

# Concession Stands: How Foreign Investment Incites Protest in Africa <sup>\*</sup>

Darin Christensen <sup>†</sup>

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## Abstract

Why do foreign investments that can improve economic welfare also induce protest? Using a newly compiled dataset on commercial mining, commodity prices, and protest in Africa, I first establish that foreign investment projects increase the probability of protest. I then develop a theoretical model to explain these conflicts. I argue that communities have to strike a bargain with companies but have limited information about the value of the project they are hosting. When communities' expectations exceed what companies are willing to pay, protests result. I marshal two pieces of empirical evidence consistent with this model: first, protests are more likely when mineral prices are elevated and, thus, communities hold inflated expectations; and second, this relationship between mineral prices and protests is mitigated by policies that increase transparency and, thus, help correct the informational asymmetry that generates conflict. I do not find empirical support for alternative explanations for protest related to environmental risks, in-migration, inequality within mining communities, or reporting bias. Despite claims that resource extraction fuels armed conflict, I also do not find that these commercial mining projects increase the likelihood of rebel activity at or near mine sites.

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<sup>†</sup>Ph.D. Candidate in Political Science, Stanford University: darinc@stanford.edu. I acknowledge the support of the Stanford Graduate Fellowship.

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). Extractive industries have been important drivers of this upward trend (UNCTAD 2013*a*).

These investments can contribute to local development, bringing new jobs and infrastructure. “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.” By creating these new economic opportunities, some argue that foreign investment reduces deprivation and, thus, ameliorates the grievances that motivate conflict (see Rothgeb 1991, for a summary of this liberal view). Consistent with this claim, Rothgeb (1990, 266) shows that poor countries receiving more foreign investment in mining also experience less protest. Yet, contrary to these rosy earlier claims, this paper employs a more credible (difference-in-differences) research design and finds that new mining investments more than double the probability of protest (section 1).<sup>1</sup> This first finding motivates a second question: why do projects that can improve economic welfare induce protest?

I argue that protests are a tactic used by communities as they bargain with companies over how to split any rents (section 2). Communities often have limited information about the value of the project they are hosting. 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 investors. As all investors are wont to claim that they cannot meet such demands, protests provide a tactic for separating the firms that really cannot pay from those attempting to low-ball their hosts. I marshal two pieces of empirical evidence consistent with this model: first, protests are more likely when world commodity prices are high and, thus, communities hold inflated expectations about

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<sup>1</sup>This finding comports with Robertson and Teitelbaum (2011), who demonstrate a robust positive correlation between FDI and industrial conflict at the country-level, particularly in autocracies.

projects' margins;<sup>2</sup> and second, this relationship between prices and protests is mitigated by policies, such as the Extractive Industries Transparency Initiative (EITI), that promote transparency and, thus, help correct the informational asymmetry that I argue generates conflict.

I address whether and why these foreign investments incite protest and, in doing so, advance three debates.<sup>3</sup> First, existing research focuses on the determinants of foreign investment, not its political or social consequences (e.g., Jensen 2008; Biglaiser et al. 2012). These works highlight how hold-up problems deter investment to weak states, but they do not consider the informational problems (and, thus, local resistance) that investors confront in these contexts. This paper, therefore, makes both an empirical contribution by identifying the effects of foreign investment on conflict, as well as a theoretical contribution by illustrating how informational asymmetries strain investor-host relations.

Second, although these commercial projects incite protest, I do not find that they increase rebel activity or armed conflicts. This null finding contrasts with earlier research arguing that minerals and other primary commodities provide an easy source of funding and, thus, tempting target for rebels (e.g., Collier and Hoeffler 2002; Lujala, Gleditsch and Gilmore 2005; Berman et al. 2014). This analysis contributes to a new and growing body of work on the “resource curse,” which recognizes that how natural resources are produced or owned conditions their effects on conflict and regime type (e.g., de la Sierra 2014; Andersen and Ross 2014; Ross 2015). It also has important policy implications. Many countries in and beyond Africa have promoted foreign investment in minerals as a national development strategy. This research suggests that, in doing so, they are not trading off direct investment in rural areas for an increased likelihood of rebellion in those places.

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<sup>2</sup>Below, I explain why mineral price changes during the commodity boom led to mistaken inferences about mining projects' margins.

<sup>3</sup>I employ data from the mining sector, because this is a major component of FDI to Africa (and globally) and high-quality data exists on the location and timing of these investments. However, many of the theoretical arguments extend to, for example, agribusiness companies that face similar challenges in meeting local expectations for wages or development expenditure.

Finally, the private sector has been omitted from recent studies of African political economy.<sup>4</sup> Combing through the Millennium Development Goals reports from 2005 to 2015, the words firm, company, industry, and corporation (and their plurals) appear a total of 16 times; for comparison, the word education appears nearly 500 times, and even bird(s) receive more mentions.<sup>5</sup> This omission is glaring given the out-sized societal role that large foreign companies often assume in their host communities, filling in for absent governments by providing infrastructure and public services. By considering why, and to what effect, host communities mobilize outside of state institutions to affect these firms' behavior, this study extends work on "private politics" that has been applied in more developed contexts (Baron 2003; 2012).

## **1. Do Foreign Investment Projects Provoke Protest?**

### **1.1 Bargaining with Complete Information: The Null Hypothesis**

Foreign mining projects 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 Africa are unable to fully exploit their resource endowments in the absence of foreign investment. Allowing foreign firms to initiate mining projects can generate economic activity that would not otherwise occur.<sup>6</sup>

To establish and operate a mining concession, investors need to coordinate with government agencies 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

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<sup>4</sup>Arriola (2013) being a notable recent exception, and Reno (2000, 456) offering a qualitative assessment of foreign capital's historic role in financing African leaders' "shadow states."

<sup>5</sup>To my knowledge, Chris Blattman was the first to note this disparity.

<sup>6</sup>Farole and Winkler (2014, 9) argue that "for many developing countries, domestic capital accumulation remains too low to stimulate sufficient growth. In this context, FDI represents an important source of private capital..."

securing of the support of local communities.”<sup>7</sup> Since 2009, Ernst & Young has included maintaining a “social license to operate” among the top business risks facing the mining sector (Stevens et al. 2013, 23). Companies need to negotiate, and frequently renegotiate, formal and informal agreements, which allow them to operate undisturbed in their host community. This can include how many workers will be employed and at what wage, compensation for households that must be relocated due to mining, rents for land occupied by the company, or expenditure on infrastructure and public facilities (e.g., local health clinics and schools).

In the ideal scenario, investors and their host communities quickly and amicably reach such agreements, and both parties share in any surplus generated by a new project. When can we expect these parties to frictionlessly decide how to divide up the returns generated by a new investment? Well-known results from bargaining theory suggest that, if both the company and community know the project’s surplus (and each other’s costs to delaying), then they should immediately settle on a mutually agreeable split of the pie (Osborne and Rubinstein 1990, 45). The logic is straightforward: the company, for example, proposes a split that leaves the community indifferent between accepting today and counter-offering after some (costly) delay.

I quickly present this bargaining game of alternating offers between two informed parties, as this provides the foundation for the model developed in section 2 and establishes the first-best outcome. Consider a game of complete information between a Community and a Firm that owns a project with positive 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 ( $t \in [t, \infty)$ ). 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

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<sup>7</sup>Community is actually a term of art in the sector: “[t]he *local* or *host* community is usually applied to those living in the immediate vicinity of an operation, being indigenous or non-indigenous people, who may have cultural affinity, claim, or direct ownership of an area in which a company has an interest” (emphasis original; qtd. in Evans and Kemp 2011, 1768).

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.**  $\Gamma = \frac{\delta_F}{\delta_F + \delta_C}$

**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.* See appendix A. □

This first proposition demonstrates that, in a complete information setting, firms and communities immediately split project's proceeds, with the more patient party retaining a larger share. Critically, in this scenario, costly delays that defer production and profits, such as protests or work stoppages, do not occur in equilibrium. Firms and their host communities should bargain away conflict. While this null hypothesis will strike some readers as pollyannish, it comports with earlier empirical work that found a null or negative relationship between foreign investment in mining and protest in poor countries (Rothgeb 1991).

There is a second reason, specific to natural resource production, that we might expect to see fewer social conflicts in localities hosting mining projects relative to other towns or cities in the same country. An increase in national mineral exports can increase exchange rates, hurting other tradable sectors, a dynamic commonly referred to as Dutch Disease (Sachs and Warner 1997). 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 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 below that protests increase in localities receiving new investments. This leads me to reject hypotheses that new mining investments have no, or even a negative, effect on protest.

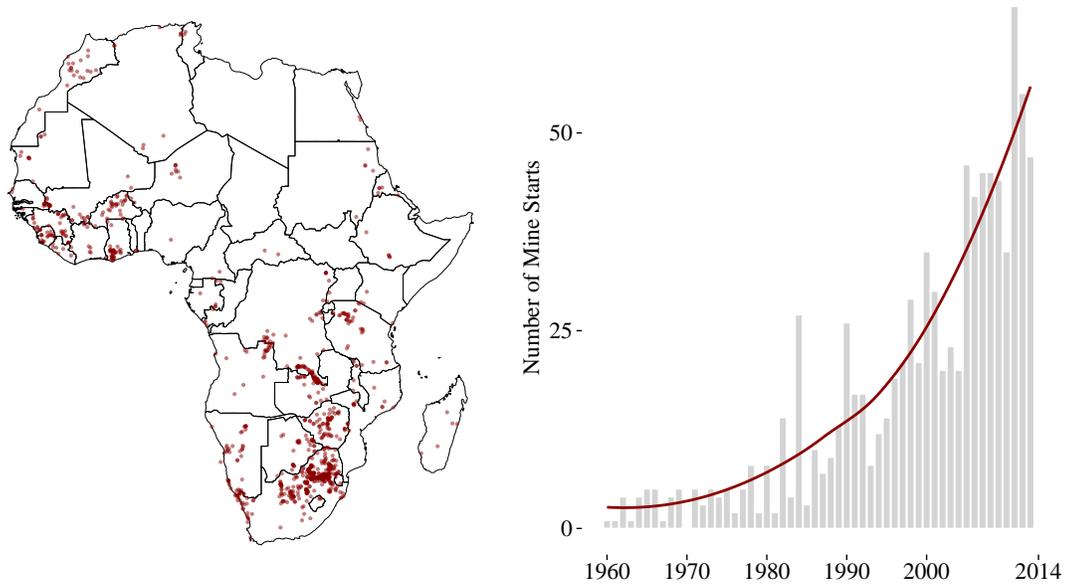
First, I use information from three major repositories of mining data (IntierraLive, SNL Metals and Mining, and Mining eTrack) to geo-locate unique commercial mining projects and determine their start years. Figure 1 displays the location of these projects, as well as the number of new projects in each year from 1960 to 2014. Since the mid-1980s, mine starts in Africa have increased dramatically: in 2011 more new mines were brought on-line than in all of the 1970s. Most projects in Africa are owned by companies based in other parts of the world: companies based in Australia, Canada, China, Switzerland, the UK, and the US own over half of all projects on the continent.<sup>8f</sup>

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, 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. While these datasets are all derived from media and other reports on social conflicts, ACLED and SCAD use human coders to process these reports, whereas GDELT and ICEWS employ a machine coding system. I discuss the composition and limitation 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, but I show in the appendix that the paper's results hold across all four datasets (appendix B).

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<sup>8</sup> Although investment from China has increased recently, Chinese companies still own a relatively small share (less than three percent) of all mining projects in Africa, according to the SNL Metals and Mining database.

**Figure 1: Mine Locations and Start Years.**  
*Mining investments in Africa have increased dramatically.*



The map on the **left** 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 figure on the **right** then plots how many of these projects were started in each year since 1960 (the gray bars) and a loess fit (span = 0.75) of this trend (the solid red line).

I spatially merge these data on mining activity and protests using a grid comprising cells that measure  $5 \times 5$  kilometers at the equator. As most conflict events are geo-coded using the names of towns, I chose grid cells that are slightly smaller than the median city size of 37 square kilometers.<sup>9</sup> This grid excludes cells with no inhabitants (or coded as missing) based on the 2012 LandScan data (Oak Ridge National Laboratory 2012).

To recover the effect of mining projects 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 populated areas that do not host new projects. I estimate this difference-in-differences using a panel regression with cell

<sup>9</sup>By contrast the PRIO grid uses cells that are 3,025 square kilometers, an area 84 times larger than the median city.

( $\alpha_i$ ) and year ( $\delta_t$ ) fixed effects, and a indicator ( $D_{it}$ ) for an active mining project:

$$y_{it} = \alpha_i + \delta_t + \beta D_{it} + \varepsilon_{it} \quad (1)$$

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

**Table 1:** Mining Activity and Pr(Protest)

	<i>Dependent variable:</i>				
	$\mathbb{1}(\text{Protest or Riot})$				
	1	2	3	4 (Border $\leq 2$ )	5 (Placebo)
$\mathbb{1}(\text{Mine}) (D_{it})$	0.011* (0.003)	0.011* (0.003)	0.006* (0.003)	0.009* (0.003)	
$\mathbb{1}(\text{Placebo}) (P_{it})$					0.0003 (0.002)
Cell FEs	764,361	764,361	764,361	13,612	764,016
Year FEs	18				
Country $\times$ Year FEs		900		702	900
Cell $\times$ 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  $\times$  year (2, 4-5), or cell  $\times$  period fixed effects (3). 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 appendix D for details). 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 nearly triples 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

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

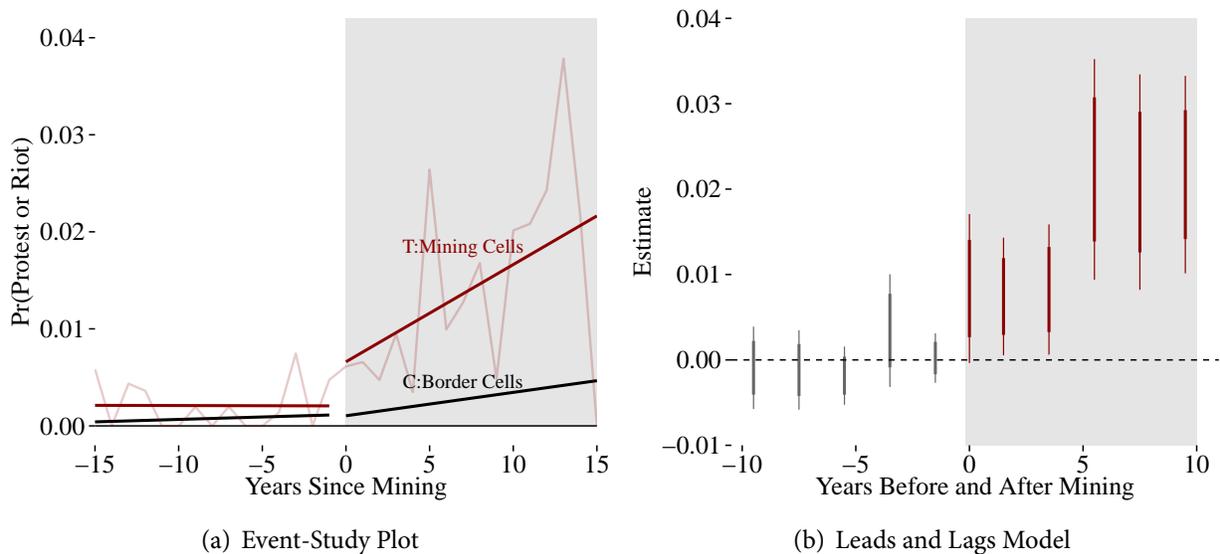
Statistic	N	Mean	St. Dev.	Min	Max
$D_{it}$	13,758,498	0.00063	0.02514	0	1
$P_{it}$	13,748,253	0.00017	0.01300	0	1
$\mathbb{1}(\text{Protest or Riot})$	13,758,498	0.00037	0.01915	0	1

not change if I cluster on larger geographies (including country) to account for spatial dependence within larger geographic units. In models 2-4, I modify equation 1 and the composition of the control group to demonstrate robustness. First, models 2 and 4 substitute the year dummies for country $\times$ year fixed effects. This larger set of indicators absorbs any shocks that affect an entire country in a given year (e.g., national elections or currency fluctuations). Second, model 3 includes cell $\times$ 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 their immediately 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.<sup>10</sup> 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%. By contrast, the median population in mining cells was less than 600 people; yet, the probability of protest was 4.2%.

An identifying assumption for the difference-in-differences is that protest trends would have been parallel in mining and control cells had no mines started. While this assumption is untestable,

<sup>10</sup>The results are robust to limiting the control group to immediately bordering cells.

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



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 mining indicator.

is it plausible in this context? If companies seek to minimize political risk, it seems unlikely that they choose sites experiencing escalating conflict. Rather, investors may seek out relatively docile host communities, a selection process that, in theory, should push towards a null finding.

A data-driven approach for assessing the parallel-trends assumption looks at pre-treatment trends. 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% (and thicker 80%) confidence intervals for five (two-year) leads and lags of my treatment indicator (See Autor 2003, figure 3 for an early implementation of this strategy). Again, I find no evidence of

anticipatory effects, bolstering the parallel trends assumption.<sup>11</sup> Finally, in the last column of table 1, I report null results from a “placebo test” that recodes treatment as the five-year period prior to the initiation of mining.<sup>12</sup> This placebo test confirms that firms do not select into areas with escalating levels of social conflict.

Upon seeing these results, readers’ first concern may be that localities hosting investments receive 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.<sup>13</sup> 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 11).<sup>14</sup>

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 induces protest? First, despite stories suggesting that Chinese-owned mines generate more conflict (e.g., Okeowo 2013), 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 North America and Western Europe (see table 10 and figure 6). It could still be that Chinese investors select into more unstable environments than their western counterparts, but these results do not suggest that Chinese business

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<sup>11</sup>The leads and lags plot suggests that the effect of these investments on protest increases five to ten years after mining starts. It is commonly recognized that early-stage mining projects service large debts and struggle to turn a profit. If the community knows that there is little or no surplus to share during a mine’s early years, then it has less of a reason to mobilize protests demanding a larger cut.

<sup>12</sup>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.

<sup>13</sup>I use the GDELT data to estimate the same difference-in-differences as equation 1, using the average number of articles or sources per protest as outcome variables. This analysis suggests that there is no increase in the reporting resources allocated to areas hosting investments.

<sup>14</sup>In the next section, I find no evidence that mining activity increases the probability of armed conflict. This further alleviates concerns about reporting bias, as the data on armed conflict is also derived from the same media sources. If differential reporting resources in mining areas led to higher rates to discovery, we would expect this same positive bias to be apparent when looking at changes in the incidence of other types of conflict.

or labor practices — should such uniform practices exist — exacerbate protest. Second, projects where the host government is a partial owner generate a much smaller increase in the likelihood of protest.<sup>15</sup> While it may be tempting to conclude that exclusively *foreign* investment provokes conflict, this finding does not permit a clear 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 investments provoke 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.

### 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; Dal Bó and Dal Bó 2011; Dube et al. 2008).<sup>16</sup> These papers offer a compelling logic: mines, particularly during periods of high prices, represent attractive sources of funding and, thus, tempting targets for rebels.

Recent empirical work by Berman et al. (2014) builds upon this work, finding that new mining activity and commodity prices are associated with more conflict events in Africa.<sup>17</sup> The authors interpret these results as evidence that rebel groups are battling for control of mining areas, because seized mines provide funds to sustain and intensify rebellion (19). However, while Berman et al.'s

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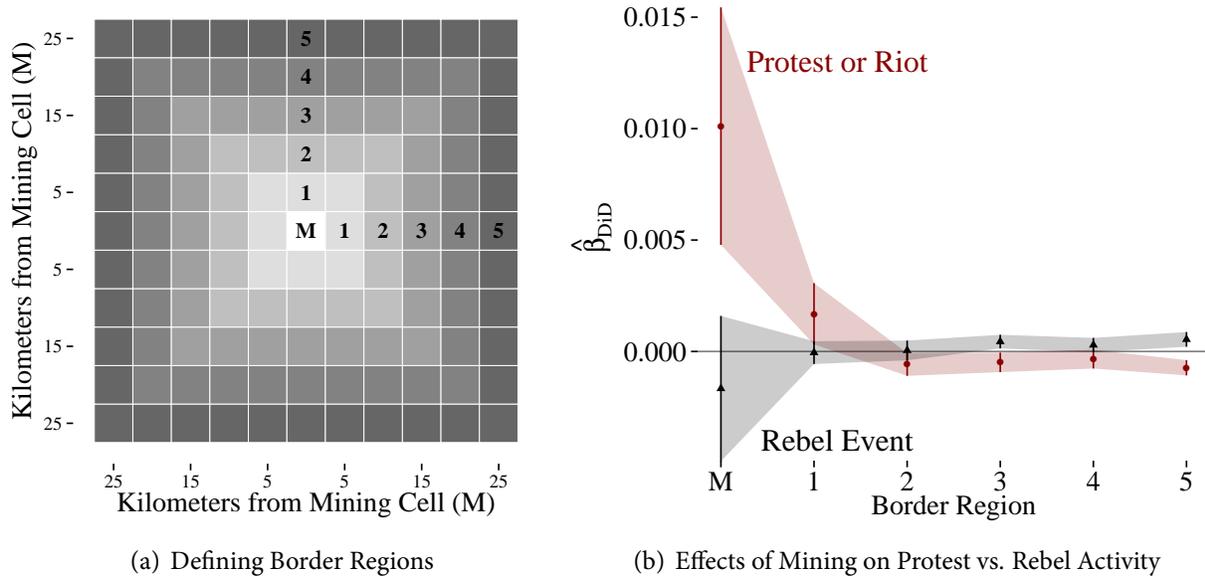
<sup>15</sup>This analysis comes with a caveat: projects with host government ownership account for only 10% of mining areas in the data.

<sup>16</sup>Fearon (2005) demonstrates the fragility of early results from Collier and Hoeffler (2002) regarding the relationship between primary commodity exports and civil war risk. 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.”

<sup>17</sup>There are differences between the data used by Berman et al. (2014) and in this paper: the authors focus on the ACLED data from 1997-2010, employ a subset of mining projects, 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). While mine starts still appear to incite protest using this coarser grid, I find no evidence in the ACLED or UCD datasets that mine starts increase armed conflict.

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.<sup>18</sup> 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 rebel activity (see table 12).<sup>19</sup>

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



The **left** figure illustrates how border regions are defined: cells that abut a mining cell (M) are in the first border region; cells touching those first border cells are in the second border region; and so on, radiating outward. The **right** figure displays the difference-in-differences estimates for cells that fall in each of these border regions (see specification in footnote 20) using indicators for protest or rebel activity as the dependent variable. Both outcomes are coded from ACLED data, spanning the period from 1997-2014.

Figure 3 contrasts the effects of mining on armed and social conflict in the locality that contains the mine, as well as in the immediately surrounding areas. This figure helps make several points. First, these projects do not increase the probability of rebel activity in the community hosting the

<sup>18</sup>ACLED provides standardized actor codes that include a category for rebels.

<sup>19</sup>From the ACLED Codebook: “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 2014a, 9). Armed conflict is operationalized as battles, the establishment of a rebel headquarters or base, or violence against civilians.

mine or in the immediately surrounding areas.<sup>20</sup> A recent quote from the CEO of a major mining company, Randgold, echoes this finding: speaking in reference to 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. That is, protesters are not simply relocating their demonstrations from nearby towns to mining communities.

By separating insurgent activity from protests and riots, we can make further progress in determining who responds confrontationally to new investment projects and why. In this case, communities hosting new mines are not more likely to experience rebel activity, and this null finding casts doubt on stories about rebel groups in Africa *directly* predating on investments.<sup>21</sup> 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 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 may 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 the

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<sup>20</sup>Let  $k \in \{0, 1, \dots, 5\}$  index our border regions, where  $k = 0$  is the actual cell containing the mine. 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.

<sup>21</sup>Conflict may not happen at or near the mine site. Dube and Vargas (2013) argue that rising oil prices increased paramilitary attacks in oil-producing provinces in Colombia. They describe rebels kidnapping politicians and attempting to raid government coffers as oil revenues increase. In this case, violence is not occurring near the mine. My analysis can not speak to these potential effects of mining on armed conflict at a provincial or national level.

variables, such as production methods or scale, that condition emergence of symptoms associated with the “resource curse.”

## **2. Why Do Foreign Investment Projects Provoke Protest?**

The first result indicates that active mining investments more than double the probability of protest. This raises the question: why do communities and firms not bargain away conflict?

I argue that these conflicts are caused by uncertainty among host communities regarding the returns generated by these projects. Investment 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 and increased employment. Yet, while most projects begin with this optimistic outlook, actual profitability varies dramatically: expensive and prolonged exploration can fail to discover sufficient deposits; even productive mines differ due to ore amounts and quality, as well as production and transportation costs. Cross-sectional data on mines across the world in 2013 indicates that projects vary dramatically in their net value: (1) even mines producing the same commodity vary dramatically in their estimated value of resources and reserves, and (2) there is no systematic relationship between this estimated value and production costs. Entering negotiations, whether at the onset or in later stages of mining, communities and workers cannot be certain where the particular project they are hosting falls in the distribution of profitability, and optimistic initial claims may lead to unreasonable expectations about a project’s value.

What happens if a community overestimates a project’s value and makes a demand that the company cannot afford? The company will try to convey their inability to pay, but this often falls on deaf ears. If the community were to take the company at its word, then even the most profitable firms would have an incentive to plead poverty in an effort to retain a larger share of profits. As

communities cannot rely on firms to honestly report their earnings, protests or riots that threaten production offer a strategy for separating firms with low-profit projects from those attempting to low-ball the community.<sup>22</sup>

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 that the project's revenues had recently increased, but that this had not translated into better wages for workers or improved living conditions for households resettled due to mining.<sup>23</sup> This frustration is echoed in interviews for a 2014 Human Rights Watch report on the protest: "After the exploration period was over, the company went into mining and production [in 2009-2010] and told the workers that they would get more and that everything would change for the better... We came into mining and it was no better" (Human Rights Watch 2014, 39). Later in the report, an employee at the mine states, "In 2011, management promised that 'when we start exporting, that's when things will change. We have to be patient; the investors don't have profits yet.' All the workers were fed up with this game" (47). Despite these bullish beliefs, the project's actual financial situation was 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' initial wage demands were reasonable given platinum mines' profits over the

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<sup>22</sup>This logic builds upon work by labor economists, such as Tracy (1987); Card (1990); Kennan and Wilson (1993), who model strikes as a consequence of incomplete information among workers.

<sup>23</sup>Author's interviews, May 2014. IRB Protocol #28040.

past decade.<sup>24</sup> 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 AMCU 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’s] focus on how we can work together to ... reward all our stakeholders” (Kings 2014).

Eventually, workers settled for a twenty percent annual increase in wages. If they had trusted companies’ financial 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 a costly and, thus, credible signal by the companies that they could not afford workers’ initial demands.

Third, a 2010 report on mining in Tanzania opens by stating that “arguably the most important and daunting challenge confronting any commercial mining operation is the securing of the support of local communities” (Goldstuck and Hughes 2010, 6). This is especially challenging where communities hold unreasonable expectations about the profitability of projects and, thus, their potential contribution to local development: “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” (13). As part of the report, the authors visited Barrick Gold Corporation’s mines in Tanzania, attempting to understand why the company was denied the “social license to operate” by the community surrounding its 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

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<sup>24</sup>Isaacs and Bowman (2014) rely on past data, because they claim that companies were unwilling to disclose more recent figures.

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). While there are other sources of conflict at the North Mara Mine, one source of conflict is lingering anger that the community has not shared (as promised) in the returns generated by the project.

Finally, these are not isolated cases: disputes often center on how profits are split and whether host communities regard that as fair.<sup>25</sup> In their recent study of fifty 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 of these conflicts.

Taken together, 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), who observe that

“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).

This qualitative evidence suggests that conflicts arise, because companies and communities do not agree on the value of the project they are bargaining over. As everyone recognizes the company’s incentive to understate its 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 the firms that really cannot pay from those attempting to short-change the community.

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<sup>25</sup>See also Mensah and Okyere (2014); Garvin et al. (2009), 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

When companies and communities are completely informed, my benchmark bargaining model predicts that they will frictionlessly settle on a split of the profits. Yet, the first empirical results suggest that bargaining sometimes fails, leading to an increased likelihood of protest in mining communities. The qualitative work summarized above offers a reason for these bargaining failures: an informational asymmetry that leaves communities uncertain about the value of the project they are hosting. I now consider how the bargaining game (introduced in section 1.1) changes when the community does not know — and may hold unreasonable expectations about — the surplus generated by the investment.<sup>26</sup> To preview the result, introducing this one-side informational asymmetry leads to a possibility of disruptions in equilibrium.<sup>27</sup>

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 ( $\theta \in [\underline{\theta}, \bar{\theta}]$ ;  $\bar{\theta} > \underline{\theta}$ ) 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 1.1.<sup>28</sup>

To make the analysis tractable, I make three additional assumptions. First, as the primary

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<sup>26</sup>Readers familiar with Fearon (1995) or Powell (2006) may be puzzled that I do not focus on another well-known source of bargaining failure: commitment problems. Commitment problems have been a focus of research on the impediments to (foreign) investment in states with weak property rights protections (Jensen 2003; Williamson 1979; Vernon 1971). Yet, without denying that investment may be deterred by hold up problems, the commitment problem does not provide a compelling explanation for protest. First, in the complete information game, we can allow for dramatic asymmetries in bargaining power between the Firm and Community without provoking protest. While hold-up power affects the split that the Firm and Community agree upon, it would not generate protest in equilibrium (see proposition 1). Second, unlike Fearon's two-state setting where either side can initiate an attack, the Firm can not preemptively strike. Even if the Firm recognizes that their bargaining power is waning (i.e., it faces an "obsolescing bargain"), they cannot move against the Community in an effort to prevent this shift in relative power.

<sup>27</sup>This model draws on earlier work by Admati and Perry (1987), who consider a bargaining game between an incompletely informed buyer and seller, whose valuations fall in a discrete type space.

<sup>28</sup>I continue to assume that the Community is a unitary actor, which omits the collective action problems inherent in protest. This omission is intentional: collective action problems help rationalize the null hypothesis of no protest, but they 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 resources firms invest in community relations officers.

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.*

**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 ( $\theta \geq \hat{\theta}(b^*)$ ) immediately accept.*
- (C) *Firms with projects below that cutoff value ( $\theta < \hat{\theta}(b^*)$ ) 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  $\theta$  that they face after a delay of length  $t$  ( $\theta = t^{-1}(t)$ ).

*Proof.* See appendix A. □

The probability of conflict is then the probability the Firm would rather disrupt production than immediately accept the Community's initial offer (i.e.,  $\Pr(\theta < \hat{\theta}(b^*) = F(\hat{\theta}(b^*)))$ ). 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,  $b^* = 3\bar{\theta}/4$ .<sup>29</sup> And, given this initial offer, all firms below  $\hat{\theta}(3\bar{\theta}/4) = \bar{\theta}/2$  would rather disrupt production than immediately concede; the probability that a given firm falls in this range is then  $F(\bar{\theta}/2) = 1/2$ .<sup>30</sup>

To state the result less formally, communities' initial demands sometimes exceed what firms are able or willing to pay. When this happens, firms with lower value projects can credibly signal their weaker financial position by enduring protests that shut down production. Why is that an informative signal to communities? Citizens know that firms with lucrative projects face higher opportunity costs and, thus, are more eager to concede to avoid protests. However, for firms with projects that are struggling to turn a profit, shutting down the mine is a less costly prospect and, thus, these types are more willing to endure costly delays to reduce the communities' expectations. Protests serve then to separate firms that cannot meet large demands from those that, absent the threat of protest, might be tempted to short-change their hosts.

The cases discussed above suggest that communities not only do not know the surplus generated by mines, but they also tend to hold inflated expectations about projects' profits. One way to incorporate these inflated expectations is to allow the Community's prior beliefs to diverge from

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<sup>29</sup>Note that  $b^*/2$  is the actual split that the community would receive if this initial offer is accepted.

<sup>30</sup>In this model extending 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.

the true distribution of firms. 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  $\theta \sim U[0, \bar{\theta}] = \tilde{F}(\cdot)$  (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 with one modification: the Community's initial offer now reflects their inflated prior beliefs ( $\tilde{F}(\cdot)$ ) and not the true distribution of firm types.<sup>31</sup> 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 ( $\tilde{F}(\cdot)$ ), 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 falls in this range now depends on the Community's prior beliefs:  $\Pr(\text{Protest}) = F(\bar{\theta}/2) = \frac{1}{2} \left( \frac{\bar{\theta}}{\bar{\theta} - \omega} \right)$ . When the Community's beliefs match the true distribution of firms (i.e.,  $\omega = 0$ ), the probability of protest is (as before)  $1/2$ ; however, this probability increases when the Community exaggerates the likelihood of hosting a highly profitable mine.<sup>32</sup> In short, when communities' overestimate projects' profitability, they are more likely to make large initial demands of struggling projects, prompting protests.

## 2.2 Explaining Variation in Protest Across Investments

This model 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,

<sup>31</sup>The equilibrium is no longer unique, as there are now a range of  $k$  values that support separation.

<sup>32</sup>This result echoes Harrison and Stewart (1994, 527), who offer a similar explanation for the pro-cyclicality of strikes in developed economies: "Only firms doing badly suffer strikes therefore, but if the union's subjective probability,  $p$ , is based on how well, on average, firms are doing (which information might, e.g., be collected and reported by a statistical agency), strikes are nevertheless more likely to occur when the economy is healthy. By contrast, when all firms are doing badly, the strike condition is not satisfied ..."

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 incidence in more developed countries, which find that industrial conflicts increase during high points in the business cycle.<sup>33</sup>

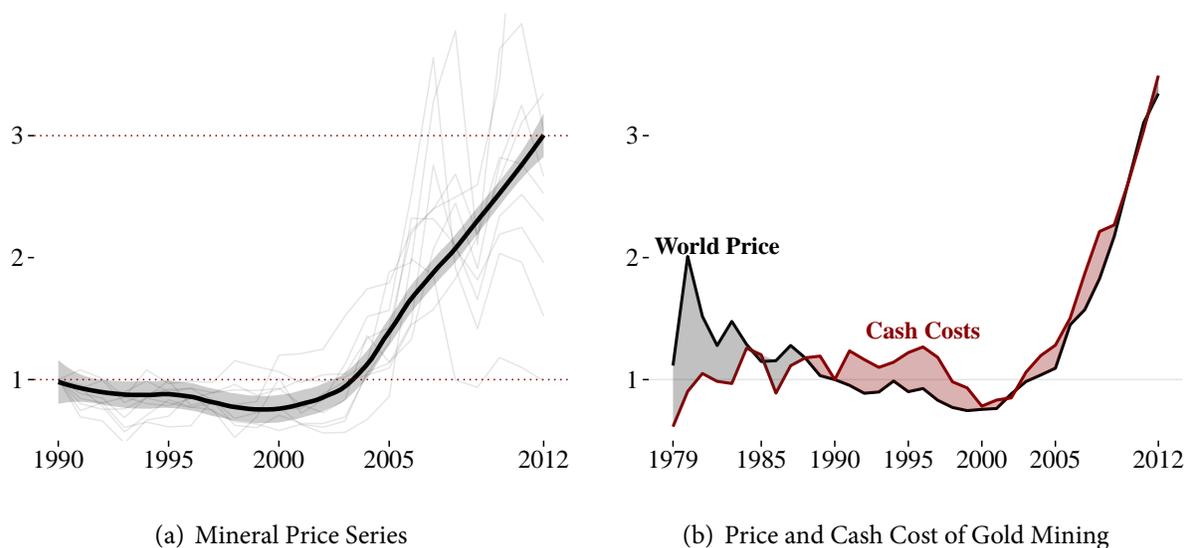
The question then is when should we expect communities to be bullish about projects' returns? Goldstuck and Hughes (2010, 11) argue that mining companies in Tanzania are perceived to be immensely profitable "based on the assumption that companies' profits are calculated on the basis of gold production 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 new "calls for the country to receive its 'fair share' of the profits ... [and] [t]he assumption behind such demands is invariably that the current share is not fair ..." (47). This research suggests that price increases during the recent commodity boom raised communities' expectations (see figure 4a for mineral price trends).

Communities seem to be making a reasonable inference: projects' profits increase in step with commodity prices, expanding the size of the pie to be split. However intuitive, this overstates the extent to which rising commodity prices during the recent boom increased projects' margins. In fact, during this period, industry analysts noted a marked and "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

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<sup>33</sup>In addition to their own findings, Harrison and Stewart (1994, 528) cite a number of other studies that find strikes are pro-cyclical: "Five recent articles, two based on Canadian data and three based on U.S. data, have included variables to capture business-cycle fluctuations in models of the probability of a strike... With the exception of Gramm's work, the studies reveal a significantly positive relationship between incidence and the business cycle."

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



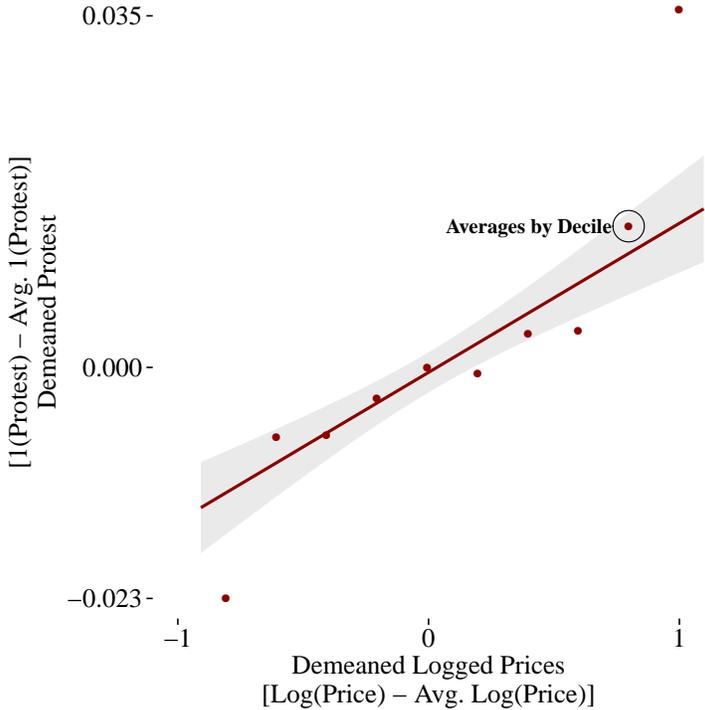
The **left** figure displays mineral prices (indexed to 1990 values) from the World Bank as grey lines. The thicker loess curve is weighted by the number of projects producing a given mineral in my sample of mining projects. The **right** figure displays the price and cash cost of gold mining indexed 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.

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 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 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 many industry outsiders, a group which includes the communities hosting these mining investments.

**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).

The model predicts that, if rising prices inflate expectations, then they should also increase the likelihood of protest. Anecdotally, rising gold prices raised expectations among Tanzanians

and generated “palpable anger and resentment towards mining companies [which] has resulted in a confrontational relationship ...” (Goldstuck and Hughes 2010, 6). The data indicate that what was true of gold in Tanzania was true more broadly: across projects producing different minerals, I find that above average commodity prices correspond to above average levels of protest (figure 5).<sup>34</sup>

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:

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

where  $i$  indexes cells and  $t$  year.<sup>35</sup> 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 mines 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, I can restrict the sample to cells with a single mine throughout the period (model 2) or with no change interpretation the number of mines (model 3).<sup>36</sup> In these models, we are holding the company-community dyad(s) 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

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<sup>34</sup>I compile price data from the World Bank, U.S. Geological Survey, and the U.S. Energy Information Administration. The resulting dataset includes real unit prices for over 90 unique minerals, with nearly complete coverage over the study period (see appendix D for further details). On the rare occasion that a cell contains multiple mines producing different commodities, I use the price of the modal commodity.

<sup>35</sup>The results are qualitatively similar if I substitute country×year for the year fixed effects.

<sup>36</sup>Berman et al. (2014) adopt this latter approach, as cells that never host mines can be assigned zero price and included in the sample to aid in the estimation of the year or country-year fixed effects.

**Table 3: Commodity Prices and Pr(Protest)**

	<i>Dependent variable:</i>			
	$\mathbb{1}(\text{Protest or Riot})$			
	(1)	(2)	(3)	(4)
Log(Price <sub>it</sub> )	0.012* (0.006)	0.010* (0.004)	0.013* (0.003)	0.014* (0.004)
$\mathbb{1}(\text{EITI})$				-0.0002 (0.0001)
Log(Price <sub>it</sub> ): $\mathbb{1}(\text{EITI})$				-0.001* (0.0003)
Cell FEs	299	303	763,831	763,831
Year FEs	17	17	17	17
Sample	$\geq 1$ 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); <sup>†</sup> $p < 0.1$ , \* $p < 0.05$

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 <sub>it</sub> )	12,993,642	0.007	0.325	0.000	18.004
$\mathbb{1}(\text{EITI})$	12,993,642	0.161	0.367	0	1

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.<sup>37</sup>

<sup>37</sup>These results contrast with Sexton (2015), who finds that mining conflicts in Peru decline with commodity prices over the period from 2007-2014. The central government of Peru sends a portion of taxes and license payments back to the provinces that contain mining projects, and Sexton finds that these transfers increase with commodity prices. It is

I cluster the standard errors in the first three models on commodity; using a block bootstrap does not affect the inferences. As was true of the first finding, these results hold up across three other event datasets (see table 7).

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 (in copper mining areas) is roughly half as large as the effect of other commodity prices.<sup>38</sup> Note that all level-difference across these mining areas are absorbed by the cell fixed effects.

### **2.2.1 The Moderating Effects of Transparency**

If informational asymmetries, exacerbated by high prices, provoke protest, then transparency could have a pacifying effect, mitigating 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 indicator 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 countries to "disclose information on tax payments, licenses, contracts, production and other key elements around resource extraction" (EITI 2015). By the initiative's own account, this increased transparency provides governments "enhanced trust and

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possible then that, at the province-level, increased transfers ameliorate conflict, especially in localities located further from mines. This pacifying effect could more than offset increases in protest that occur in the immediate vicinity of mines. As I demonstrate in section 1.3, the effects of mining and prices on protest are very geographically concentrated near mine sites.

<sup>38</sup>This regression uses the same sample as model 2 and simply interacts the price variable with an indicator for whether the cell contains a copper mine.

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 in 2007 and, as of 2014, there were 26 countries globally (16 African countries) considered compliant members of the EITI in good standing. I use information on the EITI's website to construct a country-year panel that includes information about whether a country was a candidate in a given year.

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, this effect is modest and does not suggest that EITI eliminates the positive relationship between commodity prices and protest.<sup>39</sup>

This research design rules out several obvious sources of endogeneity. First, the cell fixed effects absorb any time-invariant variables that might explain differences in social conflict across countries that do and do not become EITI candidates. Second, including country-specific time trends ameliorates concerns that the results reflect differential (linear) trends in the likelihood of protest across countries that do and do not opt into the regime.<sup>40</sup> 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 (Kaufmann, Kraay and Mastruzzi 2010), I do not find a positive correlation between EITI candidacy and other measures of

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<sup>39</sup>The EITI standard requires that reports are "are comprehensible, actively promoted, publicly accessible, and contribute to public debate" (EITI 2015) EITI also includes civil society organizations in their multi-stakeholder groups, in part, to aid in the dissemination of their findings. That said, a common criticism of EITI is that their activities are limited to country capitals, and that the information contained in reports does not achieve widespread circulation. These implementation problems could partially account for these modest results.

<sup>40</sup>The results are robust to including second- or third-order time trends.

governance.<sup>41</sup> Including the control of corruption in the model (both directly and interacted with prices) does not change the coefficient reported in table 3. These points notwithstanding, this analysis is not without limitations. EITI candidacy may, for example, be accompanied by other reforms related to the regulation of extractive industries. As such, these heterogeneous effects could reflect a bundle of policy interventions that improve transparency, but also oversight.

### **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 Kotsadam et al. (2015) suggest that crime (which does not increase 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 soil or water resources that are critical to the livelihoods of host communities. Increased protest activity near mining projects could then be motivated by environmental harms caused by the mine. However, I find no evidence that surface mining techniques, which are widely perceived to pose a greater environmental risk, are more likely to provoke protest than underground mines (see table 16).<sup>42</sup> The increase in the likelihood of protest reported in table 1 is not confined to those projects that pose the greatest environmental risk.

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<sup>41</sup>The WGI includes measures related to voice and accountability, political stability, government effectiveness, regulatory quality, the rule of law, and the control of corruption.

<sup>42</sup>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...”

## 3.2 Migration

Mining projects create jobs in the formal sector, attracting migrants. This in-migration may intensify when commodity prices are high, and individuals are hopeful about the project's ability to deliver employment or development expenditure. Long-time residents may resent attempts by these new arrivals to share in any wealth generated by the mining project and such anger could boil over into protests.<sup>43</sup>

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).<sup>44</sup> 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 mining started.<sup>45</sup> This follows the approach of Kotsadam and Tolonen (2013).

I find that rising commodity prices increase the probability that a respondent has ever moved or moved after the mine started (table 17).<sup>46</sup> However, I find no compelling evidence that the probability of protest in mining areas increases with the proportion of respondents that have ever moved or moved subsequent to mining activity. None of the coefficients in table 18 are significant nor do their magnitudes suggest a large effect.<sup>47</sup> High commodity prices attract migrants, but this influx does not appear to engender social conflict.<sup>48</sup>

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<sup>43</sup>Recent violence (in April 2015) in Durban, South Africa demonstrates the intensity and destructiveness of anti-immigrant sentiment (Onishi 2015).

<sup>44</sup>To merge the DHS surveys to mining projects, I construct circular buffers (with a 25 kilometer radius) around each mining point. If a survey cluster falls within a mine's buffer then it is associated with this mining project. If a cluster falls in the intersection of two buffers, its observations are assigned to both projects.

<sup>45</sup>The use of DHS data in this analysis comes with an important caveat: the individual-level data from DHS with the widest coverage only includes female respondents.

<sup>46</sup>Two notes about the measure of commodity prices used in this analysis: first, if a mine produces multiple minerals, then I use the mean price across those commodities; second, because households can not relocate instantaneously in response to prices, the price measure is lagged one year. As most mines produce one mineral, this first decision is not consequential. If I do not lag prices by one year, then the relationship between prices and in-migration disappears.

<sup>47</sup>This conclusion does not change if I estimate these models using weighted least squares, using the number of respondents as weights.

<sup>48</sup>The models used in this analysis all include fixed effects for each mining project and year dummies. As such, they leverage within-project variation in commodity prices, mobility, and protest.

Why is there no relationship between in-migration and protests in mining areas? First, it may be that anger and violence directed at migrants takes the form of discrimination, vandalism, or assault — targeted harassment rather than public protests. Second, according to data on household assets from the DHS, there does not appear to be a material basis for resentment between individuals that have never moved and those that have. In mining areas, individuals that have moved or moved after mining commenced are not more wealthy: the estimated relationship between these indicators for mobility and an index of households assets is precisely estimated at close to zero. Furthermore, individuals that have moved do not appear to benefit disproportionately when commodity prices rise. In fact, it appears that plausible commodity price increases are not associated with meaningful increases in household assets for either stationary or mobile households: a one standard deviation increase in the logged commodity price increases stationary households' assets by less than 0.01 (or four percent of the average within-unit standard deviation in the asset index). What this analysis reveals is that households' assets are not increasing with commodity prices, pointing again to the possibility that protests result from anger because projects are not delivering economic development at those moments when communities expect projects to be flush with funds.

### **3.3 Inequality**

The onset of mining and rising commodity prices may enrich some households, while delivering relatively little to others. If mining increases economic inequality in host communities, and this inequality, in turn, motivates protest, then this provides an alternative causal story to explain some of the results presented in sections 1 and 2. Following the same logic as the previous section, I first explore whether the onset of mining or increasing commodity prices raise economic inequality in the communities proximate to mining projects. Second, I look for evidence that mining areas with higher levels of inequality are more prone to protest.

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.<sup>49</sup> McKenzie (2005) demonstrates that this measure has both desirable theoretical properties and provides a good proxy for inequality in living standards. Given the available inputs, this measure captures wealth inequality, rather than disparities in households' consumption or incomes.

In short, 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 20 estimates equations 1 and 2, using wealth inequality as the dependent variable. The coefficient estimates are negative and insignificant, providing no indication that mining or high prices increase wealth inequality in mining areas. Moreover, the results in table 21 do not suggest a positive relationship between wealth inequality and protest occurrence.<sup>50</sup>

The relevant disparity may not be between households, but rather between local political elites and their constituents. However, a recent paper by Kotsadam et al. (2015) compiles and geo-codes data on perceptions of corruption from the Afrobarometer. When these authors employ 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 (23, 25).<sup>51</sup> Given that perceptions of corruption do not increase after mining commences, it is unlikely that anger about local corruption motivates the increase in protests reported above.

### **3.4 Conflicts with Small-Scale Miners**

Finally, protests may be organized by artisanal miners, who are displaced by these larger commercial operations. Moreover, these conflicts could intensify when commodity prices are high, and

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<sup>49</sup>In short, the recipe is to (a) take the first component from a principal components analysis of household assets (where all survey waves are pooled), (b) compute the standard deviation of this first component for each mine area-year, and (c) take the ratio of that standard deviation and the standard deviation of the first component over the full sample.

<sup>50</sup>Estimating the models in tables 20 or 21 using weighted least squares yields similar results.

<sup>51</sup>In some specifications, they find evidence that reports of police bribes increase, though perceptions of police corruption do not. Overall, their evidence does not indicate that mining undermines local governance; rather, police appear to take advantage of increased economic activity to extract more bribes (p. 25).

small-scale miners have a strong incentive to trespass and mine (tailings) on commercial sites. However, the results reported above are robust to dropping commodities (namely, gold and gemstones) that are also produced artisanally. Moreover, both this alternative, and the others presented above, cannot explain the moderating effect of transparency.

## Conclusion

Foreign investment in sub-Saharan Africa has increased dramatically over the last three decades. This paper answers two questions raised by this trend: are these new projects met with resistance; 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 in localities hosting new mining projects. To bolster the credibility of my empirical design, I confirm that areas receiving investments do not have differential trends in protest prior to mining. 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 discovery raises the question of why these conflicts occur, given the jobs and expenditure that often accompany such investments.

Second, drawing on qualitative 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 the projects they host, and all companies — rich and poor alike — have an incentive to understate their 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 then marshal two pieces of empirical evidence consistent with this theory. I demonstrate that protests are more likely when world commodity prices are high and, thus, communities hold

inflated expectations about projects' margins. I then show that this relationship between prices and protests is mitigated (though not eliminated) by policies, such as the Extractive Industries Transparency Initiative, that promote transparency in extractive industries 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 rule out 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, or conflicts with artisanal miners explain my results. Furthermore, using two different datasets on armed conflicts in Africa, I also 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 in mining communities are better understood as a consequence of bargaining over profits than instances of predation by insurgents.

This study expands research on the political economy of foreign investment in two respects. First, existing work focuses on the determinants of foreign investment, and not its political or social consequences. Yet, recent reports raise concerns that foreign investors are engaged in "land grabbing" across Africa, establishing mining and agricultural concessions without fairly compensating their hosts (Cotula et al. 2009; Anseeuw et al. 2012). These claims indicate a pressing need for work that helps us understand the impacts — both positive and negative — of these large-scale investment projects. Second, in explaining investment flows, scholars have concentrated on how commitment problems deter investors. They omit the informational problems that, I argue, greet investors once they are on the ground and can lead to social conflict.

While less work has considered the consequences of foreign investment, many scholars have been concerned about the impacts of natural resource extraction. One symptom of the "resource curse" is an increased likelihood of armed conflict. Yet, I do not find that these mining projects are the targets of increased rebel activity; rather, the conflicts that arise are lower-level social conflicts.

This null finding with respect to armed conflict could relate to the scale of these investments: unlike small-scale alluvial mines, large commercial mining projects may be difficult for rebels to seize and productively operate. This is merely a hypothesis and more research is needed about how the scale or method of extraction (or the black market for different commodities) condition the relationship between natural resources and armed conflict.

Finally, an influential literature in political economy, the “varieties of capitalism,” stresses the role that firms play in explaining variation across the welfare states of Western Europe and North and South America. In Africa, far less attention has been devoted to firms’ political roles. Yet, these mining companies often assume an out-sized societal role in the communities in which they operate, building roads, repairing schools, and digging wells. In these places, the politics of development — how societies foster economic growth and distribute its benefits and costs — center on firms’ negotiations with their workers and host communities. This paper focuses on those negotiations and 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 Incites Protest in Africa

Following text to be published online.

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## A. Proofs

### A.1 Proposition 1

**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  $V_R^C$ .

$$\begin{aligned}
 (1 - V_R^F) &= V_R^C e^{-t_F \delta_C} \\
 (1 - V_R^C) &= V_R^F e^{-t_C \delta_F} \\
 1 > V_R^C &= \frac{1 - e^{-t_C \delta_F}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0 \\
 1 > V_R^F &= \frac{1 - e^{-t_F \delta_C}}{1 - e^{-t_F \delta_C} e^{-t_C \delta_F}} > 0
 \end{aligned} \tag{3}$$

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  $\varepsilon$  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  $\underline{t} \rightarrow 0$ ,

$$\lim_{\underline{t} \rightarrow 0} V_R^C = \frac{\delta_F}{\delta_C + \delta_F} \quad (4)$$

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

## A.2 Proposition 2

### A.2.1 Lemmas

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

**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  $\theta$  can not improve their payoff by delaying infinitesimally more or less to mimic a different type  $\tilde{\theta}$ . 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  $u(t(\tilde{\theta}) | \theta)$  be the payoff that type  $\theta$  gets when it mimics the delay strategy of type  $\tilde{\theta}$  and makes the offer that type  $\tilde{\theta}$  makes in equilibrium. This must be the offer that  $\tilde{\theta}$  makes in the complete information game, since we are conjecturing a fully separating equilibrium, stationarity, and assumptions 2 and 3.

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

$$\left. \frac{\partial}{\partial \tilde{\theta}} D(\tilde{\theta} | \theta) \right|_{\tilde{\theta}=\theta} = 0$$

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

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

Solving this differential equation,

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

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

**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  $\theta$  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  $D(\tilde{\theta} | \theta)$  as

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

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

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

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

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

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

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

If  $\theta' \leq \bar{\theta}$ , then a firm with type equal to  $\theta'$  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.  $\square$

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

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

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

We need to consider three cases:

- (i) If  $\theta' < \check{\theta}$ , then a firm of type  $\theta'$  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  $\theta \in (\check{\theta}, \bar{\theta}]$  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.  $\square$

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

### 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  $\theta$ . 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 ( $\theta \geq \hat{\theta}(b^*)$ ) immediately accept.*
- (C) *Firms with projects below that cutoff value ( $\theta < \hat{\theta}(b^*)$ ) 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  $\theta$  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  $\bar{\theta}$  after observing no delay (and places no positive probability on  $\theta > \bar{\theta}$ ), then  $k = \log \bar{\theta}/\delta$  (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  $\hat{\theta}(b)$  be the type that is indifferent between accepting an initial offer of  $b$  and delaying  $t(\hat{\theta}(b))$ .  $\hat{\theta}$  is then defined by the following indifference condition:

$$\begin{aligned}\hat{\theta}(b) - \frac{b}{2} &= \frac{\bar{\theta}}{2} e^{-\delta t(\hat{\theta}(b))} \\ \hat{\theta}(b) &= \bar{\theta} - \sqrt{\bar{\theta}(\bar{\theta} - b)}\end{aligned}$$

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

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



## B. Robustness to Other Event Datasets

### B.1 Mining and Pr(Protest)

**Table 5: Mining Activity and Pr(Protest)**  
*Mining projects increase the probability of protest.*

	<i>Dependent variable:</i>							
	$\mathbb{1}(\text{Protest or Riot})$		$\mathbb{1}(\text{Soc. Conf.})$		$\mathbb{1}(\text{Protest})$		$\mathbb{1}(\text{Protest})$	
	ACLEDE	ACLEDE	SCAD	SCAD	GDELT	GDELT	ICEWS	ICEWS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}(\text{Mine}) (D_{it})$	0.011*	0.011*	0.002 <sup>†</sup>	0.002 <sup>†</sup>	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 $\times$ 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; <sup>†</sup> $p < 0.1$ , \* $p < 0.05$

Columns 1-6: linear probability model regressions (see equation 1). All models include grid-cell and year or country $\times$ 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; outcome data comes from the ACLEDE, SCAD, GDELT, and ICEWS event datasets.

**Table 6: 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
ACLEDE: $\mathbb{1}(\text{Protest or Riot})$	13,758,498	0.00037	0.01915	0	1
SCAD: $\mathbb{1}(\text{Soc. Conf.})$	17,580,303	0.00014	0.01202	0	1
GDELT: $\mathbb{1}(\text{Protest})$	27,516,996	0.00067	0.02587	0	1
ICEWS: $\mathbb{1}(\text{Protest})$	15,287,220	0.00029	0.01704	0	1

## B.2 Prices and Pr(Protest)

**Table 7: Commodity Prices and Pr(Protest)**  
*Increases in commodity prices increase the probability of protest.*

	<i>Dependent variable:</i>							
	$\mathbb{1}(\text{Protest or Riot})$ ACLED		$\mathbb{1}(\text{Soc. Conf.})$ SCAD		$\mathbb{1}(\text{Protest})$ GDELT		$\mathbb{1}(\text{Protest})$ ICEWS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log}(\text{Price}_{it})$	0.0134* (0.0049)	0.0130* (0.0048)	0.0020 (0.0017)	0.0020 (0.0017)	0.0065 <sup>†</sup> (0.0034)	0.0063 <sup>†</sup> (0.0034)	0.0046 <sup>†</sup> (0.0025)	0.0045 <sup>†</sup> (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; <sup>†</sup> $p < 0.1$ , \* $p < 0.05$

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 8: Summary Statistics: Commodity Prices and Pr(Protest)**

Statistic	N	Mean	St. Dev.	Min	Max
Year	26,728,310	1996	10.100	1979	2013
$\text{Log}(\text{Price}_{it})$	26,728,217	0.001	0.134	0.000	20.800
$\mathbb{1}(\text{EITI Candidate})$	26,728,310	0.078	0.268	0	1
ACLED: $\mathbb{1}(\text{Protest or Riot})$	12,982,322	0.0003	0.018	0	1
SCAD: $\mathbb{1}(\text{Soc. Conf.})$	17,564,318	0.0001	0.012	0	1
GDELT: $\mathbb{1}(\text{Protest})$	26,728,310	0.001	0.025	0	1
ICEWS: $\mathbb{1}(\text{Protest})$	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 9:** Transparency and the Relationship between Commodity Prices and Pr(Protest)  
*Transparency regimes mitigate the positive relationship between prices and protest.*

	<i>Dependent variable:</i>			
	1(Protest or Riot) ACLED (1)	1(Soc. Conf.) SCAD (2)	1(Protest) GDELTA (3)	1(Protest) ICEWS (4)
Log(Price <sub>it</sub> )	0.015* (0.004)	0.002 <sup>†</sup> (0.001)	0.005* (0.002)	0.005* (0.002)
1(EITI)	-0.0002 (0.0001)	-0.00003 (0.00004)	-0.001 <sup>†</sup> (0.0003)	0.00001 (0.0001)
Log(Price <sub>it</sub> ) × 1(EITI)	-0.001* (0.0003)	-0.0001 <sup>†</sup> (0.0001)	0.005 (0.005)	-0.0002* (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; <sup>†</sup> $p < 0.1$ , \* $p < 0.05$

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, GDELTA, and ICEWS event datasets.

## C. Sub-group Analysis

### C.1 Owners' Countries of Origin

**Table 10:** 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.*

	<i>Dependent variable:</i>			
	$\mathbb{1}(\text{Protest} \mid \text{Riot})$ ACLED	$\mathbb{1}(\text{Soc. Conf.})$ SCAD	$\mathbb{1}(\text{Protest})$ GDELT	$\mathbb{1}(\text{Protest})$ ICEWS
$\mathbb{1}(\text{Mine})$	0.007* (0.002)	0.001 (0.001)	0.009* (0.003)	0.002 (0.001)
$\mathbb{1}(\text{Mine}) \times \mathbb{1}(\text{CHN})$	-0.016 (0.033)	0.007 (0.016)	0.052 (0.043)	0.011 (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

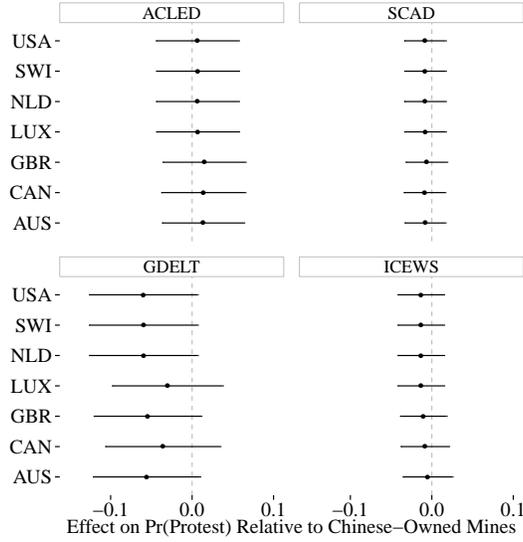
#### Analysis of ACLED Data using PRIO-Grid (55×55 km)

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 14), my estimate is positive but smaller than what Berman et al. (2014) report in their corresponding table 2, model 1 (0.085).<sup>52</sup> 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.

<sup>52</sup>The number of observations is not identical to Berman et al. (2014), which is likely due to my exclusion of unpopulated cells.

**Figure 6:** 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 11:** Mine Starts and Media Coverage  
*The intensity of media coverage does not increase after mining.*

	<i>Dependent variable:</i>			
	Mean(Art./Prot.)	Media Coverage of Protests		Mean(Src./Prot.)
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Mine}) (D_{it})$	-0.771 (0.797)	-0.363 (0.831)	-0.067 (0.055)	-0.012 (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 5, 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.

**Table 12: Mining Activity and Pr(Rebellion)**

	<i>Dependent variable:</i>		
	<i>Rebel Activity (ACLED, 1997-2014)</i>		
	$\mathbb{1}(\text{Battle})$	$\mathbb{1}(\text{Rebel Event})$	$\mathbb{1}(\text{Armed Conf.})$ $\times \mathbb{1}(\text{Rebel Event})$
	(1)	(2)	(3)
$\mathbb{1}(\text{Mine}) (D_{it})$	0.00105 (0.00210)	-0.00177 (0.00166)	-0.00198 (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 $\times$ 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 53 regarding the operationalization of the outcome variables.

**Table 13: Mining Activity and Armed Conflict (PRIO Grid)**

	<i>Dependent variable:</i>		
	$\mathbb{1}(\text{ACLED Event})$	$\mathbb{1}(\text{Protest or Riot})$	$\mathbb{1}(\text{ACLED Event w/Civilians})$
	(1)	(2)	(3)
$\mathbb{1}(\text{Mine}) (D_{it})$	0.011 (0.015)	0.003 (0.009)	0.014 (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 14: Mining Activity and Armed Conflict (PRIO Grid)**

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

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

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 13).<sup>53</sup> Rather, the effects are negative and significant at the 5% 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 15.

**Table 15: Mining Activity and Armed Conflict (UCDP; PRIO Grid)**

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

*Note:* Robust Std. Errors Clustered on cell; † $p < 0.1$ , \* $p < 0.05$

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 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.

<sup>53</sup>“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 2014a, 9). Armed conflict is operationalized as battles, the establishment of a rebel headquarters or base, or violence against civilians.

## C.4 Environmental Harm

**Table 16: Mining Activity and Pr(Protest) by Mining Method**  
*Despite greater environmental risks, surface mines do not generate larger increase in protest.*

	<i>Dependent variable:</i>			
	$\mathbb{1}(\text{Protest or Riot})$ ACLEDE	$\mathbb{1}(\text{Soc. Conf.})$ SCAD	$\mathbb{1}(\text{Protest})$ GDELT	$\mathbb{1}(\text{Protest})$ ICEWS
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Mine})$	0.0110* (0.0052)	0.0029 (0.0020)	0.0074* (0.0035)	0.0019 (0.0018)
$\mathbb{1}(\text{Mine}) \times \mathbb{1}(\text{Surface Mine})$	-0.0034 (0.0060)	-0.0020 (0.0024)	0.0091 (0.0062)	0.0003 (0.0025)
Country×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×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 ACLEDE, SCAD, GDELT, and ICEWS event datasets.

## C.5 In-Migration

**Table 17:** Commodity Prices and In-Migration  
*Mining areas attract migrants during commodity booms.*

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

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

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 18: In-Migration and Protest**  
*Mining areas with more migrants are not more prone to protest.*

	<i>Dependent variable:</i>			
	1(Protest or Riot) ACLED (1)	1(Soc. Conf.) SCAD (2)	1(Protest) GDELTA (3)	1(Protest) ICEWS (4)
Prop. Moved	-0.2534 (0.2816)	0.0137 (0.0828)	0.1339 (0.1850)	0.1335 (0.3371)
Observations	211	235	235	216
Mining Cells	✓	✓	✓	✓

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

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, GDELTA, and ICEWS event datasets.

**Table 19: Mobility and Wealth**

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

	<i>Dependent variable:</i>			
	Asset Index			
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Moved})$	0.0040 (0.0025)		0.0028 (0.0111)	
$\mathbb{1}(\text{Moved Post-Mine})$		0.0022 (0.0033)		-0.0020 (0.0149)
$\text{Log}(\text{Price}_{it})$			0.0578* (0.0272)	0.0548* (0.0261)
$\mathbb{1}(\text{Moved}) \times \text{Log}(\text{Price}_{it})$			-0.0004 (0.0008)	
$\mathbb{1}(\text{Moved Post-Mine}) \times \text{Log}(\text{Price}_{it})$				-0.0002 (0.0011)
$\mathbb{1}(\text{Urban})$	0.1794* (0.0082)	0.1786* (0.0081)	0.2117* (0.0145)	0.2106* (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 20:** Mining, Commodity Prices, and Wealth Inequality  
*Mining does not exacerbate inequality in mining areas.*

	<i>Dependent variable:</i>		
	Wealth Inequality		
	(1)	(2)	(3)
$\mathbb{1}(\text{Mine})$	-0.0227 (0.0277)		
$\text{Log}(\text{Price}_{it})$		0.0799 (0.0617)	
$\text{Log}(\text{Price}_{it})$ (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; †  $p < 0.1$ , \*  $p < 0.05$

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

	<i>Dependent variable:</i>			
	1(Protest or Riot) ACLED (1)	1(Soc. Conf.) SCAD (2)	1(Protest) GDELT (3)	1(Protest) ICEWS (4)
Wealth Inequality	-0.0576 (0.1532)	0.0017 (0.0947)	-0.2234 (0.1751)	0.0154 (0.1200)
Observations	532	455	553	537
Mining Cells	✓	✓	✓	✓

*Note:*

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

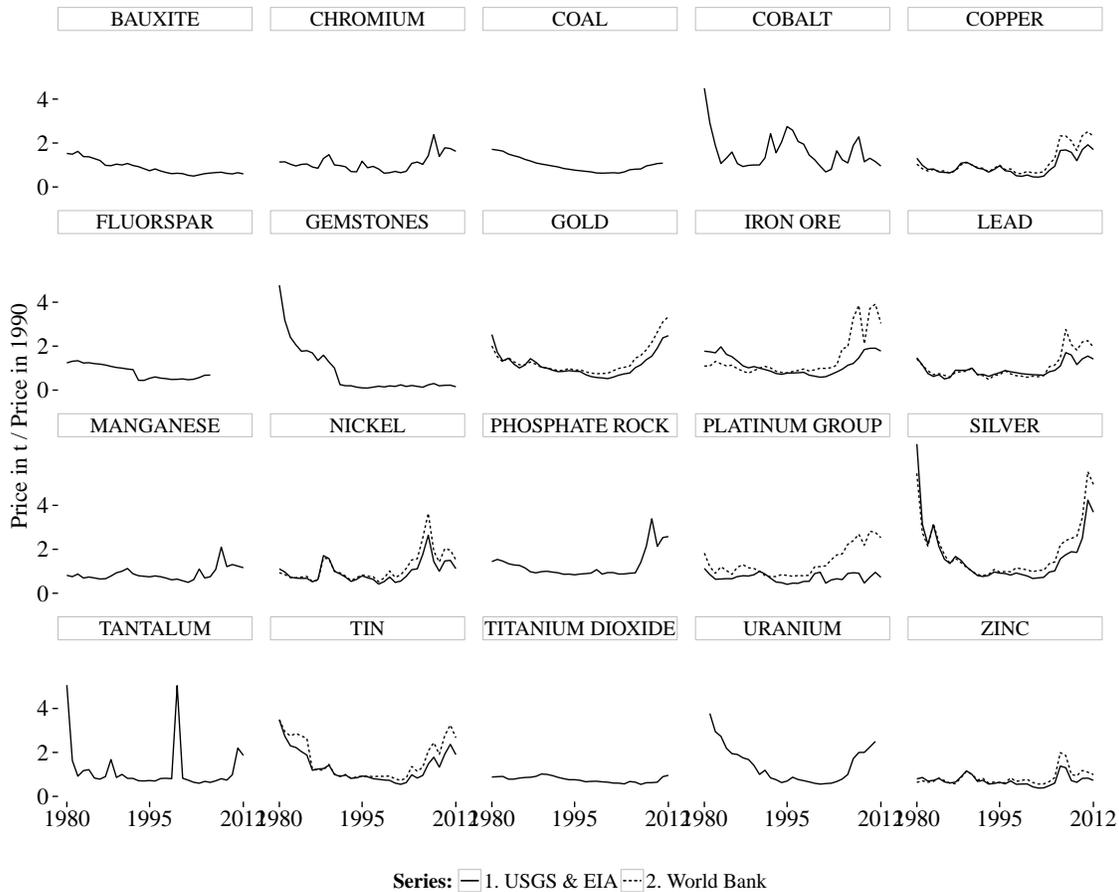
Columns 1-4: linear probability model regressions. Equation 1 is modified to include a measure of wealth inequality developed by McKenzie (2005), rather than mining starts. All models include mine and year fixed effects. The unit of analysis is the the mining area-year. A mining area is defined as a 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.<sup>54</sup> Where prices for the same commodity are available from both WB and USGS, I use WB prices. Figure 7 graphs the price series for the twenty most common minerals (according to the number of cell-years for which the commodity is coded as the modal commodity).

**Figure 7: Commodity Price Series (Base Year = 1990)**



<sup>54</sup>I choose 1998, because the USGS data provides real prices in 1998.

## 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.<sup>55</sup>

**Table 22:** 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, 201	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

<sup>55</sup>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.

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 8 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.

### **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.<sup>56</sup> 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.

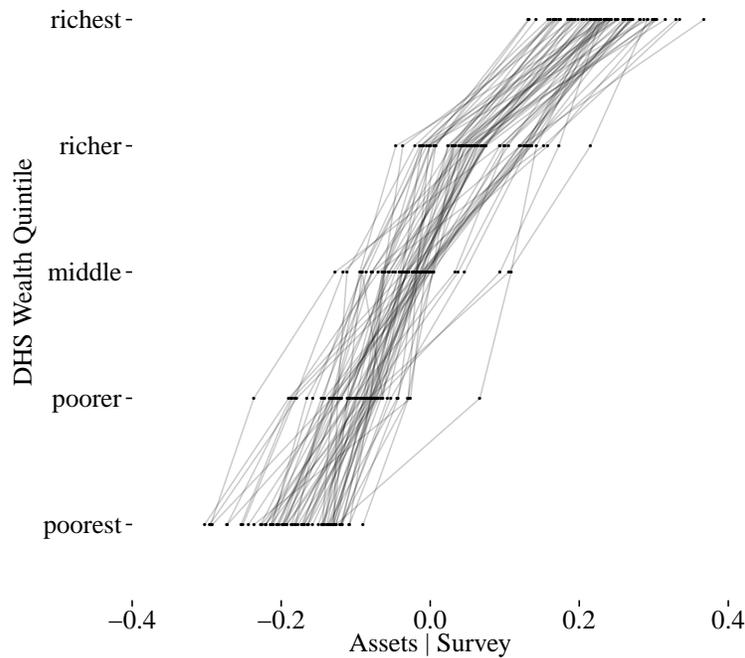
#### **Completeness**

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.

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<sup>56</sup>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.

**Figure 8:** 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.

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.<sup>57</sup> 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 asymmetries should be especially pronounced for operations where little or no information about the project exists.

<sup>57</sup>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.

## 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 23:** 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 2014a). 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 2014b, 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 and Salehyan 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**

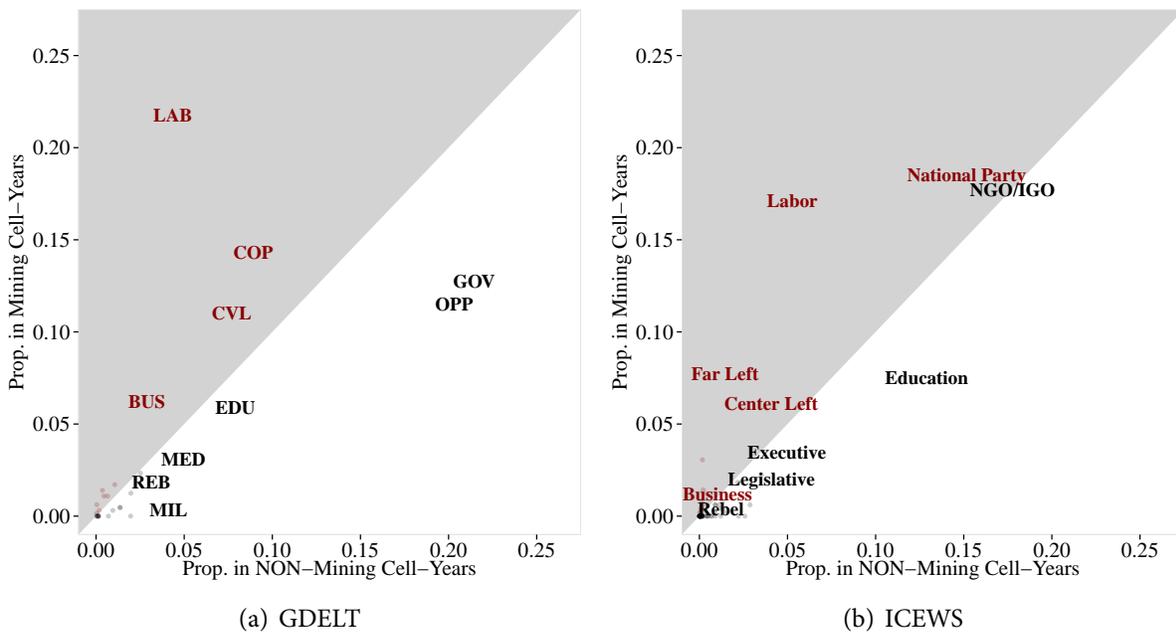
The empirical models estimated in the first two sections of the paper always include cell fixed effects. As a consequence, I leverage *changes* in protest activity in areas near mines after mining commences or as commodity prices change. I do not claim (or require) that all protests in mining areas are 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 9).<sup>58</sup> 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.

**Figure 9:** Proportion of Protests Attributed to Different Actors in Mining vs. Non-Mining Cells



Taken together, this evidence suggests that the events occurring in the same  $5 \times 5$  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.

### 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).

<sup>58</sup>I focus specifically on Actor 1 in GDELT and the Source Sector in ICEWS.

I first compute the absolute difference  $\left( \sum_{t=1990}^{2012} |x_{it} - y_{it}| \right)$  between the binary outcomes (i.e.,  $\mathbb{1}(\text{Protest})$ ) reported by the three datasets (see table 24). 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 24, 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 25).

**Table 24:** Average Absolute Distance in  $\mathbb{1}(\text{Protest})$  across Cells between Different Datasets

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

Years  $\in [1997, 2012]$

**Table 25:** Average Absolute Distance in  $\mathbb{1}(\text{Protest})$  across Cells between Different Datasets  
*Sample Limited to Cells Experiencing  $\geq 1$  Protest.*

	ACLED	SCAD	GDELТ	ICEWS
ACLED	0	0.527	1.815	1.815
SCAD		0	0.665	0.562
GDELТ			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 26). I find that the protest counts in the SCAD, GDELТ, and ICEWS datasets are correlated at above 0.5. As noted above, the GDELТ 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 GDELТ or ICEWS code a protest event, but ACLED does not. The reverse — cases in which ACLED codes a protest, but GDELТ and ICEWS do not — is far less

common.

**Table 26:** 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.