Supporting Information

Concession Stands:
How Mining Investments Incite Protest in Africa

Following text to be published online.

Contents

A. Mining's Effects on Armed Conflict

A.1 ACLED Data

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

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

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

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

Table A.2: Mineral Prices and Pr(Armed Conflict)

	Dependent variable:					
	$\mathbb{1}$(Battle)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Price})_{it}$	0.003	0.004	0.001	0.0004	0.001	0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Mean(y_{it})	0.0043	0.0043	0.0019	0.0019	0.0003	0.0003
	Dependent variable:					
	$\mathbb{1}$(Rebel Event)					
$\log(\text{Price})_{it}$	0.002	0.001	-0.001	$-0.002^{\dagger}$	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Cell FEs	940	940	284	284	1,499,840	1,499,840
Year FEs	17		17		17	
Country-Year FEs		608		532		952
Mean(y_{it})	0.0025	0.0025	0.0019	0.0019	0.0003	0.0003
Mining Cell-Years Only	✓	✓	✓	✓		
Var(# Mines) = 0			✓	✓	✓	✓
Observations	8,776	8,776	4,851	4,851	25,497,303	25,497,303

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

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

A.2 UCDP Data

Table A.3: Mining Activity and Pr(Armed Conflict) in UCDP-GED

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

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

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

B. Lagged Commodity Prices and Protest

Table A.4: Effect of World Mineral Prices (Lagged) on Pr(Protest or Riot)

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

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

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

C. Evidence on Mechanisms

C.1 Reporting Bias

Table A.5: Mining Activity and Media Coverage

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

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

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

C.2 Owners' Characteristics

Table A.6: Mining Activity, Pr(Protest), and Owners' Origins

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

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

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

C.3 Environmental Hazards

Table A.7: Mining Activity, Environmental Hazards, and Pr(Protest or Riot)

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

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

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

Table A.8: World Mineral Prices, Environmental Hazards, and Pr(Protest or Riot)

	Dependent variable:			
	$\mathbb{1}(\text{Protest})_{it}$			
	(1)	(2)	(3)	(4)
log(Price$_{it}$)	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
log(Price$_{it}$)$\times\mathbb{1}$(Surface Mine)$_i$	-0.002			
	(0.005)			
log(Price$_{it}$)$\times$Min(Dist. Protected Area)$_i$		-0.0001		
		(0.0001)		
log(Price$_{it}$)$\times$Avg. Water Stress$_i$			0.002	
			(0.003)	
Env. Risk Exposure$_{ct}$				-0.003
				(0.01)
Cell FEs	621	932	937	939
Country-Year FEs	540	608	608	592
Mean(y_{it})	0.0177	0.0134	0.0134	0.0134
Observations	6,256	8,703	8,748	8,760

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

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

C.4 In-Migration and Displacement

Table A.9: Mining Activity or World Mineral Prices and Migration

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

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

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

Table A.10: Migration in Mining Areas and Pr(Protest or Riot)

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

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

Table A.11: Wealth Differences between Permanent Residents and Migrants

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

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

C.5 Inequality

Table A.12: Mining Activity and Inequality or Wealth

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

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

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

Table A.13: Inequality in Mining Areas and Pr(Protest or Riot)

	Dependent variable:			
	$\mathbb{1}$(Protest or Riot)			
	10km	10km	20km	20km
	(1)	(2)	(3)	(4)
Inequality$_{it}$	-0.03	-0.07	-0.01	-0.01
	(0.09)	(0.08)	(0.04)	(0.03)
Mine FEs	395	395	544	544
Year FEs	17		17	
Country-Year FEs		89		99
Mean(y_{it})	0.11	0.11	0.12	0.12
Observations	836	836	1,696	1,696
Note:	Robust standard errors clustered on mine; $^{\dagger}p < 0.1$, $^{*}p < 0.05$			

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

Table A.14: World Mineral Prices and Inequality or Wealth

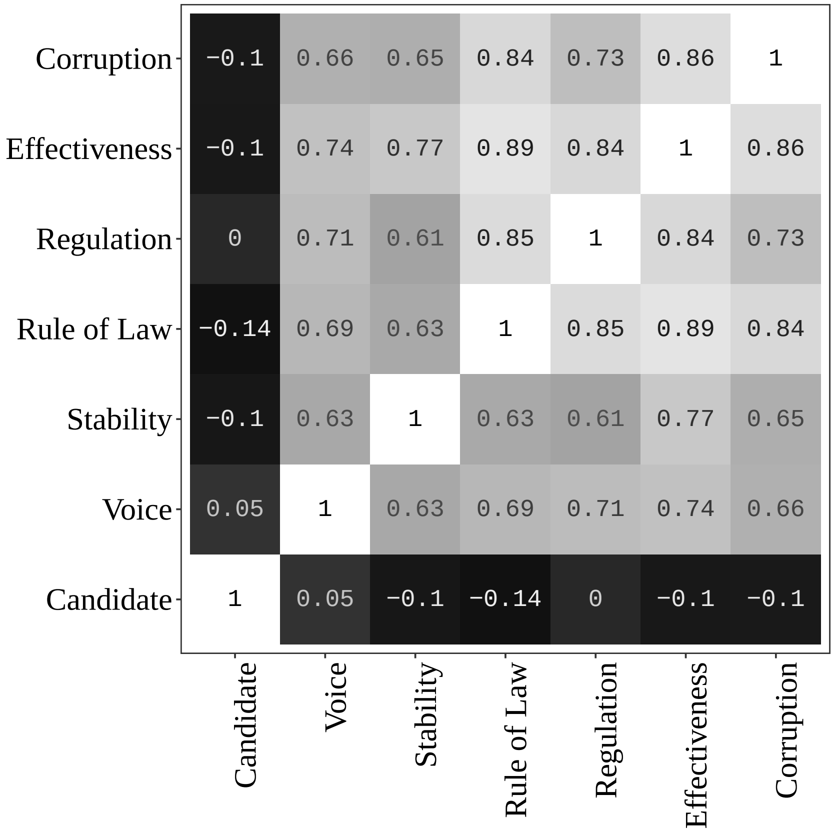
	Dependent variable:							
	Inequality				Avg. HH Assets			
	10km	10km	20km	20km	10km	10km	20km	20km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{Price})_{it}$	-0.05	-0.09	-0.03	-0.03	-0.03	0.03	-0.04	-0.06
	(0.09)	(0.16)	(0.04)	(0.07)	(0.05)	(0.09)	(0.03)	(0.04)
Mine FEs	239	239	339	339	245	245	340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

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

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

C.6 Correlation between EITI and the Worldwide Governance Indicators

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



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

D. Other Event Datasets

Table A.15: Effect of Mining Activity on the Pr(Protest)

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

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

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

Table A.16: Effect of World Mineral Prices on the Pr(Protest)

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

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

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

E. Proofs

E.1 Complete-Information Game

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

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

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

Proof. Stationarity implies that the each responder's value function is the same after each history: $V_R^i(h_t) = V_R^i$ 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.

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

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

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

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

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

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

E.2 One-sided Informational Asymmetry

In this modified game the Firm knows its project's profitability ($\theta \in \mathbb{R}^1_+$), but the Community only knows the range of profitability ($\theta \in [\underline{\theta}, \overline{\theta}]$; $\overline{\theta} > \underline{\theta}$) and holds a prior belief ($F(\cdot)$) about the distribution of projects over this range. In each round, the player making the offer proposes a payout to the Community of x_C with $x_F = \theta - x_C$ being retained by the Firm. The game is otherwise identical to the complete information game of alternating offers described in section E.1.[114]

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

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

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

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

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

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

E.2.1 Lemmas

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

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

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

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

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

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

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

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

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

Solving this differential equation,

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We need to consider three cases:

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

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

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

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

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

E.2.2 Proof of Proposition 2

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

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

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

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

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

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

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

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

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

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

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

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

□

E.3 Extension: Inflated Expectations

The probability of protest in the model with incomplete information is the probability the Firm would rather disrupt production than immediately accept the Community's initial offer (i.e., $\Pr(\theta < \widehat{\theta}(b^*) = F(\widehat{\theta}(b^*)))$. To compute this probability, I assume that project profitability is distributed uniformly between zero and some upper bound $\overline{\theta}$. We can now determine the community's optimal initial offer, $b^* = 3\overline{\theta}/4$. And, given this initial offer, all firms below $\widehat{\theta}(3\overline{\theta}/4) = \overline{\theta}/2$ would rather disrupt production than immediately concede; the probability that a given firm falls in this range is then $F(\overline{\theta}/2) = 1/2$.[115]

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

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

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

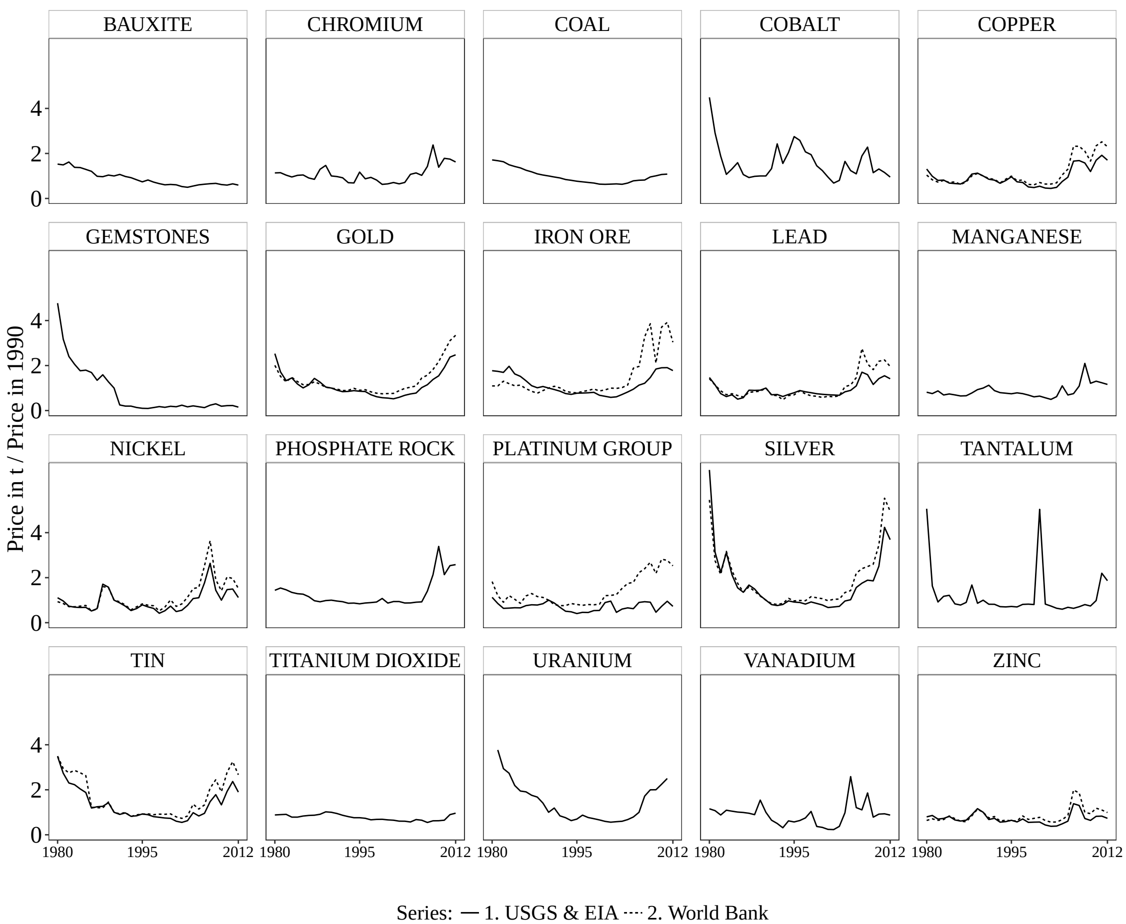
[115] Manipulating the upper bound on firms' profitability ($\overline{\theta}$) does not affect the probability of disruptions, because the community adjusts their offer as the upper bound of profits changes.

F. Data Sources

F.1 Commodity Prices

I employ World Bank (WB) commodity prices, the supply-demand statistics from the US Geological Survey (USGS), and coal and uranium prices from the US Energy Information Administration (EIA). WB prices are based on major commodity markets. The USGS uses a variety of trade journals and open market prices. Finally, the EIA bases its coal prices on open market prices, and its uranium series on the prices paid by civilian operators of US nuclear power reactors. I convert all units to USD per metric ton and deflate prices to real 1998 USD.[116] Where prices for the same commodity are available from both WB and USGS, I use WB prices. Figure A.2 graphs the price series for the twenty most common minerals (according to the number of cell-years for which the commodity is coded as the modal commodity).

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



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

F.2 Demographic and Health Surveys

The Demographic and Health Surveys are nationally representative surveys of between 5,000 and 30,000 households that focus on outcomes related to population, health, and nutrition (http://www.dhsprogram.com/What-We-Do/Survey-Types/DHS.cfm). In many countries, multiple survey waves have been enumerated, allowing for comparisons over time. For this project, I compile the subset of surveys that also include approximate geo-coordinates. These allow researchers to locate over 99% of survey clusters to within 5km. The resulting dataset includes just under 760,000 household observations from 72 surveys.[117]

Table A.17: Included Survey Waves from DHS

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

Migration

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

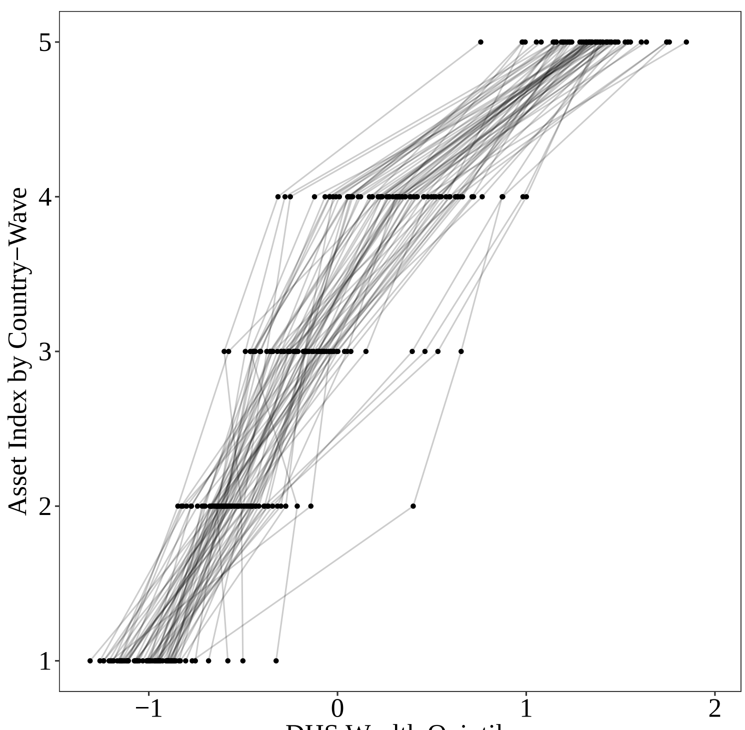
Knowing both the year of the survey wave and how long a household has lived in their current residence, I can also determine whether they moved before or after mining started, which I use in table A.11.

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

Assets and Inequality

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

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



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

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

F.3 Environmental Hazards

World Database of Protected Areas

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

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

Water Stress

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

Environmental Risk Exposure

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

F.4 Governance

The Worldwide Governance Indicators from Kaufmann, Kraay, and Mastruzzi (2010) include six measures:

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

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

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

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

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

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

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

F.5 Mining Projects

This paper draws on three sources of project-level data on global mining activity: SNL Metals and Mining, IntierraRMG, and Mining eTrack.[118] These data are only available to subscribers and primarily serve clients within the mining and financial sectors, though recent research by Knutsen, Kotsadam, Olsen et al. (2016) and Berman, Couttenier, Rohner et al. (2017) draws upon the IntierraRMG data. These providers compete on their completeness and accuracy and rely on press releases, corporate and government reports, and local and international news to compile and update their databases.

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

Completeness

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

Duplicate Mines

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

Table A.18: Number of Mining Projects by Data Source

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

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

Assigning Start and End Dates

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

F.6 Social Conflict

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

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

GDELT errs on the side of inclusion and, thus, contains more false positives than other event databases. However, head-to-head comparisons suggest that the dataset captures important *changes* in protest activity (Ward, Berger, Cutler et al. 2013). Ward, Berger, Cutler 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, Lautenschlager, O'Brien et al. 2015). Like GDELT, ICEWS machine codes events from this corpus of news stories using the Conflict and Mediation Event Observations (CAMEO) system, which includes a top-level category for protest (Schrodt and Yilmaz 2007). The dataset covers all countries over the period from 1995 to 2014. To exclude events with imprecise geo-codes, I limit my sample to events that include the name of a specific city or town.

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

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