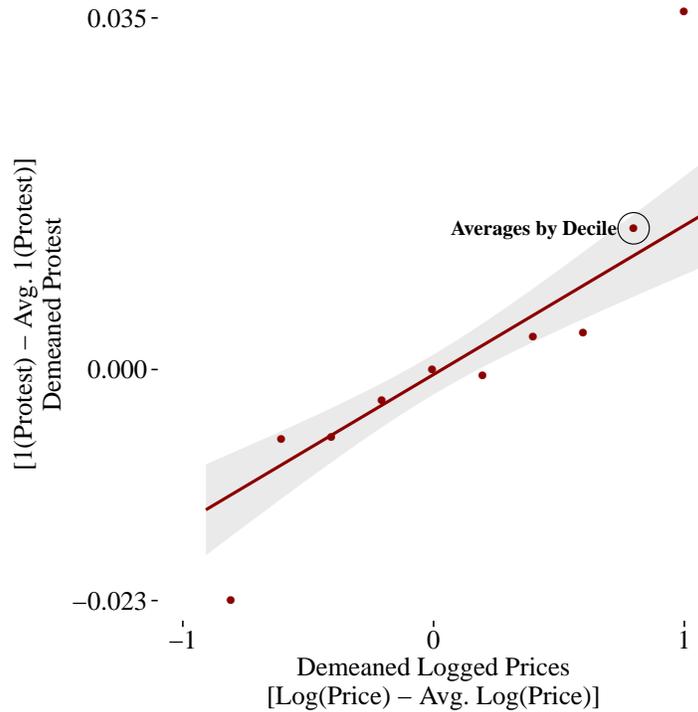
This figure presents the bivariate relationship between mineral prices (logged) and protest in mining cells, after demeaning both variables. The raw data is binned by decile and plotted as points. The sample here is restricted to cells with a single mine from 1997 to 2013 (as in table 3, model 2).

ber of mines (model 3). In these models, we are holding the company-community dyads fixed and looking at how price changes affect the likelihood of protest. Unfortunately, these sample restrictions select on post-treatment information by excluding areas where price increases led to the entry of new mines. Reassuringly, across these samples, I find similar estimates of the effects of commodity prices on protest. To interpret these effects: between 1997 and 2007, the log(price) of gold increased by almost one point. The estimates imply that this increase would roughly double the probability of protest. This finding that social conflict in mining areas increases with commodity prices comports with recent work by Kopas and Urpaleinen (2016) in Brazil and Sexton (2017) in Peru, though these authors attribute this positive relationship to grievances associated with mining activity, not bargaining failures.

I cluster the standard errors in the first three models on commodity; using a block bootstrap

Table 3: Commodity Prices and Pr(Protest)

			Dependent variable:	
			$\mathbb{1}$(Protest or Riot)	
	(1)	(2)	(3)	(4)
Log(Price$_{it}$)	0.012*	0.010*	0.013*	0.014*
	(0.006)	(0.004)	(0.003)	(0.004)
$\mathbb{1}$(EITI)				−0.0002
				(0.0001)
Log(Price$_{it}$):$\mathbb{1}$(EITI)				−0.001*
				(0.0003)
Cell FEs	299	303	763,831	763,831
Year FEs	17	17	17	17
Sample	≥ 1 Mine in 1997	1 Mine from 1997-2013	Var(# Mines) = 0	Var(# Mines) = 0
Observations	4,894	4,957	12,984,972	12,984,972

Note: Robust std. errors clustered on commodity (1-3) or country (4); $^{†}p < 0.1$, $^{*}p < 0.05$

Columns 1-4: linear probability models (see equation 2), all of which include cell and year fixed effects. Cells with no population are excluded. Commodity prices are compiled from the World Bank, USGS, and US EIA (see appendix D for details). I assign a cell-year the price associated with the commodity mined in that cell-year. Models 1-2 restrict attention to cells with mining activity; models 3-4 include all cells, and non-mining cells are assigned a price of zero.

Table 4: Summary Statistics: Mining Activity and Pr(Protest)

Statistic	N	Mean	St. Dev.	Min	Max
Log(Price$_{it}$)	12,993,642	0.007	0.325	0.000	18.004
$\mathbb{1}$(EITI)	12,993,642	0.161	0.367	0	1

does not affect the inferences. As was true of the first finding, these results hold up across three other event datasets (see table A.3).

The results are robust to dropping any commodity from the sample (e.g., omitting all gold mines). More interestingly, the effect of price changes on protest varies across commodities, and this variation lends further credence to the theory. PwC (2012, 5) notes that increases in the price of copper tended to better track mining firms' financial performance; copper "stands out as an exception to this disconnect [between prices and margins]." So while rising gold prices, for example, led to inflated expectations, rising copper prices should not have generated a large divergence in

communities' beliefs and projects' bottom lines. As I would expect, the effect of copper prices on protest is roughly half as large as the effect of other commodity prices. All level-differences across these areas mining different commodities (e.g., method) are absorbed by the cell fixed effects.

2.2.1 The Moderating Effects of Transparency

If protests result from an informational asymmetry, then transparency could have a pacifying effect and mitigate the relationship between commodity prices and protest. Where communities have alternative sources of information about companies, they may be less dependent upon world prices as an predictor of projects' profitability.

The adoption of the Extractive Industries Transparency Initiative (EITI) provides an opportunity to assess whether transparency has this effect in practice. The EITI requires companies in member countries to "disclose information on tax payments, licenses, contracts, production and other key elements around resource extraction" (`eiti.org`). EITI claims that increased transparency "enhance[s] trust and stability in a volatile sector. Companies benefit …from an improved and more stable investment climate in which they can better engage with citizens and civil society. 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.

Model 4 in 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 in a given year. I find that EITI candidacy reduces the relationship between logged prices and protest by roughly six percent. While this result is consistent with the theory, the effect is modest and does not suggest that EITI eliminates the positive relationship between commodity prices and protest.[29]

This research design rules out some sources of endogeneity. First, the cell fixed effects absorb any time-invariant variables that might explain differences in social conflict across countries that

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[29]EITI requires that reports are "are comprehensible, actively promoted, publicly accessible, and contribute to public debate." Yet, a common criticism of EITI is that reports are not circulated. Implementation problems, as well as delays in the dissemination of audits, could help account for these modest results.

do and do not become EITI candidates. Second, including country-specific (linear, quadratic, or cubic) time trends ameliorates concerns that the results reflect differential trends in the likelihood of protest across countries that do and do not opt into the regime. Third, by restricting the sample to cells with no change in the number of mines throughout the study period, I am focusing on projects that were initiated before EITI was announced in 2002. The results cannot then be driven by more profitable or generous companies selecting into EITI-candidate countries. Fourth, EITI does not track overall improvements in governance. Using the Worldwide Governance Indicators (WGI) (Kaufmann, Kraay and Mastruzzi 2010), I do not find a positive correlation between EITI candidacy and other measures of governance.[30] Including, for example, the WGI's control of corruption variable in the model (both directly and interacted with prices) does not change the coefficient reported in table 3.

This analysis is not without limitations. EITI candidacy may, for example, be accompanied by other reforms to the regulation of extractive industries. As such, these heterogeneous effects could reflect a bundle of interventions that improve transparency, as well as oversight. To better isolate the effects of transparency, I look at whether the pacifying effects of EITI are concentrated in areas with cell phone access — cell phones being one potential channel through which the information contained in EITI reports might disseminate.[31] As expected, I find that the moderating effect of EITI reported in table 3 (model 4) is driven by mining areas with some cell phone coverage. In these connected areas, EITI reduces the relationship between prices and protest by roughly twenty percent relative to unconnected areas in EITI countries. This effect suggests that EITI operates through the diffusion of new information, rather than country-level changes mining regulation. Yet, this quadruple difference must be regarded cautiously, as the effect is not precisely estimated: the p-value on the triple interaction, $\text{Log(Price)} \times \mathbb{1}(\text{EITI}) \times \mathbb{1}(\text{Any Cell Coverage})$, is 0.107. This

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[30]The WGI includes measures related to voice and accountability, political stability, government effectiveness, regulatory quality, the rule of law, and the control of corruption.

[31]Panel data on cell phone coverage comes from the Collins Mobile Coverage Explorer database, which is based on reports by telecoms (Pierskalla and Hollenbach 2013, use a subset of this data). The data has a resolution of 1km, and is available yearly from 2007-9 and 2012-14.

achieves conventional levels of significance if I instead substitute the indicator for coverage for the proportion of each grid cell covered by the cell phone network.

EITI is, by my estimates, not an entirely effective solution. Management scholars have also offered prescriptions, telling companies that they must build trust by communicating their financial constraints. 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." This comports with my model of protests; conflicts result when communities expect more than companies can deliver. Yet, the model also points to a limitation of this advice: communities may not place much weight on voluntary disclosures, as these are costless signals that profitable companies have reason to falsify. Consistent with this argument, I find that voluntary commitments by firms to sustainable development principles do not insulate their projects from protest. Membership in the International Council on Mining and Metals (ICMM), a standards-setting trade group, does not reduce the likelihood of conflicts: interacting ICMM membership with mining activity or prices in the first model of tables 1 or 3 yields small, insignificant coefficients.[32] While these results are not identified (e.g., the most conflict-prone companies could select into the ICMM), they reinforce an implication of the model: communities are skeptical of firms' pronouncements. Peacefully resolving communities' uncertainty requires pairing openness by companies with verification by a neutral third party.[33]

3. Alternative Explanations

Reports on conflicts in mining areas advance a number of alternative explanations that might explain these empirical relationships between mining, commodities prices, and protest. Yet, I find little evidence to support common hypotheses related to environmental risks, in-migration, inequality, or conflicts between commercial and artisanal miners. Furthermore, recent works by Axbard, Poulsen and Tolonen (2015) and Knutsen et al. (2016) suggest that crime (which does not increase

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[32]If one of the top three owners of a project has been an ICMM member since 2008 (the first year for which I have data), then the project takes a one on this indicator.

[33]ICMM asks that members conduct audits. However, the details of these audits are not public, and auditors are paid for by companies, which may compromise their perceived neutrality.

with mining or higher prices) and corruption (which is not perceived to increase after mining commences) are also unlikely alternative mechanisms.

3.1 Environmental Harm

Mining can degrade the soil or water resources of host communities. Increased protest activity near mining projects could then be motivated by environmental harms. While I cannot measure environmental degradation at each site, I find no evidence that surface mines, which are widely perceived to pose a greater environmental risk, are more likely to provoke protest than underground mines (see table A.12).[34] This suggests that environmental concerns do not systematically increase the likelihood of protest in mining areas, despite well-publicized cases (e.g., Peru's Conga Mine) where these concerns mobilized activists. In response to price increases, companies might ramp up production. In the case of open-pit mines, this could increase the mine's footprint and its incursion into the local environment, sparking protest. However, I do not find that the effects of price on protest are amplified in localities hosting surface mines: the interaction of logged prices and an indicator for surface mining in model 1 from table 3 is tiny and insignificant.

3.2 Migration

In-migration may intensify with high commodity prices. Long-time residents may resent new arrivals, and such anger could boil over into protests. Violence in Durban, South Africa demonstrates potential destructiveness of anti-immigrant sentiment in mining areas (Onishi 2015).

To assess this alternative explanation, I use individual-level data from Demographic and Health Surveys (DHS) conducted in sub-Saharan Africa (that include geo-coordinates for survey clusters).[35] The DHS data allows me to code two variables: first, an indicator for whether an individual has ever moved; and second, an indicator for whether an individual moved to their residence after

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[34]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…"

[35]To merge the DHS surveys to mines, I construct circular buffers (25 kilometer in radius) around each mine. If a survey cluster falls within a mine's buffer then it is associated with that project.

mining started. This follows the approach of Knutsen et al. (2016). I find that rising commodity prices increase the probability that a household has ever moved or moved after the mine started (table A.13).[36] However, I find no compelling evidence that the probability of protest in mining areas increases with the proportion of migrants (see table A.14). High commodity prices attract migrants, but this influx does not appear to engender social conflict.[37]

Why is there no relationship between in-migration and protests? First, anger and violence directed at migrants may take the form targeted harassment rather than public protests. Second, according to DHS data, there is no material basis for resentment. Individuals that have moved or moved after mining commenced are not more wealthy: I find a null relationship between these indicators for mobility and an index of households assets (see table A.15). Furthermore, individuals that have moved do not appear to benefit disproportionately when commodity prices rise. In fact, plausible commodity price increases are not associated with meaningful increases in household assets for either stationary or migrant households. Projects do not appear to deliver economic benefits, even when communities might, on the basis of prices, expect them to.

3.3 Inequality

The onset of mining and rising commodity prices may enrich some households, while delivering relatively little to others. This increased inequality could inspire 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.[38] McKenzie (2005) demonstrates that this provides a good proxy for inequality in living standards.

I do not find evidence that mining starts or rising commodity prices increase levels of inequality or that increasingly unequal mining areas have a higher probability of protest. Table A.16 estimates equations 1 and 2, using wealth inequality as the dependent variable. The coefficient estimates are

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[36] If a mine produces multiple minerals, then I use the mean price across those commodities; second, because households cannot immediately relocate as prices change, I lag the price measure one year.

[37] The models used in this analysis all include fixed effects for each mining project and year.

[38] The recipe is to take the first principal component of household assets, compute the standard deviation for each unit, and take the ratio of that to the standard deviation for the full sample.

negative and insignificant. Moreover, the results in table A.17 do not suggest a positive relationship between wealth inequality and protest occurrence.

3.4 Local Corruption

Citizens may feel that mining enriches local officials, and anger about bribes or other forms of rent-seeking might manifest in protests. However, a recent paper by Knutsen et al. (2016) geo-codes data on perceptions of corruption from the Afrobarometer. Using an empirical design similar to my analysis of DHS data, they do not find that the onset of mining significantly increases reports of bribes for permits or perceptions of local corruption among respondents that live within 50 km of a mine (Table 2). The authors find some evidence that bribes to police increase, though perceptions of police corruption do not. Their evidence does not indicate that mining undermines local governance; rather, police appear to take advantage of increased economic activity to extract more bribes (12). Given that perceptions of corruption do not increase after mining, it seems unlikely that anger about local corruption motivates protests.

3.5 Conflicts with Small-Scale Miners

Finally, protests may be organized by artisanal miners, who are displaced by larger commercial operations. Such conflicts could intensify when commodity prices are high, and small-scale miners have a strong incentive to trespass on commercial sites. However, the results reported above are robust to dropping commodities (namely, gold and gemstones) that are also produced artisanally. Moreover, none of these alternative explanations can explain the moderating effect of EITI.

Conclusion

Foreign investment in sub-Saharan Africa, particularly in natural resources, has increased dramatically over the last three decades. This paper answers two questions raised by this trend: are these new projects met with conflict; and, if so, why?

First, using fine-grained data on mining projects and protests across Africa, I show that the probability of protest more than doubles with mining. To bolster the credibility of my empirical design, I confirm that areas receiving investments do not have differential pre-mining trends. Moreover, the result is robust to limiting the control observations to areas that immediately border mining areas and, thus, are likely to be experiencing similar demographic changes. This first finding

raises the question of why these conflicts occur.

Second, drawing on accounts from mining areas across Africa, I argue that communities rarely oppose investment; rather, they organize protests because they believe companies could contribute more to local development. Unfortunately, communities often lack information about the value of these projects, and all companies have an incentive to understate projects' profitability in an effort to limit their payouts to the community. Faced with this informational problem, protests provide communities a tactic for learning what a project is worth and, thus, how big of a pie is available to be split. I formalize this argument in a bargaining model and marshal two pieces of empirical evidence consistent with this theory. I demonstrate that protests increase when rising commodity prices inflate communities' expectations about projects' margins. I then show that this 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.

As this is not the only potential explanation for conflict in mining areas, I cast doubt on a set of alternative theories that could relate mining, commodity prices, and protest activity. In short, I find no evidence that reporting bias, environmental harm, migration, wealth inequality, corruption, or conflicts with artisanal miners explain my results. Furthermore, I do not find evidence that areas hosting these large-scale mining projects are systematically targeted by rebels. My analysis suggests that the conflicts we observe are better understood as conflictual bargaining over profits than instances of predation by insurgents.

While the private sector has been largely omitted from recent research in African politics, firms play an important role in work on more developed countries. Most relevant to this study, 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 — are largely private and center on firms' negotiations with workers and 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 Foreign Investment in Mining Incites Protest in Africa

Following text to be published online.

Contents

A. Proofs

A.1 Proposition 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: $V_R^i(h_t) = V_R^i$ 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 $x < V_R^F$ and accept when $x \geq V_R^F$. Obviously, the Firm has to accept if $x > V_R^F$, but it must also accept if $x = V_R^F$. Suppose it did not and rejected with some probability $\rho > 0$. The Community could then profitably deviate by offering just slightly more, $V_R^F + \varepsilon$ where $\varepsilon > 0$, which the Firm would certainly accept. To see how, note that $V_R^F + V_R^C \leq 1$. This implies that $V_R^F + V_R^C e^{-t_F \delta_C} < 1$, 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 $\varepsilon \in (0, \rho(1 - V_R^F - V_R^C e^{-t_F \delta_C}))$ that makes the deviation profitable.

Given the Firm's optimal unique strategy, the Community must offer V_R^F to the Firm. The Community does not want to offer more, as they could ensure acceptance and a larger share by

offering exactly $x = V_R^F$. The Community also does not want to offer less, as rejection yields a lower payoff, since $1 - V_R^F > V_R^C e^{-t_F \delta_C}$, 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.

$$(1 - V_R^F) = V_R^C e^{-t_F \delta_C}$$

$$(1 - V_R^C) = V_R^F e^{-t_C \delta_F}$$

$$1 > V_R^C = \frac{1 - e^{-t_C \delta_F}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0$$

$$1 > V_R^F = \frac{1 - e^{-t_F \delta_C}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0 \tag{3}$$

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. 3) and taking the limit as $\underline{t} \to 0$,

$$\lim_{\underline{t} \to 0} V_R^C = \frac{\delta_F}{\delta_C + \delta_F} \tag{4}$$

by L'Hopital's rule. Equation 4 is how Γ is defined. $\qquad \square$

A.2 Proposition 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 A.1.[39]

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.*

A.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*

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[39]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.

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.

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:

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

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. $\quad\square$

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 $\mu\big[\theta | t'; t(\theta)\big] = \theta'$. 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. $\quad\square$

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 $\mu[\theta|t = 0; t(\theta)] = \theta' \in [\underline{\theta}, \overline{\theta}]$.

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 $t(\theta) = \dfrac{\log(\overline{\theta}) - \log(\theta)}{\delta}$.

A.2.2   Proof of Proposition 2

Let $t : \Theta \rightarrow \mathbb{R}^1_+$ 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 $\mu[\theta|t; t(\theta)]$ 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

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

$\square$

A.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 $\bar{\theta}$. We can now determine the community's optimal initial offer, $b^* = 3\bar{\theta}/4$. And, given this initial offer, all firms below $\widehat{\theta}(3\bar{\theta}/4) = \bar{\theta}/2$ would rather disrupt production than immediately concede; the probability that a given firm falls in this range is then $F(\bar{\theta}/2) = 1/2$.[40]

To extend the model, suppose that the true distribution of firms is $\theta \sim U[0, \bar{\theta} - \omega] = F(\cdot)$ where $\omega \in (0, \bar{\theta}/2)$. Yet, the Community continues to believe that $\theta \sim U[0, \bar{\theta}] = \widetilde{F}(\cdot)$ (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 $b^* = 3\bar{\theta}/4$, and all firms below $\bar{\theta}/2$ 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: $\Pr(\text{Protest}) = F(\bar{\theta}/2) = \frac{1}{2}\left(\frac{\bar{\theta}}{\bar{\theta} - \omega}\right)$. 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.

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

B. Robustness to Other Event Datasets

B.1 Mining and Pr(Protest)

Table A.1: Mining Activity and Pr(Protest)
Mining projects increase the probability of protest.

	Dependent variable:							
	$\mathbb{1}$(Protest or Riot)		$\mathbb{1}$(Soc. Conf.)		$\mathbb{1}$(Protest)		$\mathbb{1}$(Protest)	
	ACLED	ACLED	SCAD	SCAD	GDELT	GDELT	ICEWS	ICEWS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Mine) (D_{it})	0.011^*	0.011^*	$0.002^\dagger$	$0.002^\dagger$	0.015^*	0.014^*	0.006^*	0.006^*
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Cell FEs	764,361	764,361	764,361	764,361	764,361	764,361	764,361	764,361
Year FEs	18		23		36		20	
Country × Year FEs		900		1,150		1,800		1,000
Observations	13,758,498	13,758,498	17,580,303	17,580,303	27,516,996	27,516,996	15,287,220	15,287,220

Note: Robust Std. Errors Clustered on Cell; $^\dagger p < 0.1$, $^* p < 0.05$

Columns 1-6: linear probability model regressions (see equation 1). All models include grid-cell and year or country×year fixed effects. Cells with no population according to the LandScan data in 2012 are excluded from the sample. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; outcome data comes from the ACLED, SCAD, GDELT, and ICEWS event datasets.

Table A.2: Summary Statistics: Mining Activity and Pr(Protest)

Statistic	N	Mean	St. Dev.	Min	Max
D_{it}	27,516,996	0.00045	0.02114	0	1
ACLED: $\mathbb{1}$(Protest or Riot)	13,758,498	0.00037	0.01915	0	1
SCAD: $\mathbb{1}$(Soc. Conf.)	17,580,303	0.00014	0.01202	0	1
GDELT: $\mathbb{1}$(Protest)	27,516,996	0.00067	0.02587	0	1
ICEWS: $\mathbb{1}$(Protest)	15,287,220	0.00029	0.01704	0	1

B.2 Prices and Pr(Protest)

Table A.3: Commodity Prices and Pr(Protest)
Increases in commodity prices increase the probability of protest.

	Dependent variable:							
	𝟙(Protest or Riot)		𝟙(Soc. Conf.)		𝟙(Protest)		𝟙(Protest)	
	ACLED	ACLED	SCAD	SCAD	GDELT	GDELT	ICEWS	ICEWS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Price$_{it}$)	0.0134*	0.0130*	0.0020	0.0020	0.0065†	0.0063†	0.0046†	0.0045†
	(0.0049)	(0.0048)	(0.0017)	(0.0017)	(0.0034)	(0.0034)	(0.0025)	(0.0025)
Cell FEs	763,816	763,816	763,777	763,777	763,666	763,666	763,782	763,782
Year FEs	17		23		35		19	
Country×Year FEs		850		1,150		1,750		950
Var(# Mines) = 0	✓	✓	✓	✓	✓	✓	✓	✓
Observations	12,984,972	12,984,972	17,567,057	17,567,057	26,728,285	26,728,285	14,511,941	14,511,941

Note: Robust Std. Errors clustered on Cell; $^\dagger p < 0.1$, $^* p < 0.05$

Columns 1-8: linear probability model regressions (see equation 2). All models include grid-cell and year or country×year fixed effects. Cells with no population are excluded from the sample. Commodity prices are compiled from the World Bank, USGS and US EIA. If no mining occurs, these cells are assigned a price of zero. Outcome data comes from the ACLED, SCAD, GDELT, and ICEWS event datasets.

Table A.4: Summary Statistics: Commodity Prices and Pr(Protest)

Statistic	N	Mean	St. Dev.	Min	Max
Year	26,728,310	1996	10.100	1979	2013
Log(Price$_{it}$)	26,728,217	0.001	0.134	0.000	20.800
𝟙(EITI Candidate)	26,728,310	0.078	0.268	0	1
ACLED: 𝟙(Protest or Riot)	12,982,322	0.0003	0.018	0	1
SCAD: 𝟙(Soc. Conf.)	17,564,318	0.0001	0.012	0	1
GDELT: 𝟙(Protest)	26,728,310	0.001	0.025	0	1
ICEWS: 𝟙(Protest)	14,509,654	0.0003	0.017	0	1

Sample from models 5-6 using GDELT data.

B.3 Prices, Transparency, and Pr(Protest)

Table A.5: Transparency and the Relationship between Commodity Prices and Pr(Protest)
Transparency regimes mitigate the positive relationship between prices and protest.

	Dependent variable:			
	$\mathbb{1}$(Protest or Riot) ACLED	$\mathbb{1}$(Soc. Conf.) SCAD	$\mathbb{1}$(Protest) GDELT	$\mathbb{1}$(Protest) ICEWS
	(1)	(2)	(3)	(4)
Log(Price$_{it}$)	0.015^*	$0.002^\dagger$	0.005^*	0.005^*
	(0.004)	(0.001)	(0.002)	(0.002)
$\mathbb{1}$(EITI)	-0.0002	-0.00003	$-0.001^\dagger$	0.00001
	(0.0001)	(0.00004)	(0.0003)	(0.0001)
Log(Price$_{it}$)$\times$ $\mathbb{1}$(EITI)	-0.001^*	$-0.0001^\dagger$	0.005	-0.0002^*
	(0.0003)	(0.0001)	(0.005)	(0.0001)
Cell FEs	763,816	763,777	763,666	763,782
Year FEs	17	23	35	19
Observations	12,984,695	17,566,784	26,728,217	14,511,685
Var(# Mines) = 0	✓	✓	✓	✓
Linear Country Time Trends	✓	✓	✓	✓

Note: Robust Std. Errors Clustered on Country; $^\dagger p < 0.1$, $^* p < 0.05$

Columns 1-4: linear probability model regressions. Equation 2 is modified to include the interaction of price with an indicator for EITI candidacy, as well as linear country-specific time-trends. All specifications include grid-cell and year fixed effects. Cells with no population are excluded from the sample. Commodity prices are compiled from the World Bank, USGS and US EIA. EITI candidacy data is compiled from the EITI website (`https://eiti.org/countries`). Outcome data comes from the ACLED, GDELT, and ICEWS event datasets.

C. Sub-group Analysis

C.1 Owners' Countries of Origin

Table A.6: Mining Activity and Pr(Protest): The Effect of Chinese Ownership
No evidence that Chinese-owned mines generate a larger increase in the probability of protest.

	Dependent variable:			
	$\mathbb{1}$(Protest $\mid$ Riot) ACLED	$\mathbb{1}$(Soc. Conf.) SCAD	$\mathbb{1}$(Protest) GDELT	$\mathbb{1}$(Protest) ICEWS
$\mathbb{1}$(Mine)	0.007*	0.001	0.009*	0.002
	(0.002)	(0.001)	(0.003)	(0.001)
$\mathbb{1}$(Mine) $\times$ $\mathbb{1}$(CHN)	−0.016	0.007	0.052	0.011
	(0.033)	(0.016)	(0.043)	(0.019)
Observations	13,756,428	17,578,143	27,514,088	15,285,015

Note: Robust Std. Errors clustered on Cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-4: linear probability model regressions. Equation 1 is modified to include the interaction of mine starts with an indicator Chinese ownership. All specifications include grid-cell and year fixed effects. Cells with no population according to the LandScan data in 2012 are excluded from the sample. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining for the subset of mines that include information on their primary owners country of origin. Outcome data comes from the ACLED, SCAD, GDELT, and ICEWS event datasets.

C.2 Reporting Bias

C.3 Mining Projects and Rebellion

Analysis of ACLED Data using PRIO-Grid (55×55 km)

In an effort to more faithfully replicate the analysis of Berman et al. (2014), I aggregate the mining and ACLED data to PRIO's 55×55 km grid and only include the years from 1997 to 2010.

If I employ an indicator for any ACLED event (as in model 1, table A.10), my estimate is positive but smaller than what Berman et al. (2014) report in their corresponding table 2, model 1 (0.085).[41] Moreover, if we use an indicator for a protest or riot (model 2) or for an ACLED event involving protesters, rioters, or civilians (model 3), we find positive, if not, significant effects of mining activity.

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[41]The number of observations is not identical to Berman et al. (2014), which is likely due to my exclusion of unpopulated cells.

Figure A.1: Mining Activity and Pr(Protest) for Chinese- and Western-Owned Mines
Chinese-owned mines do not provoke more protest than mines owned by investors from OECD.
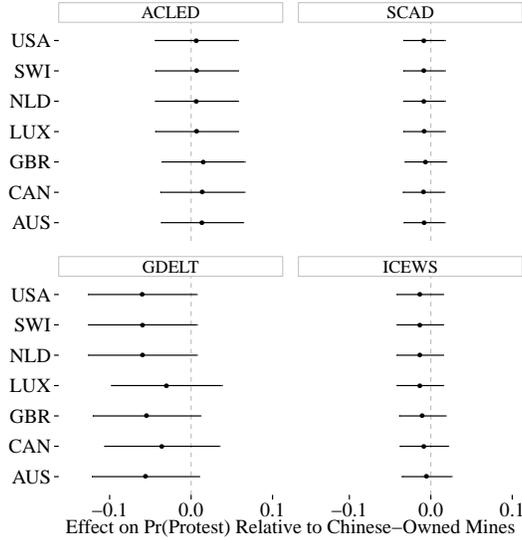
The figure plots point estimates and 90% confidence intervals for the interactions between $\mathbb{1}(\text{Mine})_{it}$ and indicators for whether a mine lists as its first owner a company based in Australia, Canada, the UK, Luxembourg, the Netherlands, Switzerland, or the US. *These are the effects relative to the omitted category, Chinese-owned mines.*

Table A.7: Mine Starts and Media Coverage
The intensity of media coverage does not increase after mining.

	Dependent variable:			
	Media Coverage of Protests			
	Mean(Art./Prot.)	Mean(Art./Prot.)	Mean(Src./Prot.)	Mean(Src./Prot.)
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Mine})$ (D_{it})	−0.771	−0.363	−0.067	−0.012
	(0.797)	(0.831)	(0.055)	(0.060)
Country x Year FE		✓		✓
Observations	18,428	18,428	18,428	18,428

Note: Robust Std. Errors clustered on grid-cell.

Columns 1-4: OLS regressions (see equation 1), where the dependent variable is the average number of news articles or news sources reporting on each protest within a cell-year. All models include grid-cell and year or country×year fixed effects. This analysis uses the same sample of cells as table A.1, models 5-6. However, the outcome variable can not be measured in grid-cell-years that do not experience protest; hence, the reduced sample. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; outcome data comes from GDELT.

However, when I use an indicator for (1) battles, (2) events involving rebels, or (3) armed conflicts involving rebels, I do not find that mining activity appears to incite these types of conflict

Table A.8: Mining Activity and Pr(Rebellion)

	Dependent variable:		
	Rebel Activity (ACLED, 1997-2014)		
	$\mathbb{1}$(Battle)	$\mathbb{1}$(Rebel Event)	$\mathbb{1}$(Armed Conf.) $\times\mathbb{1}$(Rebel Event)
	(1)	(2)	(3)
$\mathbb{1}$(Mine) (D_{it})	0.00105	−0.00177	−0.00198
	(0.00210)	(0.00166)	(0.00170)
Country x Year FE	✓	✓	✓
Observations	13,758,498	13,758,498	13,758,498

Note: Robust Std. Errors Clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-3: linear probability model regressions (see equation 1). All models include cell fixed effects and country×year fixed effects. The unit of analysis is the cell-year. Cells with no population are excluded. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; outcome data comes from the ACLED dataset. See footnote 42 regarding the operationalization of the outcome variables.

Table A.9: Mining Activity and Armed Conflict (PRIO Grid)

	Dependent variable:		
	$\mathbb{1}$(ACLED Event)	$\mathbb{1}$(Protest or Riot)	$\mathbb{1}$(ACLED Event w/Civilians)
	(1)	(2)	(3)
$\mathbb{1}$(Mine) (D_{it})	0.011	0.003	0.014
	(0.015)	(0.009)	(0.016)
Country x Year FE	✓	✓	✓
Observations	110,530	110,530	110,530

Note: Robust Std. Errors Clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Table A.10: Mining Activity and Armed Conflict (PRIO Grid)

	Dependent variable:		
	$\mathbb{1}$(Battle)	$\mathbb{1}$(ACLED Event w/Rebels)	$\mathbb{1}$(Armed Conf. w/Rebels)
	(1)	(2)	(3)
$\mathbb{1}$(Mine) (D_{it})	−0.002	−0.009	−0.008
	(0.012)	(0.006)	(0.006)
Country x Year FE	✓	✓	✓
Observations	110,530	110,530	110,530

Note: Robust Std. Errors Clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

(table A.9).[42] Rather, the effects are negative and significant at the 5 percent level.

This negative or null relationship between large mining projects and armed conflict also holds if I employ the Uppsala Conflict Data Program's Geo-referenced Event Dataset (UCDP-GED), which spans 1989-2010 (Melander and Sundberg 2012). In this dataset, an event is defined as: "The incidence of the use of armed force by an organised 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." I merge the UCDP-GED and the mining data to the PRIO grid and regress the incidence of (1) an event, (2) an event involving 25 or more battle deaths (according to the best estimate), and (3) an event involving less than 25 battle deaths on an indicator for mining activity. The results from these specifications, which include country-year and grid cell fixed effects, are reported in table A.11.

Table A.11: Mining Activity and Armed Conflict (UCDP; PRIO Grid)

	Dependent variable:		
	$\mathbb{1}$(UCDP Event)	$\mathbb{1}(\geq 25$ Deaths)	$\mathbb{1}(< 25$ Deaths)
	(1)	(2)	(3)
$\mathbb{1}$(Mine) (D_{it})	-0.011	-0.0001	-0.011
	(0.010)	(0.003)	(0.008)
Country x Year FE	✓	✓	✓
Observations	173,690	173,690	173,690

Note: Robust Std. Errors Clustered on cell; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

These findings are consistent with industry analysts' assessments of the risks facing Africa's mining sector: while the communities opposition to projects is seen as a primary concern (Stevens et al. 2013, 23), predation by rebels on large (and largely foreign-financed) projects rarely receives mention as a major risk. There is much to be commended in Berman et al. (2014); yet, the decision

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[42]"ACLED defines a battle as 'a violent interaction between two politically organized armed groups at a particular time and location.' Typically these interactions occur between government militaries/militias and rebel groups/factions within the context of a civil war" (Raleigh, Linke and Dowd 2014, 9). Armed conflict is operationalized as battles, the establishment of a rebel headquarters or base, or violence against civilians.

to aggregate different forms of conflict (which is common practice) leads to different conclusions about the consequences of foreign investment in mining for conflict in Africa.

C.4   Environmental Harm

Table A.12: Mining Activity and Pr(Protest) by Mining Method
Despite greater environmental risks, surface mines do not generate larger increase in protest.

	Dependent variable:			
	$\mathbb{1}$(Protest or Riot) ACLED	$\mathbb{1}$(Soc. Conf.) SCAD	$\mathbb{1}$(Protest) GDELT	$\mathbb{1}$(Protest) ICEWS
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Mine)	0.0110*	0.0029	0.0074*	0.0019
	(0.0052)	(0.0020)	(0.0035)	(0.0018)
$\mathbb{1}$(Mine) $\times$ $\mathbb{1}$(Surface Mine)	-0.0034	-0.0020	0.0091	0.0003
	(0.0060)	(0.0024)	(0.0062)	(0.0025)
Country$\times$Year FEs	✓	✓	✓	✓
Observations	13,756,435	17,578,181	27,514,096	15,285,030

Note: Robust Std. Errors clustered on Cell; $^{\dagger}p < 0.1$, $^*p < 0.05$

Columns 1-4: linear probability model regressions. Equation 1 is modified to include the interaction of mine starts with an indicator for surface mining methods, a proxy here for environmental risk. All specifications include cell and country$\times$year fixed effects. Cells with no population according to the LandScan data in 2012 are excluded from the sample. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining for the subset of mines that include information on their mining method. Outcome data comes from the ACLED, SCAD, GDELT, and ICEWS event datasets.

C.5 In-Migration

Table A.13: Commodity Prices and In-Migration
Mining areas attract migrants during commodity booms.

	Dependent variable:			
	𝟙(Moved)		𝟙(Moved Post-Mine)	
		w/Svy Wts		w/Svy Wts
	(1)	(2)	(3)	(4)
Log(Price$_{it}$) (Lag, 1)	0.2267*	0.2644*	0.4021*	0.4090*
	(0.0758)	(0.0897)	(0.0876)	(0.0975)
Individual Control for 𝟙(Urban)	✓	✓	✓	✓
Observations	17,797	17,797	17,430	17,430

Note: Robust Std. Errors Clustered on Mining Project;
Distance Cutoff: 25 km; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-4: linear probability model regressions, where columns 2 and 4 are estimated with survey weights. Whether an individual has moved or moved after the onset of mining is regressed on the logged price of the mineral being mined in the area (lagged one year). All models include mine and year fixed effects. The unit of analysis is the individual-year. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; price data comes from the World Bank, USGS, and US EIA; and data individuals' migration status is compiled from selected DHS surveys (female recode files).

Table A.14: In-Migration and Protest

Mining areas with more migrants are not more prone to protest.

	Dependent variable:			
	$\mathbb{1}$(Protest or Riot) ACLED	$\mathbb{1}$(Soc. Conf.) SCAD	$\mathbb{1}$(Protest) GDELT	$\mathbb{1}$(Protest) ICEWS
	(1)	(2)	(3)	(4)
Prop. Moved	−0.2534	0.0137	0.1339	0.1335
	(0.2816)	(0.0828)	(0.1850)	(0.3371)
Observations	211	235	235	216
Mining Cells	✓	✓	✓	✓

Note: Robust Std. Errors Clustered on Mining Project;
Distance Cutoff: 25 km; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-4: linear probability model regressions. The indicator for mining starts in equation 1 is substituted for the proportion of households that have ever moved or moved after mining starts. All models include mine and year fixed effects. The unit of analysis is the the mining area-year. A mining area is defined as a 25 km circular buffer centered on the mines latitude and longitude coordinates. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; information on migration comes from selected DHS surveys; and outcome data comes from the ACLED, SCAD, GDELT, and ICEWS event datasets.

Table A.15: Mobility and Wealth

Migrant households are not wealthier and do not benefit more from commodity price increases.

			Dependent variable:	
			Asset Index	
	(1)	(2)	(3)	(4)
𝟙(Moved)	0.0040		0.0028	
	(0.0025)		(0.0111)	
𝟙(Moved Post-Mine)		0.0022		−0.0020
		(0.0033)		(0.0149)
Log(Price$_{it}$)			0.0578*	0.0548*
			(0.0272)	(0.0261)
𝟙(Moved)×Log(Price$_{it}$)			−0.0004	
			(0.0008)	
𝟙(Moved Post-Mine)×Log(Price$_{it}$)				−0.0002
				(0.0011)
𝟙(Urban)	0.1794*	0.1786*	0.2117*	0.2106*
	(0.0082)	(0.0081)	(0.0145)	(0.0143)
Observations	39,085	38,294	17,093	16,774
Mining Cells			✓	✓

Note:	Robust Std. Errors Clustered on Mining Project;
	Distance Cutoff: 25 km.; $^{†}p < 0.1$, $^{*}p < 0.05$

Columns 1-2: OLS models that regress household wealth (as measured by an asset index) on indicator for whether a household has moved or moved following the onset of mining. Columns 3-4 restrict attention to areas with active mines regress household wealth on the logged price of the mineral produced by the mine, as well as the interaction of that logged price with whether a household has moved. All models include mine and year fixed effects. The unit of analysis is the individual-year. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; price data comes from the World Bank, USGS, and US EIA; and data on both households assets and individuals' migration status is compiled from selected DHS surveys (both the household and female recode files).

C.6 Inequality

Table A.16: Mining, Commodity Prices, and Wealth Inequality
Mining does not exacerbate inequality in mining areas.

	Dependent variable:		
	Wealth Inequality		
	(1)	(2)	(3)
$\mathbb{1}$(Mine)	−0.0227		
	(0.0277)		
Log(Price$_{it}$)		0.0799	
		(0.0617)	
Log(Price$_{it}$) (Lag, 1)			0.0286
			(0.0608)
Observations	1,053	501	542
Mining Cells		✓	✓

Note: Robust Std. Errors Clustered on Mining Project;
Distance Cutoff: 25 km; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-3: OLS regressions. Equations 1 and 2 are modified to include a measure of wealth inequality developed by McKenzie (2005) as the outcome variable. All models include mine and year fixed effects. The unit of analysis is the the mining area-year. A mining area is defined as a 25 km circular buffer centered on the mines latitude and longitude coordinates. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; price data comes from the World Bank, USGS, and US EIA; and data on households assets is compiled from selected DHS surveys.

Table A.17: Wealth Inequality and Protest in (Active) Mining Areas
More unequal mining areas are not more prone to protest.

	\mathbb{1}(Protest or Riot) ACLED	\mathbb{1}(Soc. Conf.) SCAD	\mathbb{1}(Protest) GDELT	\mathbb{1}(Protest) ICEWS
	Dependent variable:			
	(1)	(2)	(3)	(4)
Wealth Inequality	−0.0576	0.0017	−0.2234	0.0154
	(0.1532)	(0.0947)	(0.1751)	(0.1200)
Observations	532	455	553	537
Mining Cells	✓	✓	✓	✓

Note: Robust Std. Errors Clustered on Mining Project; Distance Cutoff: 25 km; $^{\dagger}p < 0.1$, $^{*}p < 0.05$

Columns 1-4: linear probability model regressions. Equation 1 is modified to include a measure of wealth inequality developed by McKenzie (2005), rather than mining starts. All models include mine and year fixed effects. The unit of analysis is the the mining area-year. A mining area is defined as a 25 km circular buffer centered on the mines latitude and longitude coordinates. Data on mining activity is taken from Mining eTrack, IntierraLive, and SNL Metals and Mining; outcome data comes from the ACLED, SCAD, and GDELT event datasets.

D. Data Sources

D.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.[43] 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).

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

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

Series: ── 1. USGS & EIA ···· 2. World Bank
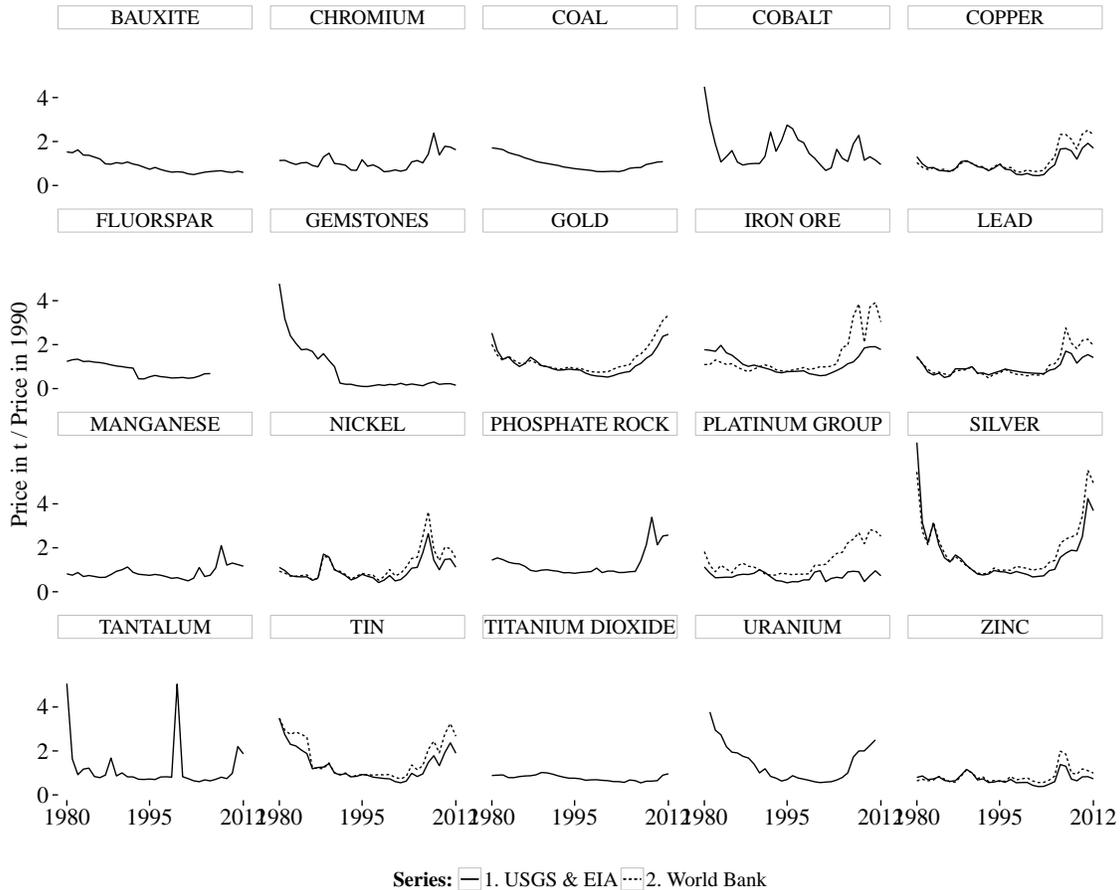
D.2 Households Assets

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.[44]

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[44]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.

Table A.18: DHS Survey Waves in SSA with GIS Information

|	Country	Survey Years		Country	Survey Years
1	Angola	2011	16	Madagascar	1997, 2009, 2013
2	Burkina Faos	1993, 1999, 2003, 2010	17	Mali	1996, 2010, 2012
3	Benin	1996, 2001, 2011	18	Malawi	2004, 2010, 2012
4	Burundi	2012	19	Mozambique	2009, 2011
5	D.R. Congo	2007, 2013	20	Nigeria	2003, 2008, 2013
6	Central African Republic	1994	21	Niger	1992, 1998
7	Cote d'Ivoire	1998, 2012	22	Namibia	2000, 2007, 2013
8	Cameroon	1991, 2004, 2011	23	Rwanda	2005, 2008, 2010
9	Ethiopia	1997, 2003	24	Sierra Leone	2008, 2013
10	Gabon	2012	25	Senegal	1997, 2005, 2008, 2011
11	Ghana	1993, 1998, 2003, 2008	26	Togo	1998
12	Guinea	1999, 2005, 2012	27	Tanzania	1999, 2010, 2012
13	Kenya	2003, 2009	28	Uganda	2001, 2009, 2011
14	Liberia	2009, 2013	29	Zambia	2007
15	Lesotho	2004, 2009	30	Zimbabwe	1999, 2005, 2010

Surveys sometimes span multiple years. I use the modal year in which respondents were interviewed for the purposes of this table.

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.

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 demean my asset index by survey (to remove variation due to cross-country or over-time variation) and then plot the average value of my asset index against the DHS's wealth classification. I connect these average 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.

Figure A.3: Asset Index vs. DHS's (Relative) Wealth Classifications
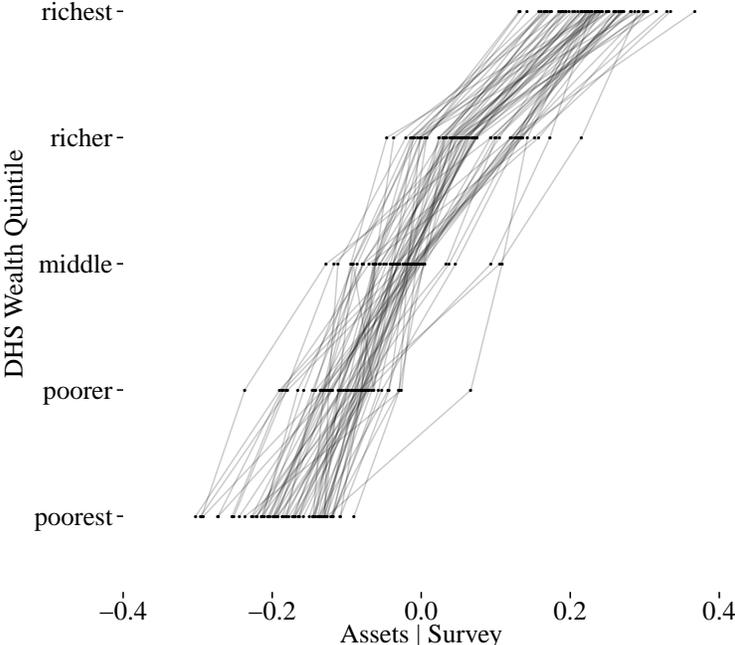
Households' scores on the asset index are first demeaned by survey. I then take the average of these demeaned scores for each wealth quintile. Finally, these averages are connected by a line, with one line for each unique survey.

D.3 Mining Projects

This paper draws on three sources of project-level data on global mining activity: SNL Metals and Mining, IntierraRMG, and Mining e-Track.[45] These data are only available to subscribers and primarily serve clients within the mining and financial sectors, though recent research by Kotsadam and Tolonen (2013) and Berman et al. (2014) 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.

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 large-scale foreign investments. The omission of artisanal, illegal, and small-scale miners is, thus, appropriate.[46] Of greater concern is the *potential* omission of large-scale projects due to the absence of source materials. Fortunately, it seems implausible that missing data could account for the reported results; more likely, such omissions lead to an understatement of the average effect of investments in commercial mining on conflict. First, the primary concern in Africa is that some projects backed by the Chinese government are not included in the database. Anecdotally, these mines have been especially prone to conflict due to their heavier reliance on imported labor. Second, the informational

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[45] In 2014, IntierraLive 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.

[46] How *might* the results change if we could include these smaller scale projects? First, as these projects tend to be less capital intensive, they may be more subject to expropriation by armed groups. The types of conflicts surrounding these sites may then be more violent. Second, small-scale projects are more likely to escape the attention of international audiences or investors, and, thus, their owners may face fewer financial repercussions if their operations provoke conflicts with their host communities.

asymmetries should be especially pronounced for operations where little or no information about the project exists.

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.19: Number of Mining Projects by Data Source

Source	N
SNL	453
Mining e-Track	96
IntierraLive	59
SNL, IntierraLive	159
SNL, Mining e-Track	161
SNL, IntierraLive, Mining e-Track	134
IntierraLive, Mining e-Track	10

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

D.4 Social Conflict

Descriptions of Datasets

The Armed Conflict Location and Event Data Project (**ACLED**) covers all countries on the African continent from 1997 to 2014 (Raleigh, Linke and Dowd 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, Linke and Dowd 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.

I also employ event data on protests, riots, and strikes from the Social Conflict in Africa Database (**SCAD**) (Hendrix et al. 2012). The SCAD is culled from *Associated Press* and *Agence France Presse* news wire stories between 1990 and 2012 for African countries. A pool of stories that contain key words associated with mobilization or violence are sorted, read, and hand-coded. Even if multiple stories are written about an event, it only enters the data one time. Yet, if an event takes place in multiple locations (e.g., a protest that takes place simultaneously in multiple cities), each location receives separate entries with distinct coordinates. The SCAD excludes all events that take place within the context of an armed civil conflict (as defined by the start and end dates in the Uppsala Armed Conflict Database). I only use events with precise geo-codings.

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 (Steinart-Threlkeld 2014; 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).

In section C.3, 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. As this data primarily captures armed conflict and not protests, I do not consider it below when I look at agreement across the event datasets.

Protest Actors

The empirical models estimated in the first two sections of the paper always include cell fixed effects. As a consequence, I leverage *changes* in protest activity in areas near mines after mining commences or as commodity prices change. I do not claim (or require) that all protests in mining areas are directly related to mining; the identification strategy can accommodate level differences in protest activity across cells that are unrelated to the presence of a mine or prices.

Nevertheless, knowing something about the identity of protesters in mining areas might suggest what motivates conflict. The actor codes included in ACLED are too vague to be of use. SCAD includes unsystematic notes about the actors involved in social conflicts. Among SCAD events that occur in mining areas, over 40% specifically mention mines or miners among the actors.

Both GDELT and ICEWS provide codes for the actors or sectors involved in protests. While some of the commonly used actor codes are too vague to identify protesters' identities (e.g,. "civilians"), the datasets also employ more specific codes, including for business, labor, government, etc. Taking all events with non-missing actor codes, I calculate the proportion of protests involving different actors in mining and non-mining cell-years (see figure A.4).[47] In both the GDELT and ICEWS datasets, I find that Labor (LAB) and Business (BUS) make up a larger proportion of protests in mining areas; the ICEWS data also suggests that leftist parties are more active in protests near mines. On the other hand, protests involving students (EDU or Education), government, or rebels make up a larger proportion of events in non-mining areas, as compared with mining areas.

Taken together, this evidence suggests that the events occurring in the same 5×5 km grid cells as mining projects are often directly related to mining or include workers and companies as actors. This composition actors is consistent with the theory presented above, in which mines engender material conflicts over how to distribute profits.

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[47] I focus specifically on Actor 1 in GDELT and the Source Sector in ICEWS.

Figure A.4: Proportion of Protests Attributed to Different Actors in Mining vs. Non-Mining Cells

(a) GDELT

(b) ICEWS
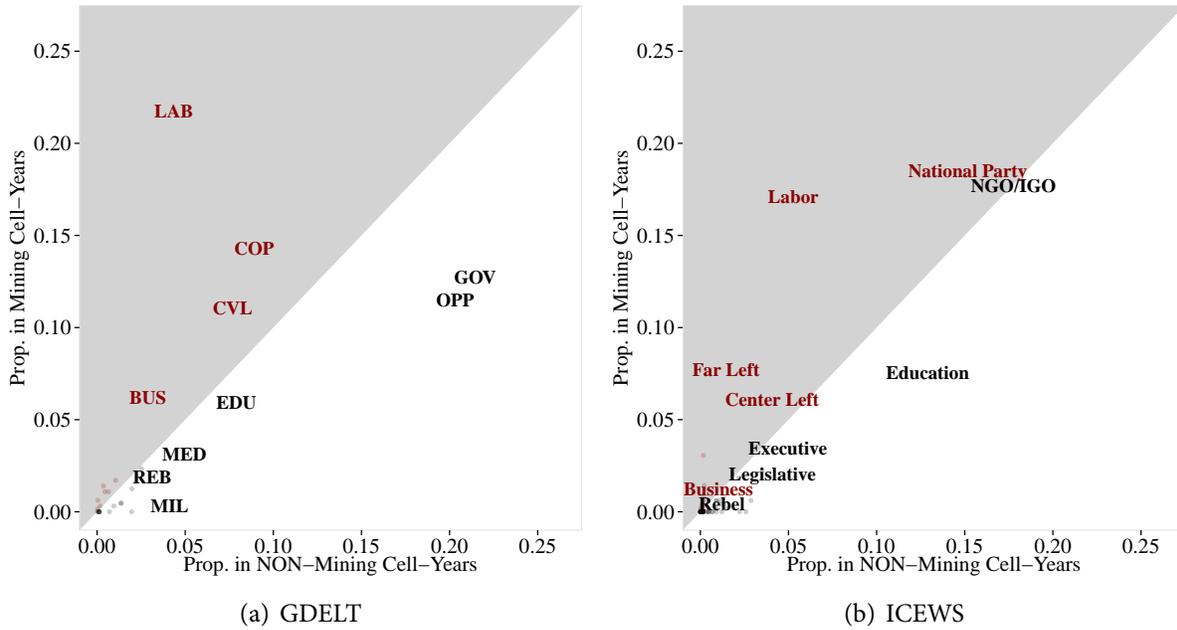
Agreement across Event Datasets

Scholars have compared the extent to which these different event datasets agree about when and where protests occur. Typically, these comparisons restrict attention to a small number of countries or a restricted date range (e.g., Steinart-Threlkeld 2014; Ward et al. 2013). Below I compare the extent to which these three datasets agree on whether a protest (or how many protests) took place in a given cell-year across Africa between 1997 (first year of ACLED data) and 2012 (last year of SCAD data).

I first compute the absolute difference $\left(\sum_{t=1990}^{2012} |x_{it} - y_{it}| \right)$ between the binary outcomes (i.e., $\mathbb{1}$(Protest)) reported by the three datasets (see table A.20). If I compare the ACLED and SCAD data, for example, this formula returns a count (for each cell) of the number of times ACLED codes a protest and SCAD does not or vice versa. In table A.20, I then average this count across cells. As we can see the average absolute distance is quite low, suggesting considerable agreement across datasets. However, these low average distances could be driven, in part, by cells that never experience protests according to any of the datasets. When such cells are excluded the average absolute distances increase, but remain relatively low (see table A.21).

Table A.20: Average Absolute Distance in $\mathbb{1}$(Protest) across Cells between Different Datasets

	ACLED	SCAD	GDELT	ICEWS
ACLED	0	0.005	0.018	0.018
SCAD		0	0.007	0.006
GDELT			0	0.018
ICEWS				0

Years $\in$ [1997, 2012]

Table A.21: Average Absolute Distance in $\mathbb{1}$(Protest) across Cells between Different Datasets
Sample Limited to Cells Experiencing $\geq$ 1 Protest.

	ACLED	SCAD	GDELT	ICEWS
ACLED	0	0.527	1.815	1.815
SCAD		0	0.665	0.562
GDELT			0	2.155
ICEWS				0

Years $\in$ [1997, 2012]

Second, I look at the sum of protests reported in each cell-year (rather than the indicator variables). I pool the observations and calculate the correlation coefficient for the number of protests reported by different pairs of the datasets (see A.22). I find that the protest counts in the SCAD, GDELT, and ICEWS datasets are correlated at above 0.5. As noted above, the GDELT and ICEWS datasets contain more events, both because they draw upon a larger number of news sources and may contain more false positives. The lower correlation between ACLED and these datasets appears to be driven by cell-years in which GDELT or ICEWS code a protest event, but ACLED does not. The reverse — cases in which ACLED codes a protest, but GDELT and ICEWs do not — is far less common.

Table A.22: Correlation of Protest Counts across Datasets

	ACLED	SCAD	GDELT	ICEWS
ACLED	1	0.501	0.324	0.347
SCAD		1	0.531	0.616
GDELT			1	0.905
ICEWS				1

Using pairwise complete observations.

These tables should increase confidence that, although the datasets employ different primary sources and coding procedures, they largely agree on whether and how many protests occur in given place and in a given year.

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