The global distribution of critical mining impacts[*]

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Abstract

Critical minerals and metals are essential for the clean energy transition, but their extraction raises concerns over local environmental and socioeconomic impacts. We combine a global registry of 9,836 critical mineral and metal mines with geospatial data and leverage exogenous commodity price variations to causally identify local mining impacts. We find that price booms for critical minerals and metals increase deforestation and economic activity around mines—but only in places with high corruption or where mines are operated by firms from weakly governed countries. The cumulative increase in critical commodity prices between 2000-2022 reduced forest cover by 3.6% and raised economic activity by 6% near mining sites, relative to baseline levels. This suggests that environmental and anti-corruption regulations mitigate deforestation but also limit local economic benefits by constraining firms' responsiveness to price changes. Household survey data show critical mining booms also raise local wealth and off-farm employment, indicating positive welfare spillovers. The results underscore the trade-offs and distributional consequences involved in expanding critical mineral supply for the clean energy transition.

Keywords: Critical minerals and metals, mining, energy transition, governance
JEL Codes: Q32, L72, Q56, O13, O43

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1 Introduction

Efforts to mitigate global climate change have accelerated the build-out of clean energy technologies. Between 2022 and 2023, worldwide solar photovoltaic capacity additions grew by 85%, wind energy capacity additions by 60%, and electric vehicle production by 35% (IEA, 2024a). Renewable energy capacity is forecast to expand a further two to three times by 2030, and battery production is forecast to grow by a factor of five (IEA, 2024b). Clean energy technologies require large quantities of "critical" mineral and metal inputs, including cobalt, copper, graphite, lithium, nickel, and rare earth metals, leading to booming demand for these commodities (World Bank, 2020). Total demand for critical minerals and metals is forecast to grow 68%-92% by 2050 depending on the pace of the energy transition, with demand for lithium projected to grow by up to 945% and graphite by up to 252% (IEA, 2024a).[1] This demand explosion presents both opportunity and risk for the communities and countries where critical mineral deposits are found, as previous mining booms have led to rising incomes and export revenues on one hand, and environmental degradation and social conflict on the other (Luckeneder et al., 2025; Girard et al., 2022; Mamo et al., 2019; von der Goltz and Barnwal, 2019; Berman et al., 2017; Aragon and Rud, 2013).

As critical mineral and metals mining expands to meet the booming demand of the energy transition, what is the emerging impact of extraction, and how is this impact distributed? In this paper, we combine a global registry of 9,836 critical mineral and metal mines from the S&P Global Mining and Metals Database (2023) with high-resolution, longitudinal geospatial data on land use changes, economic activity, air pollution, violent conflict, and socioeconomic development indicators between 2000 and 2022 to measure local socioeconomic and environ-

[1]There is no fixed, universal definition of which minerals and metals are "critical," as the applicability of this term to specific commodities evolves over time with demand and supply risks, production and reserve levels, and stakeholders' position in supply chains (Ramdoo et al., 2023). In this study, we define critical minerals and metals to include alumina, antimony, bauxite (aluminum ore), chromite (chromium ore), chromium, cobalt, copper, graphite, heavy mineral sands, ilmenite (titanium ore), lanthanides, lithium, manganese, molybdendum, nickel, niobium, palladium, platinum, rutile (titanium ore), scandium, tantalum, tin, titanium, tungsten, vanadium, yttrium, zinc, and zircon. This classification is drawn from the International Energy Agency's Final List of Critical Minerals (IEA, 2022) and omits minerals and metals that do not appear as primary commodities for any mine in the S&P Global database. Copper was notably absent from the IEA's 2022 list, as well as lists maintained by the US and EU prior to 2023, but has since been added to these lists in consideration of copper's essential role in electricity infrastructure and its potential for supply chain disruptions (Cossins-Smith, 2023). Non-critical minerals and metals include coal (20% of non-critical mines), diamonds, gold (50.6% of non-critical mines), iron ore (8.2% of non-critical mines), lead, phosphate, potash, silver, and uranium oxide. Throughout this paper, sites where critical minerals are extracted are referred to as "critical mines."

mental outcomes at varying distances around critical mining sites. To identify causal impacts of mining on these outcomes, we estimate fixed effects specifications that leverage exogenous variations in world commodity prices.

Furthermore, building on evidence that mine ownership and governance are important determinants of local mining impacts (Christensen et al., 2023), we test whether effects of commodity price shocks vary along two dimensions of institutional quality. First, we use data on subnational corruption (Crombach and Smits, 2024) to measure local corruption levels around each mine. Second, we combine information on mining companies' headquarters countries with data on country-level governance (World Bank, 2024) to measure home-country institutional constraints on mine operators. Whether local and home-country institutional quality amplify or dampen mine-level responsiveness to price changes is ultimately an empirical question. On one hand, corruption and institutional voids may raise transaction costs, uncertainty, and security risks, limiting mining companies' ability to scale when prices rise. On the other hand, weak institutions may enable firms to avoid permitting and compliance requirements, co-opt local officials, and overcome community opposition—consistent with "greasing-the-wheels" mechanisms of corruption (Dreher and Gassebner, 2013; Kaufmann and Wei, 1999). Likewise, mining companies based in poorly governed countries may face greater expropriation risk or financing constraints, but may also be less constrained by extraterritorial anti-corruption rules and could possess tacit know-how for navigating complex political economies, potentially increasing their effectiveness in high-corruption settings (Rexer, 2024). Our empirical strategy tests which of these forces dominates.

Our data reveal that the number of registered critical mines around the world grew by up to 6.5 times between 2000 and 2022, with the highest growth in mine count observed for graphite, lithium, and rare earth metals.[2] The majority of critical mines are concentrated in Asia-Pacific (32%) and the US and Canada (31%) and operated by companies based in Canada (23%), Australia (15%), China (12%), and the United States (12%). Despite the popular association of critical mining with extreme poverty and conflict, 59% of critical mines operating

[2]While the S&P Global Mining and Metals Database (2023) offers high-quality, reliable information on mine locations, commodities produced, and ownership over time, information on dates of mine opening or production start are less reliable. We use the year of mine registration in the S&P database as a proxy for mine opening. Based on these registration dates, the number of critical mines grew by somewhere between 1.8 and 6.5 times during the study period, with these high and low bounds representing extreme assumptions of whether all or none of the mines included in a major data acquisition by S&P Global in 2013 were present prior to 2000. Growth in critical mines is notably higher than growth in non-critical mines (1.6 to 5.2 times) over the same period.

in 2022 were located in high-income countries, compared to just 7% in low-income countries. Approximately 94% of critical mines did not experience any violent conflict within 20km of their location between 2000 and 2022.[3] Using Demographic and Health Survey data (which cover over 90 low and middle-income countries), areas around critical mines exhibit slightly lower than average household wealth and sanitation access, but higher than average levels of education, literacy, and birth weight and equivalent levels of infant mortality. Thus, looking across socioeconomic indicators, critical mining areas are not disproportionately disadvantaged, even within this developing country sample.

Regression results indicate that, on average, a 10% increase in world critical mineral prices reduces forest cover by 0.3p.p. and increases economic activity by 0.9% around critical mines. Applying these estimates to baseline levels of forest cover and economic activity reveals that the more-than doubling of critical minerals prices between 2000-2022 cumulatively accounted for a 3.6% reduction in forest cover and 6% increase in economic activity in areas near critical mines. This environment-growth tradeoff is strongest in places with severe local corruption, where a 10% increase in mineral prices reduces forest cover by 2p.p. and increases GDP by 3.8% around critical mines. A similar, though weaker, pattern holds for mines operated by companies based in countries with weak governance. Mapping the global distribution of deforestation and economic effects from the critical mining boom highlights that while critical mines are found in every region of the world and at all income levels, the most meaningful environmental and economic impacts are concentrated in emerging countries in Asia, Latin America, and sub-Saharan Africa.

We also find a positive correlation between local corruption around mining sites and weak governance in multinational mining companies' headquarters locations. This indicates positive-assortative matching between mines and operators, through which weakly governed companies specialize in mining in challenging institutional contexts. There are no measurable effects of price shocks on forest cover or economic activity for mines in low-corruption places or around mines operated by companies based in countries with good governance. There are also no measurable effects of commodity price shocks on levels of violent conflict or air

[3]Some critical mining does occur in conflict hotspots. A tantalum mine in Vichada, Colombia experienced 12 conflict events within a 20km radius over this period, a graphite mine in Kitgum, Uganda experienced 14 conflicts, a lithium mine in Tanganyika, DRC experienced 21 conflicts, a copper mine in Davao de Oro, Philippines experienced 16 conflicts, and a cobalt mine in Haut-Katanga, DRC experienced 5 conflicts.

pollution near critical mines.

Finally, we use household-level data from the Demographic and Health Surveys (DHS) to assess the degree to which economic gains from mining booms translate into broader welfare gains for mining communities. We find that night light intensity around mines is significantly correlated with indicators of well-being such as household wealth, literacy, child mortality, and sanitation. Furthermore, regression estimates show that a 10% critical commodity price increase is associated with a 1–1.6% rise in local household wealth and 0.3–1.6% increase in non-agricultural employment. These findings indicate that mining booms can generate positive development spillovers—including structural transformation in the labor market—at least in the short-term.

1.1 Related Literature and Contributions

Previous work has documented associations between mining and social conflict (Blair et al., 2021; Berman et al., 2017), corruption (Asher and Novosad, 2023), deforestation (Ladewig et al., 2024; Goldblatt et al., 2023; Girard et al., 2022; Ranjan, 2019), air pollution—particularly for coal mining (Chu et al., 2023; Hendryx et al., 2020; Huertas et al., 2012)—and chemical pollution—particularly mercury exposure from artisanal gold mining (Soe et al., 2022). At the same time, resource booms are associated with increased economic activity, wages, and job opportunities in mining areas (Aragon and Rud, 2013; Allcott and Keniston, 2018). von der Goltz and Barnwal (2019) document higher incidence of health conditions linked to heavy metal exposure, but also increased household wealth around mining sites across 44 developing countries. Christensen et al. (2023) show that mine ownership and governance play a key role in determining whether mines impose local harms or benefits.

This body of evidence suggests there is a tradeoff between negative environmental and social externalities of mining on the one hand and economic growth on the other. Still, existing studies have tended to analyze specific commodities or country contexts, and rarely consider critical minerals. For instance, Peñaloza-Pacheco et al. (2023) study local impacts of lithium mining in Chile and document declines in groundwater levels, forest lands, and economic activity—offering a specific case where negative local economic and environmental impacts coincide. Ash (2024) conducts a qualitative case study of nickel exploration in the Solomon Islands and highlights risks to indigenous peoples. Other studies conduct engineering-based lifecycle assessments (Zapp et al., 2022; Kaunda, 2020; Arshi et al., 2018), analyze critical minerals at the country-level (Shi et al., 2023; Islam et al., 2022) or firm-level (Castillo et al., 2024), or describe supply chain issues (Berthet et al., 2024; Zhao et al., 2023; Sohag et al., 2023; McLellan et al., 2016). Carr-Wilson et al. (2024) conduct a systematic review of literature on critical mining and identify large gaps in coverage of most critical minerals and world regions. Likewise, Agusdinata et al. (2018) review the literature on lithium mining and highlight a lack of evidence on local socio-environmental impacts.

The existing *global* evidence on critical mining is primarily descriptive. Owen et al. (2023) assess the overlap between critical mining locations and lands occupied by indigenous, traditional, and peasant peoples and conclude that more than half of the critical mining resource base is located on or near these areas. Lèbre et al. (2020) intersect critical mining sites with measures of socioeconomic and environmental risk, finding that 84% of platinum mines and 70% of cobalt mines lie in areas defined as high-risk by their methodology. Our primary contribution is to provide the first causal empirical evidence on local critical mining impacts on environmental and socioeconomic development outcomes around nearly all critical mining sites in the world. In doing so, our results provide policymakers with clear guidance about the likely effects of the continuing clean energy transition on mining communities.

Local impacts of critical minerals and metals are of particular concern due to their association with conflict and worker exploitation in weak governance contexts. For instance, cobalt mining in the Democratic Republic of the Congo (DRC) provides most of the world's supply for this critical input into batteries and electronics, but the Congolese cobalt sector has been associated with armed militia conflicts, dangerous working conditions, and environmental damage (Sovacool, 2019). At the same time, policies designed to block sourcing of conflict minerals from the DRC have had unintended consequences, prompting militia groups to turn from mining to looting of civilians (Parker and Vadheim, 2017) and increasing infant mortality by depriving communities of a valuable income source (Parker et al., 2016). Careful consideration of how governance shapes harms and benefits of critical mining is therefore essential to maximize positive local impacts and minimize local damages while ensuring reliable access to material inputs for the clean energy transition. We contribute by mapping the global distribution of mining impacts and quantifying how institutional factors shift the magnitude and incidence of those impacts across places and firms.

2 Data

We construct a mine-level annual panel dataset ranging from 2000 to 2022 based on a global registry of 9,836 critical mines (S&P Global Mining and Metals Database, 2023), which includes information on each mine's production, location, and ownership.[4] To measure local mining impacts, we intersect mine locations with geospatial data on 300x300m land use classes (Copernicus Land Monitoring Service, 2024), 1x1km economic activity derived from night-time light intensity (Chen et al., 2022), socioeconomic indicators based on geo-located Demographic and Health Surveys (Demographic and Health Surveys Program, 2024), 1x1km population counts (NASA, 2023), violent conflict incidents (Uppsala Conflict Data Program, 2023), and 1x1km particulate matter (PM2.5) air pollution (Shen et al., 2024).[5] To explore heterogeneity in mining impacts based on governance, we further merge mine locations with subnational (ADM1-level, i.e. state or province) measures of corruption intensity (Crombach and Smits, 2024) and match mining companies' headquarters locations with country-level indicators of governance quality (World Bank, 2024). We draw annual data on critical mineral and metal commodity prices from the International Monetary Fund (2024) and USGS (2024). More detailed descriptions of data sources are provided in Appendix A.1.

3 Descriptive Evidence

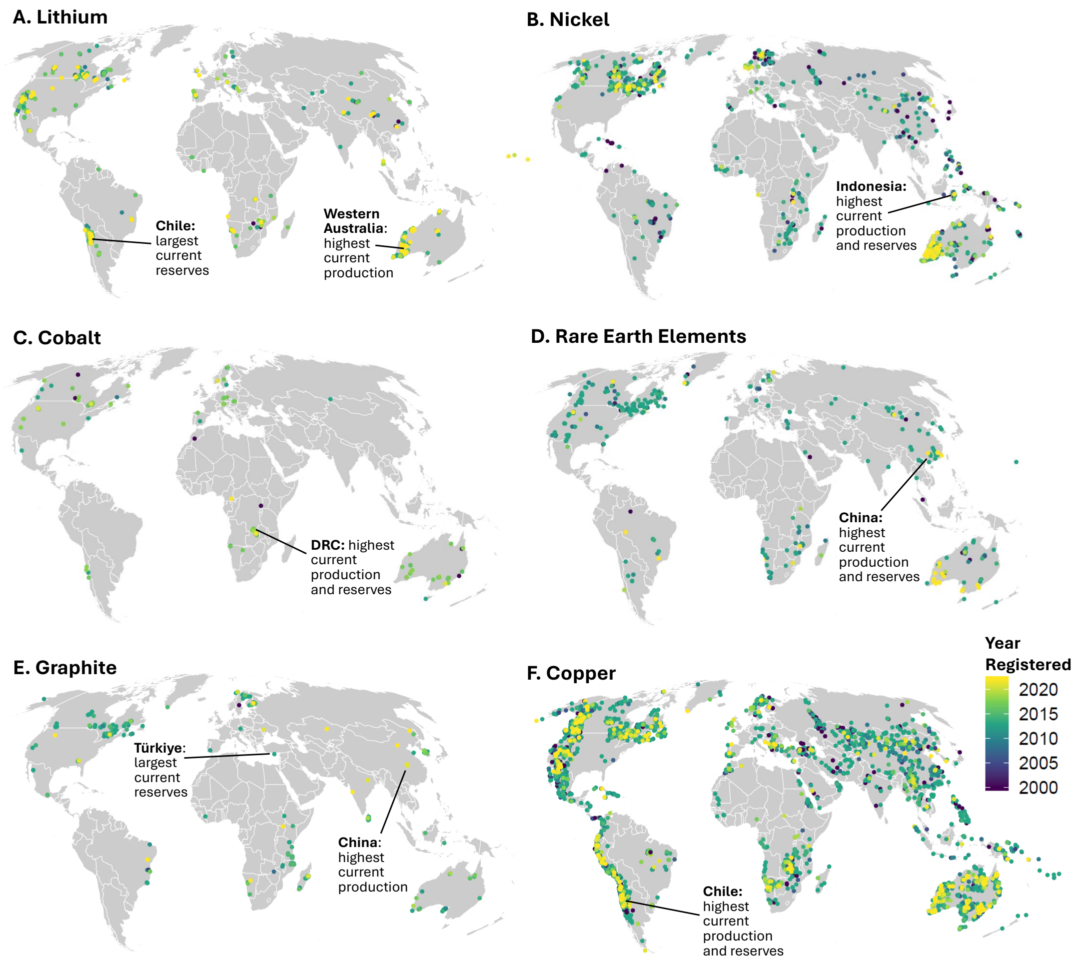
Critical mines can be found in countries across all regions and span the global income distribution. Figure 1 maps the locations of critical mines for commodities of particular global importance: lithium, nickel, cobalt, rare earth metals (lanthanides, scandium, and yttrium), graphite, and copper. A map of all critical mine locations in the database is reported in Appendix Figure A1. Socioeconomic and environmental conditions in the immediate vicinity of

[4]Informal mines are missing from this database. Rates of informality vary across commodity and location, with high-income countries having high rates of formalization and thus fewer missing mines, while low-income countries have lower rates of formalization and thus more missing data. Informality is particularly high in the artisanal and small-scale mining (ASM) sector. For cobalt mining in the DRC, the ASM sector accounts for 15-35% of production, while around 26% of global tantalum production comes from the ASM sector. Approximately 70-80% of ASM mining is estimated to be informal (IGF, 2022). Since large-scale commercial mines can take years to come online (even more so in settings with rigorous environmental permitting and regulatory requirements), ASM provides a margin of rapid supply response to price changes, with minimal environmental or social oversight. Since commercial mines are typically much larger than ASM mines, the S&P Global database likely captures the vast majority of global critical mineral and metal output.

[5]Population data are available for 2000, 2005, 2010 and 2015 and interpolated between these years.

critical mines and other mines are summarized in Appendix Table A1.

Figure 1: Critical mine locations (selected commodities)



Note: Mine locations are drawn from the S&P Global Mining and Metals Database (2023). Year registered identifies the first year a mine appears in the S&P Global registry. Selected critical commodities are reported for brevity. Rare earth elements include lanthanides, scandium, and yttrium, which are the rare earth elements available in the S&P Global database. A map of all 10,244 critical mineral and metal mines registered in the database is reported in Appendix Figure A1. Information on countries with the largest reserves and current production is drawn from the Wilson Center's report on Geographic Concentration of Critical Minerals Reserves and Processing (Wilson Center, 2022) and USGS Mineral Commodity Summaries (United States Geological Survey, 2024).

To assess patterns in the growth of critical mines since 2000, Figure 2 reports the number of mines in 2000 and 2022, disaggregated by region of mine location, country of mine ownership, and ownership structure (Figure 2A, 2B, and 2C, respectively).[6] From Figure 2A, it is apparent

[6]Because the exact date of mine opening is not consistently available in the S&P Global database, we rely on the year a mine first appeared in the database as a proxy. Mine registrations over time are plotted in Appendix Figure

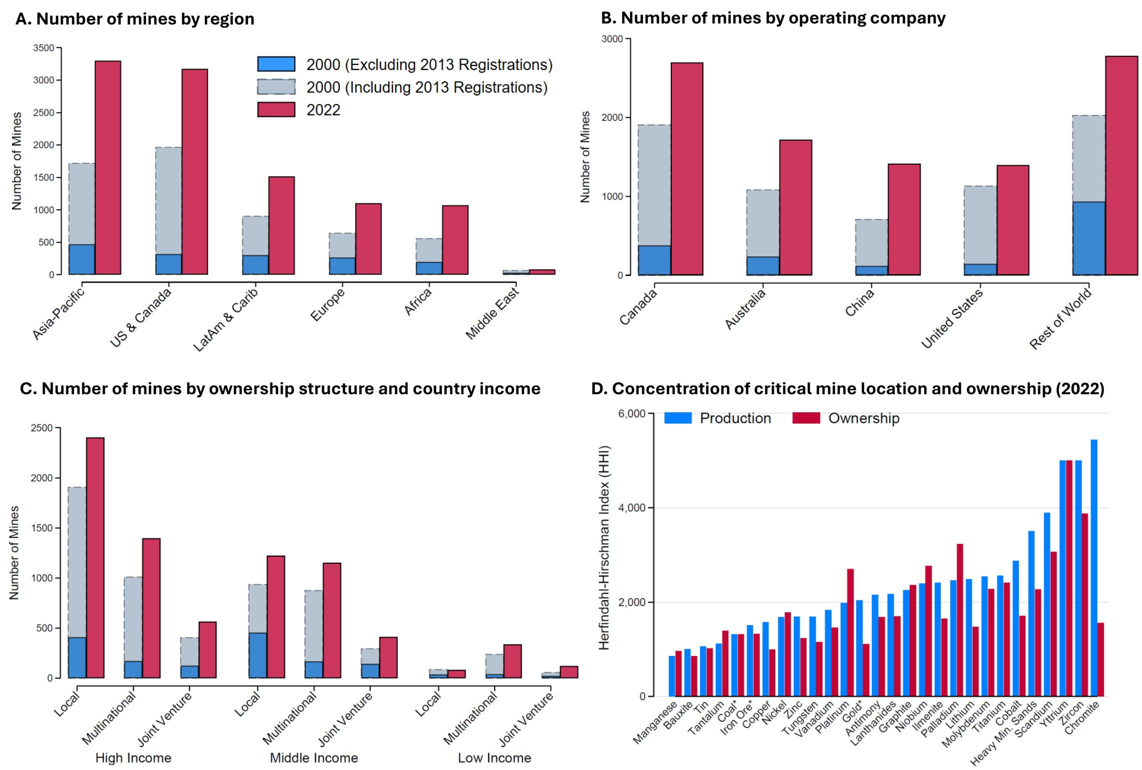
that there has been substantial growth in development of critical mines between 2000 and 2022. While all world regions experienced significant growth, the number of critical mines is highest in the Asia-Pacific (32.2% of all critical mines in 2022) and the US and Canada (31%). Latin America and the Caribbean hosts 14.8%, Europe hosts 10.7%, Africa hosts 10.5%, and the Middle East hosts 0.8%. The Asia-Pacific saw its number of critical mines grow between 2 and 7-fold between 2000-2022, while the US and Canada saw 1.6 to 10-fold growth during this period, with these ranges reflecting uncertainty in the precise year of mine opening in the S&P Global database. As shown in Figure 2B, ownership of critical mines is highly concentrated among companies based in a handful of countries. Canada-based companies held a dominant ownership stake in 22.9% of all critical mines in 2022. Australian companies held dominant stakes in 14.5% of critical mines, Chinese companies held dominant stakes in 11.9%, and US companies held dominant stakes in 11.8%.

Figure 2C disaggregates the number of critical mines in 2000 and 2022 by the income-level of countries where mines are located (high, middle, and low-income) and ownership structure (local ownership, foreign ownership, and joint-ventures – where mines are jointly owned and operated by local and multinational partners). High-income countries have an average 55% local ownership share, meaning over half of all mines are operated by a company headquartered in the same country as the mine. In contrast, multinational ownership of mines predominates in middle-income countries (43.9% local ownership) and low-income countries (15.2% local ownership). This discrepancy highlights the challenges low and middle-income countries face in seeking to impose local content requirements to develop their own mining sectors while maintaining access to the expertise and technology offered by foreign multinationals. Despite some apparent advantages of joint ventures (i.e., combining multinationals' technology and expertise with domestic firms' local knowledge and connections), joint critical mining ventures are relatively rare everywhere. Overall, 58.5% of critical mines operating in 2022 were located in high-income countries, 34.9% in middle-income countries, and 7.0%

A2, indicating that growth in the number of registered mines was relatively consistent for all years between 2000-2022 (suggesting that registrations reflect real mine openings) with the exception of 2013, when a large number of mines were registered. This jump likely reflects a large-scale data acquisition by S&P Global around this time, and mines registered in 2013 may have been present prior to 2000. At one extreme, all mines added to the registry in 2013 were present prior to 2000, while on the other extreme, all of these additions opened between 2000-2013. Overlaid blue and gray bars in Figure 2 thus bound the likely number of critical mines present in 2000. Our empirical strategy leveraging commodity price fluctuations does not rely on the exact year of mine opening, avoiding measurement error from this uncertainty.

in low-income countries. This distribution contrasts with the common perception of critical mines predominating in areas with extreme poverty and conflict.

Figure 2: Characteristics of critical mine growth between 2000 and 2022



Note: A-C show number of mines registered in the S&P Global Mining and Metals Database (2023). Blue bars represent the number of mines present in 2000, while gray bars represent this number plus all mines registered in the database in 2013, when S&P likely had a major data acquisition (see Appendix Figure A2). The difference between blue and gray bars represents bounds set by two extreme assumptions: (i) that all mines acquired by S&P in 2013 were not present in 2000, versus (ii) that all mines acquired in 2013 were present in 2000. The true number of critical mines in 2000 likely falls in the middle of this range. High, middle, and low-income country definitions follow the World Bank classification. Mines are classified as local or multinational based on the headquarters location of the largest operating company. Joint ventures indicate mines that are jointly owned by both local and multinational firms. Concentration levels for each critical commodity are calculated using the Herfindahl-Hirschman Index (HHI), which is calculated by squaring the percentage market share of each country and summing the squared values. HHIs can range from near 0 in a perfectly competitive market with many small producers, to 10,000 in the case of a complete monopoly with only one producer. HHIs are reported for both production (measuring spatial concentration of mines by country) and asset ownership (measuring concentration of mine ownership by operating companies' headquarters country). HHI values reflect data available in S&P Global and may not capture all mines in the world, including any mines registered after 2022. Non-critical commodities (included for comparison) are denoted with an asterisk.

Importer countries' focus on onshoring and diversification of critical supply chains has been motivated by high levels of concentration in critical mineral and metal extraction and processing (Fleck et al., 2024). In Figure 2D, the degree of market concentration for each critical commodity is measured with Herfindahl-Hirschman Indexes (HHIs) at the country-level, based on (i) the country where mines are located, and (ii) the country where operating companies are based.[7] Selected non-critical materials (iron ore, coal, and gold) are also plotted for comparison. Most critical minerals and metals exhibit high levels of market concentration when measured by both production location and ownership, though some, such as bauxite, manganese, copper, and tin, have competitive market structures.

Finally, Figure A3 plots distributions of socioeconomic development indicators within 20km of critical mines and other mines relative to distributions for the full sample of Demographic and Health Surveys (averaged across all survey waves between 2000-2021). Household wealth around critical mines is slightly lower than wealth levels for the full DHS sample, with areas around critical mines exhibiting a mean wealth index of 2.52 relative to 2.74 for the full sample (t-test $p = 0.00$). Despite slightly lower wealth, education and literacy levels are higher around critical mines, at 7.31 years relative to 6.19 years for the full DHS sample (t-test $p = 0.00$) and 62% literacy relative to 52% literacy (t-test $p = 0.00$). Child mortality rates around critical mines are in line with the full DHS sample, with on average 19% of households reporting a child death (t-test $p = 0.80$), while birth weights are higher. Finally, in line with slightly lower wealth levels, households near critical mines have slightly lower access to improved sanitation, at 48% relative to 55% in the full sample (t-test $p = 0.00$).

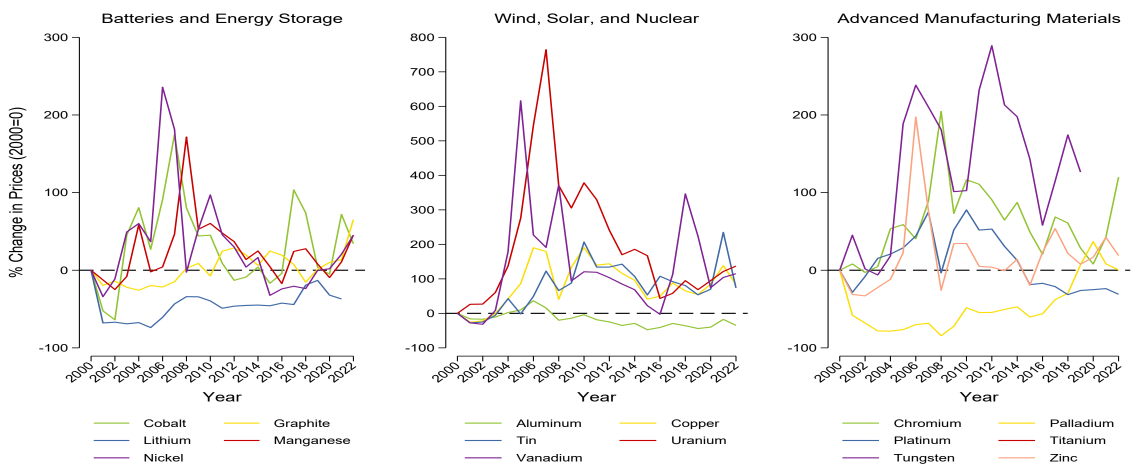
4 Empirical Strategy

Our empirical strategy leverages variations in global mineral and metal prices to identify local effects of price shocks around mines. In line with rising demand, critical mineral and metal prices have generally experienced substantial growth between 2000 and 2022, with some minerals or metals exhibiting 200-750% real price increases. However, this growth has also been accompanied by substantial volatility—in some cases, commodities have experienced 80% price crashes relative to year 2000 values. Commodity price series are plotted in

[7] The HHI is computed by squaring the percentage market share of each country and summing those squared values. Resulting HHI values range from near zero in commodities where many countries participate in the mining process, to 10,000 in the extreme case of just one country hosting or owning all the mines of a particular commodity. Typically, HHI values above 2000 are considered indicative of highly concentrated markets.

Figure 3. In general, prices for battery inputs rose sharply between 2002 and 2012 and again from 2020 to 2022. Prices for renewable energy inputs have increased by approximately 100% in real terms since 2000, with the exception of aluminum. Lithium, a key input into electric vehicle batteries, has seen a price collapse as increases in supply have outstripped demand, including large quantities from Chile and Argentina.

Figure 3: Price indices of key critical minerals over time, by usage type



Note: Nominal commodity prices are indexed to base year 2000 = 100 and deflated using the World Bank's world GDP deflator, thus reflecting percentage changes in real prices since 2000. Key commodities are organized by their typical sector of usage. Price data are drawn from International Monetary Fund (2024) and USGS (2024).

Such fluctuations in global commodity prices are exogenous to local characteristics, trends, and mining decisions because each individual mine is a price-taker globally. Positive price shocks increase mining profits (Knop and Vespignani, 2014), generating more local economic surplus and incentivizing greater production (Stuermer, 2022). We leverage these characteristics of commodity prices to identify the impact the current critical mining boom on local mining communities. This identification strategy follows an extensive literature on mining impacts (Cust and Poelhekke, 2015; Blair et al., 2021). For mine i producing commodity m located in country c and observed at time t, we estimate:

$$y_{imct} = \alpha + \beta \log(p_{m,t-1}) + \delta_m + \gamma_{ct} + \mathbf{X}'_{imct}\mu + \epsilon_{imct} \tag{1}$$

Where y_{imct} is the outcome of interest, $p_{m,t-1}$ is the one-year lag of the commodity price for

m, δ_m is a commodity fixed effect, and γ_{ct} is a country-by-year effect. Controls in $\mathbf{X}_{imct}$ include the mine latitude, the mine's year of opening (proxied by registration year), and several mine ownership characteristics observed in the initial year (multinational ownership, size of the operating firm, the HHI (concentration) of ownership shares, and the log GDP per capita of the country where the controlling operator is headquartered). These characteristics are interacted with year dummies to allow for differential trends in the outcome based on initial mine characteristics. Standard errors are clustered at the mine level to allow for serial correlation within panel units. Throughout, the analysis maintains the sample restriction that the mining site is "registered," defined as having submitted ownership data to the S&P Global Mining and Metals Database (2023).

y_{imct} captures two classes of outcomes—environmental and socioeconomic. To investigate environmental effects, forest cover is measured as the share of pixels within five kilometers of the mine that are classified as tree cover by the Copernicus land cover classification algorithm. An additional sample restriction for the forest cover regressions requires that the mine had greater than 20% forest cover in its initial year, and that it is located in the tropical rainforest belt of countries.[8] Results are robust to loosening these restrictions. The second environmental outcome is the log of the ambient air concentration of PM2.5 within 25 kilometers of the mine location, measured in $\mu g/m^3$. A larger radius is used for PM2.5 than for deforestation as air pollution is likely to travel from its source, whereas deforestation effects should be concentrated around mining infrastructure (Girard et al., 2022). The second set of outcomes is socioeconomic. Local GDP is measured as the log of the total sum of economic activity (GDP), as predicted by satellite night lights, within 25 kilometers of the mine location. Population is measured the same way. Resource-related conflict is defined as an indicator variable for whether the mine has experienced any conflict within 25 kilometers in a given mine-year. Note, again, the relatively large radius of 25 kilometers for these socioeconomic outcomes. Effects should be concentrated not only in the direct location of the mine, but also in nearby population centers. Results are robust to variations in distance radii.

[8]These are: Angola, Argentina, Australia, Bolivia, Brazil, Burundi, Cambodia, Cameroon, Colombia, Cote d'Ivoire, DRC, Dominican Republic, Ecuador, Equatorial Guinea, Fiji, Gabon, Ghana, Guatemala, Guinea, Guyana, Honduras, India, Indonesia, Jamaica, Laos, Madagascar, Malaysia, Mexico, Mozambique, Myanmar, Nepal, Nicaragua, Nigeria, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Republic of Congo, Sierra Leone, Solomon Islands, Sri Lanka, Suriname, Thailand, Togo, Uganda, Vanuatu, Venezuela, Vietnam, Zambia (Food and Agriculture Organization of the United Nations, 2003).

A key consideration of the analysis is whether the impacts of price shocks vary by local governance conditions. To test for these heterogeneous effects, the original regression in (1) is augmented with an interaction term as follows:

$$y_{imct} = \alpha + \beta_1 \log(p_{m,t-1}) \times Z_{icmt} + \beta_2 \log(p_{m,t-1}) + \beta_3 Z_{icmt} + \delta_m + \gamma_{ct} + \mathbf{X}'_{imct}\mu + \epsilon_{imct} \quad (2)$$

Where Z_{icmt} is the interaction variable. The analysis considers two sources of heterogeneity. First, the subnational corruption index (SCI) measures local governance conditions under which the mine's owners operate. Second, the quality of governance that the firms operating the asset are exposed to—and possibly constrained by—is captured with the World Bank Worldwide Governance Indicators (WGI) score of the largest operator's home country, averaged across all sub-indicators.

The first identifying assumption in the analysis is that price shocks are exogenous to the decisions made at the mine-level. This assumption is plausible given that no individual mine is likely to be a large enough player in the global market to manipulate prices directly. While this is a reasonable assumption, it is also true that countries may have large market shares in specific commodities, and governments may be able to influence production decisions across mines in that commodity (for example, if a large share of production is nationalized). Country-year fixed effects help to rule out this source of endogeneity by holding time-varying country-level natural resource policies fixed. The second identifying assumption is that of no simultaneous shocks. If other macroeconomic trends are correlated with price shocks, this might confound the estimates. Again, the fixed effects help to satisfy identification assumptions. The inclusion of country-year trends—restricting comparisons across mines to within a given country-year—helps to control for the country-specific effects of broad macroeconomic shocks. Commodity fixed effects absorb time-invariant differences in production characteristics and local impacts by commodity. Finally, baseline mine characteristics interacted with time trends reduce the scope for omitted variable bias at the mine level.

5 Results

Regression analyses in Table 1 reveal substantial negative environmental externalities of critical mining. The regression estimates in column (1) show a clear negative relationship after controlling for fixed effects and interacted mine covariates: as prices rise, forest cover falls substantially. A 10% increase in critical mineral prices reduces forest cover by 0.3 p.p. Appendix Figure A4A visualizes the linear fit of the relationship between mineral prices and forest cover around critical mines using binned scatter plots. For critical minerals, the cumulative 102% increase in average commodity prices from 2000-2022 shown in Figure 3 accounts for a 3.6% loss in baseline pre-mining forest cover in tropical areas around critical mines over this period.[9] The opposite trend is observed for air pollution in column (2), where critical minerals prices are not significantly associated with PM2.5 emissions.

Table 1: Impact of price shocks on local environmental and socioeconomic outcomes

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	-3.261**	-0.001	0.086***	0.260**	-0.002
	(1.640)	(0.008)	(0.024)	(0.110)	(0.002)
Observations	15471	88441	69829	16506	89159
R-squared	0.229	0.843	0.587	0.646	0.283
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Footnote 8) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Footnote 1. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Despite the negative impacts of mining on forest cover, the socioeconomic effects of critical

[9] Appendix Figure A5 shows estimates of forest loss by commodity. The largest effects of prices on forest cover all come from critical minerals – zircon, tin, cobalt, vanadium, and aluminum – though commodity-specific estimates are generally imprecise due to limited variation.

mineral booms are unambiguously positive on average. Column (3) shows the relationship between commodity prices and local economic activity. A positive 10% price shock increases local night lights-predicted GDP within 25 kilometers of a critical mine by 0.9%, as shown in Appendix Figure A4c. For critical minerals, the cumulative increase in average commodity prices from 2000-2022 shown in Figure 3 accounts for a 6% increase in overall economic activity around critical mines over this period. This increase in output is accompanied by substantial population growth, in column (4). The same 10% increase in critical mineral prices increases local population by 2.6% (Appendix Figure A4D). This effect is likely due to labor in-migration and is consistent with evidence from the United States on the employment effects of local oil and gas booms (Allcott and Keniston, 2018).

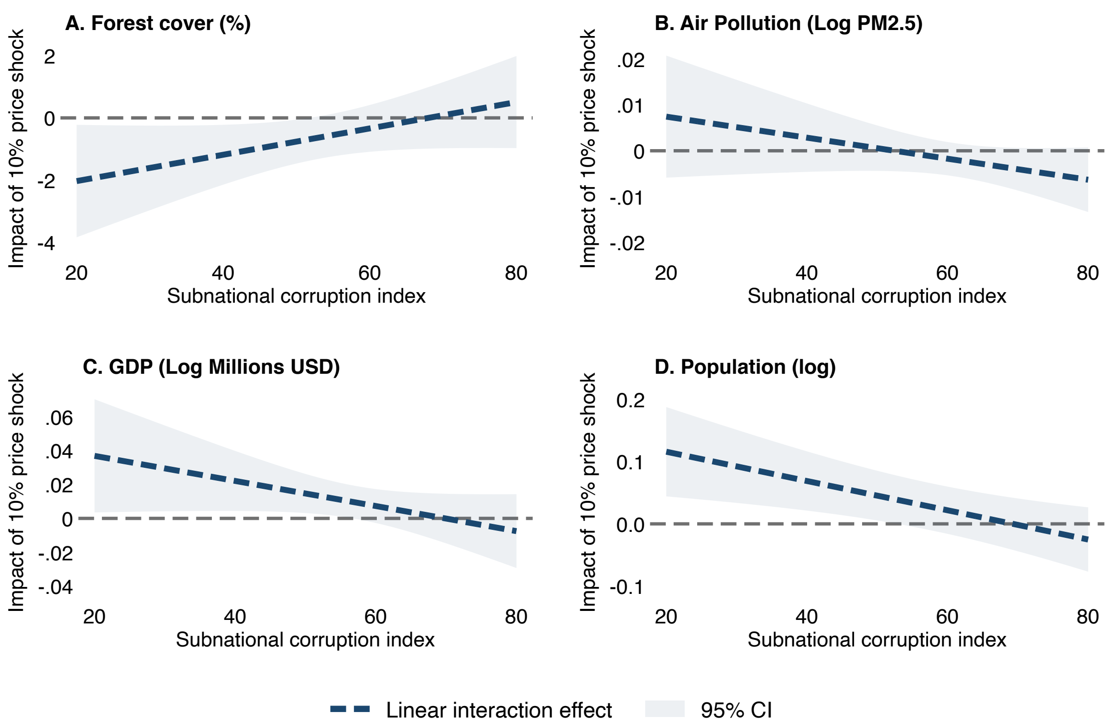
The effect of resource booms on social conflict is theoretically ambiguous. The literature has generally identified two opposite-signed effects (Dube and Vargas, 2013; Blair et al., 2021). The rapacity effect suggests that as commodity prices rise, the value of the spoils of conflict also rises, incentivizing greater fighting over control of resource rents. At the same time, the opportunity cost hypothesis suggests that as prices rise, accompanying local economic benefits render the opportunity cost of fighting prohibitively high, reducing the pool of recruits for armed groups. Table 1, column (5) tests the relationship between commodity prices and violent conflict around critical mines. Possibly because of offsetting rapacity and opportunity cost effects, there is no significant association between the probability of conflict and critical mineral prices, consistent with the results of Bazzi and Blattman (2014).

5.1 Heterogeneity by Local and Investor Governance

The results in Table 1 show that critical mining presents a clear tradeoff for mining communities: rising economic activity at the cost of greater deforestation. However, there is likely to be substantial heterogeneity in these average effects. In advanced economies, the marginal economic benefits of a mine are likely to be smaller, given more economic activity ex-ante. At the same time, the environmental effects will also be muted in hihg-income settings because the worst environmental excesses of producing firms are curbed by well-enforced regulation. As such, the environment-growth tradeoff should emerge most starkly in the worst governed places. To test this hypothesis, interaction terms between price shocks and local governance quality – measured by the Subnational Corruption Index (SCI) (Crombach and Smits, 2024) –

are added to the main regression specification.

Figure 4: Local impacts of mineral price shocks by corruption levels



Note: Plots present predicted effects of a 10% price shock from the estimation of equation (2) using OLS, residualizing commodity fixed effects, country-by-year effects, and controls for initial MNC ownership, shareholder HHI, home-country GDP per capita, firm size, mine age, and latitude, interacted with year indicators. The subnational corruption index (SCI) is defined at the ADM1 level, with larger numbers indicating less corruption. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest and mines with baseline forest cover greater than 20%. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine. Conflict is an indicator variable if there was any conflict within 25 kilometers of the mine in a given mine-year. Sample is all registered mine-years from 2000-2022 for which the outcome variable is non-missing. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Sample is all registered mine-years from 2000-2022 for which the outcome variable and SCI are non-missing.

Figure 4 plots variation in the predicted impact of a mineral price shock along the distribution of subnational corruption, using estimates from the linear interaction model in Appendix Table A2. For critical mines, the negative average effects of price increases on forest cover are largest in the worst-governed subnational regions. The interaction model predicts that in regions with an SCI of 20 – equivalent to the worst-governed regions of the Democratic Republic of Congo – a 10% increase in critical mineral prices is predicted to reduce forest cover by 2 p.p., four times more than the average effect. As local corruption levels improve, this effect attenuates, such that when the SCI reaches 80 – equivalent to the best-governed regions of Western Europe – the effect of price increases on deforestation is statistically insignificant.

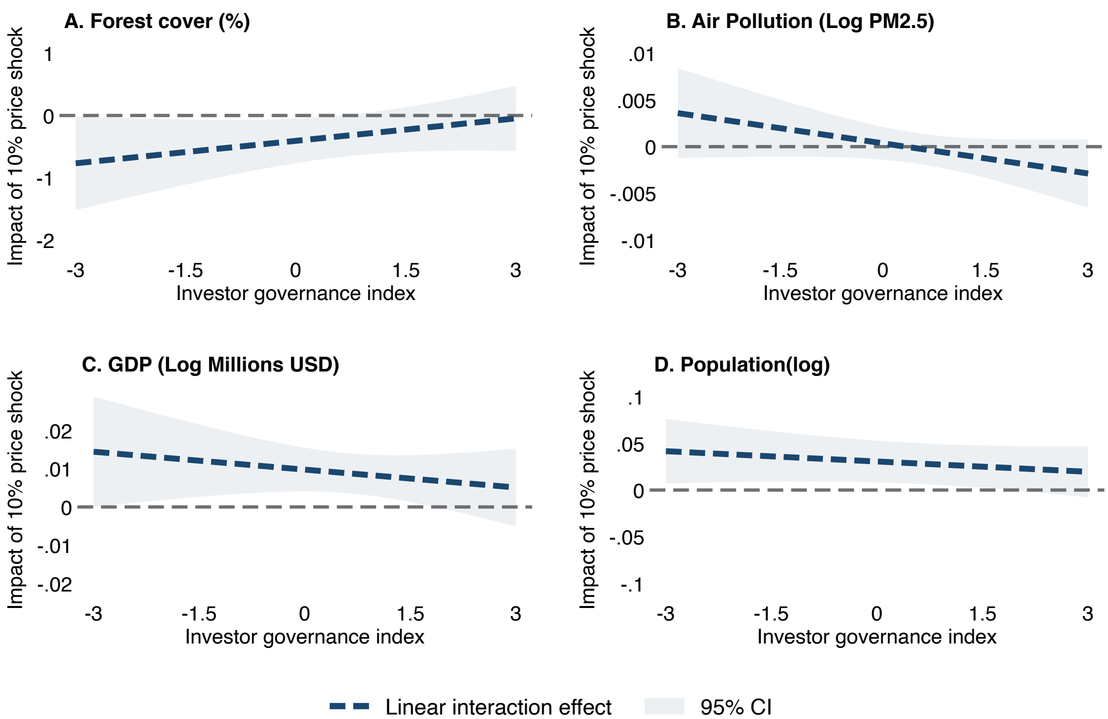
Similar patterns are observed for several other outcomes. For example, local economic impacts of mining are also concentrated primarily in the worst-governed places. In the linear model, the predicted elasticity of local GDP to critical mineral prices is 0.38 for the worst-governed regions and not significantly different from zero for the best-governed regions (estimates in Appendix Table A2). Air pollution follows a similar pattern, though the effects are not significant anywhere along the corruption distribution. Finally, consistent with the economic boom induced by rising prices, population growth responds most strongly to prices in the most corrupt regions.[10]

Firm characteristics also play an important role in determining the costs and benefits of critical mining. Firms based in weakly governed places may have a comparative advantage in operating in politically challenging markets (Rexer, 2024), or be better positioned to take advantage of institutional voids due to the absence of home-country environmental regulations and anti-corruption statutes. As shown in Appendix Figure A6, there is a positive correlation between subnational corruption around mine locations and weak governance in the headquarters locations of multinational mine operators. This indicates positive-assortative matching between mining locations and mining companies along the dimension of institutional quality.

One might therefore expect a greater supply response—and consequently larger local impacts—around mines where the operating firm is based in a country with weak governance. This hypothesis is tested by interacting the price shock with a measure of home-country corruption from the Worldwide Governance Indicators (World Bank, 2024), where "home-countries" are defined as the country where the mine's operating company is headquartered. The results, plotted with the linear interaction in Figure 5, broadly mirror the effect of host-country corruption. Mining assets controlled by firms based in states in the 10th percentile of the governance distribution exhibit deforestation responses to critical mineral

[10]We omit results on conflict, since as Table 1 shows, there is essentially no relationship with prices. The effect remains near-zero across the governance distribution.

Figure 5: Local impacts of mineral price shocks by investor country governance



Note: Plots present predicted effects of a 10% price shock from the estimation of equation (2) using OLS, residualizing commodity fixed effects, country-by-year effects, and controls for initial MNC ownership, shareholder HHI, home-country GDP per capita, firm size, mine age, and latitude, interacted with year indicators. Investor governance index is the country-level average of all Worldwide Governance Indicators (WGI) sub-indices for the country in which the largest mine shareholder is headquartered, with larger numbers indicating better governance. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest and mines with baseline forest cover greater than 20%. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine. Conflict is an indicator variable if there was any conflict within 25 kilometers of the mine in a given mine-year. Sample is all registered mine-years from 2000-2022 for which the outcome variable is non-missing. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Sample is all registered mine-years from 2000-2022 for which the outcome variable and SCI are non-missing.

price shocks that are more than twice as large as the average effect in Table 1 (linear interaction model estimates are in Appendix Table A3). The local economic benefits of critical mining are 30% larger for mines operated by firms based in countries in the bottom 10% of the governance distribution relative to the average effect, though the interaction term in this model is not statistically significant (Appendix Table A3). In general, the interaction effects are stronger and more significant for local governance than home-country governance.

5.2 Mapping Critical Impacts

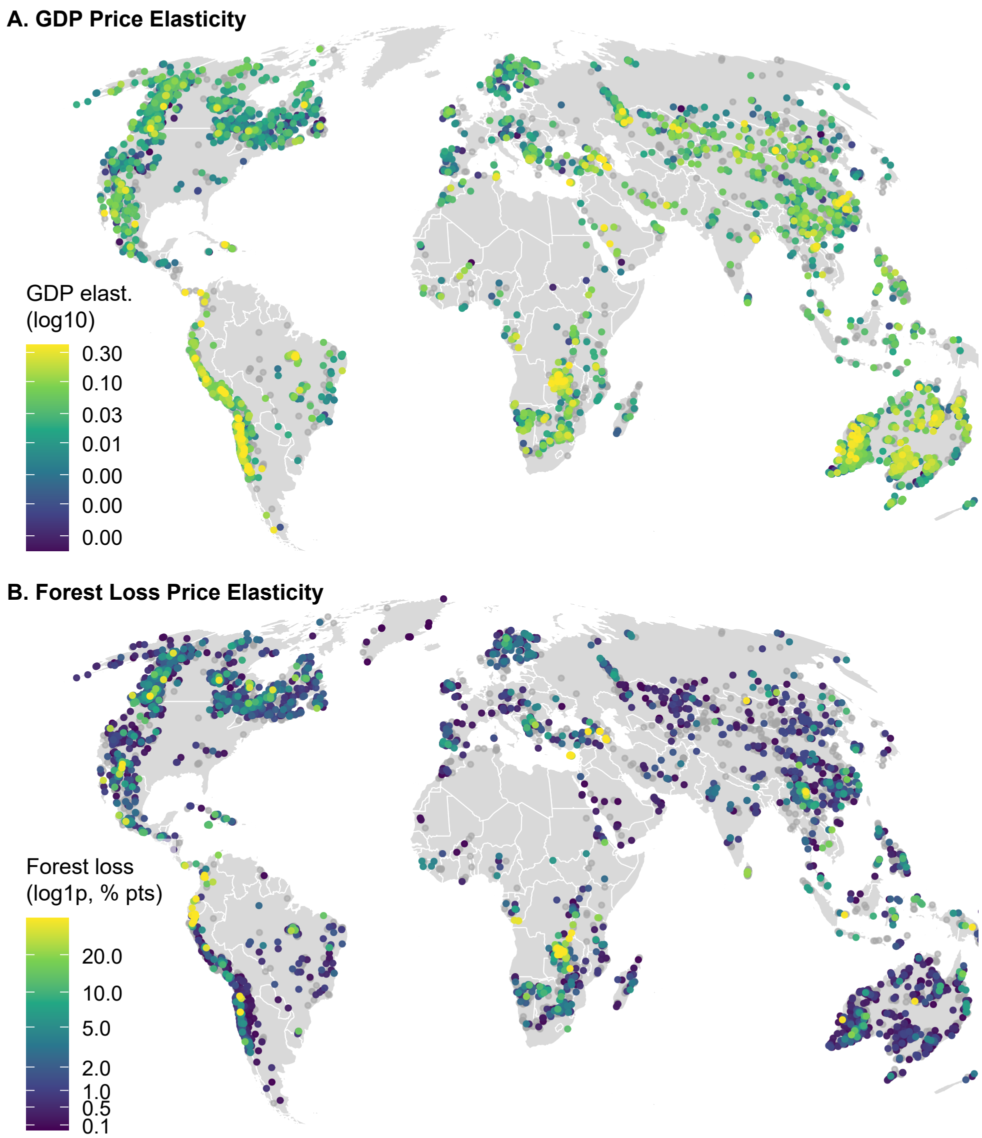
To characterize the spatial distribution of local impacts from critical commodity price shocks, we estimate mine-specific slopes in a two-step procedure. First, for each outcome (log night-lights-predicted GDP within 25km or forest cover share within 5km) we partial out fixed effects and controls by projecting both the outcome and the one-year-lagged log commodity price on mine fixed effects, commodity fixed effects, and country-by-year fixed effects, together with year dummies interacted with baseline mine characteristics (including initial mine attributes, first recorded year, and latitude). Second, for each mine with sufficient within-mine price variation, we regress the residualized outcome on the residualized price to obtain a mine-level coefficient $\hat{\beta}_i$. By construction, $\hat{\beta}_i$ for GDP is an elasticity of local economic activity with respect to price, whereas $\hat{\beta}_i$ for forest cover is a semi-elasticity (percentage-point change in forest cover per log-point change in price).

Results from this procedure are mapped in Figure 6. In line with our main empirical results, Figure 6A indicates that mines with the largest economic responsiveness to critical commodity price increases are most concentrated in low and middle-income countries—with hotspots in the South American Andean region, Central-Southern Africa, and Western Australia (a high-income exception) – though there is substantial variation and dispersion in economic responsiveness across the entire map. Figure 6B shows that forest loss associated with critical commodity price increases is even more clustered – in the northern Andes and Central America, Central-Southern Africa, the Middle East, and Southeast Asia. Forest loss hotspots correspond with areas that also show strong economic responsiveness to price shocks. It is important to note that mine operator institutional quality cuts across regions, introducing additional heterogeneity.

5.3 Welfare effects

The results in Figure A4 suggest that local economic activity rises with critical commodity prices, but how much do local communities truly benefit? Price booms may not translate into local welfare gains for several reasons. First, there are legitimate concerns about using night

Figure 6: Global distribution of critical mining impacts on economic activity and forest loss

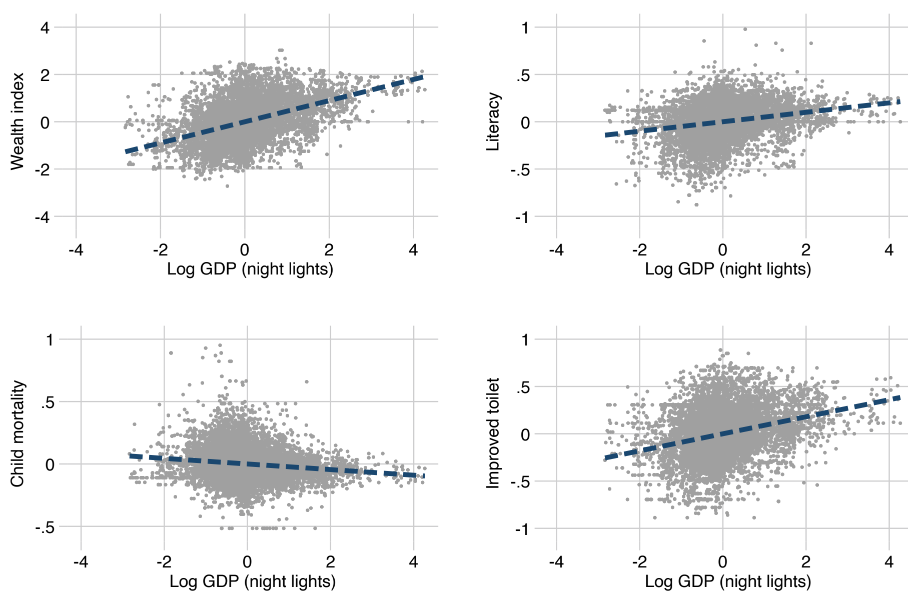


Notes: Each point represents a critical mine location, colored by mine–specific price responsiveness estimated in a two–step, within–mine procedure: first, we residualize each outcome and the one–year–lagged log commodity price with respect to mine, commodity, and country–year fixed effects as well as year–interacted baseline mine characteristics; we then regress the residualized outcome on the residualized price separately for each mine to obtain a slope $\hat{\beta}_i$. Panel A (GDP) colors mines with $\hat{\beta}_i^{\text{GDP}} > 0$, where $\hat{\beta}_i^{\text{GDP}} = \frac{\mathrm{d}\ln(\text{GDP})}{\mathrm{d}\ln(\text{price})}$. Non–positive sites are shown in gray. The color bar is on a $\log_{10}$ scale for contrast, values are trimmed to the 2nd–98th percentiles to facilitate visualization, and tick labels show the original (unlogged) units. Panel B (forest loss) colors mines with $\hat{\beta}_i^{\text{Forest}} < 0$, where $\hat{\beta}_i^{\text{Forest}} = \mathrm{d}(\text{tree–cover share})/\mathrm{d}\ln(\text{price})$ (semi–elasticity). Sites with no forest loss response ($\hat{\beta}_i^{\text{Forest}} \geq 0$) are gray. Colors map to $\log(1 + |\hat{\beta}_i^{\text{Forest}}|)$; limits are set to the 2nd–98th percentiles. Legend tick labels report raw percentage–point magnitudes. Mines with insufficient within–mine price variation or very short panels are excluded.

lights to predict local economic activity, particularly since rising luminosity in the area around mines may reflect new mining infrastructure and operations, rather than meaningful positive spillovers to local markets. Second, even if night lights accurately measure economic activity, given the capital-intensity of most mining operations, local gains may be captured primarily by a small group of highly skilled or foreign expatriate workers or local elites.

To address the question of local welfare spillovers, we use several survey-based indicators of well-being from the Demographic and Health Surveys (DHS), measured as survey-weighted averages within 20 kilometers of a given mine. As our measure of household well-being, we primarily consider the DHS wealth index, as well as auxiliary welfare indicators such as literacy, child mortality, and access to improved sanitation.

Figure 7: Measurement validation of satellite night lights-predicted GDP



Note: Plots present partial correlations between local GDP and DHS outcomes at the mine level, controlling for country-by-year effects. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine. Wealth index is measured as the standardized DHS asset index. Literacy is the share of the adult population that is literate. Child mortality is the share of births in which the child died before their 5th birthday. Improved sanitation measures the share of households in the DHS sample with. All mine-level DHS estimates use survey weights and are defined within 20 kilometers of the mine. Sample is all registered mine-years from 2000-2019 for which DHS data is available.

Night lights-based economic activity around mines is significantly related to these welfare measures. Figure 7 plots the relationship between night lights-predicted GDP and local welfare outcomes, after controlling for country-by-year fixed effects. Across all outcomes, there is a strong correlation between night lights-predicted economic activity and average living standards. Regression estimates in Appendix Table A13 confirm that these associations are statistically significant. The results suggest that night lights are a good proxy for overall economic development.

However, even if night lights are a plausible measure of local economic activity, this does not necessarily imply that the spillovers from mining activity meaningfully raise local living standards. To test this proposition, we re-estimate our main price regression equation on the subsample of mines for which DHS data is available, using the DHS wealth index as the outcome. Table 2 shows the regression estimates. Commodity price shocks are significantly associated with local wealth indices as measured by the Demographic and Health Surveys (DHS). This result is robust to various combinations of controls and fixed effects. In columns (1)-(3), a 10% increase in prices is associated with a 1-1.6% increase in local household wealth, relative to the sample mean. These results hold except in the most stringent specification (column 4), which includes country-by-year fixed effects. However, this estimate is likely to be unreliable because of limited within-unit variation: there are only 8 unique mines per country-year in the data after all the sample restrictions are imposed.

Table 2: Impact of price shocks on DHS wealth index

Outcome	Wealth index				Non-agricultural employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log price, $t-1$	0.455***	0.324**	0.269**	0.037	0.026	0.095**	0.124***	0.038
	(0.088)	(0.146)	(0.130)	(0.161)	(0.024)	(0.043)	(0.044)	(0.045)
Observations	1222	1222	1222	1222	1219	1219	1219	1219
R-squared	0.237	0.306	0.411	0.466	0.100	0.212	0.374	0.515
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Country FE	No	No	Yes	No	No	No	Yes	No
Country $\times$ Year FE	No	No	No	Yes	No	No	No	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Dependent variable is the DHS Wealth Index, measured as the standardized DHS asset index in (1)-(4) or the share of employed adults in non-agricultural occupations in (5)-(8). All mine-level DHS estimates use survey weights and are defined within 20 kilometers of the mine. Critical minerals definition can be found in Appendix A.1. Sample is all registered mine-years from 2000-2019 for which DHS data is available. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Employment shifts represent a key mechanism that might drive broad economic spillovers from critical mining booms. Mining activity generates labor demand both directly, and indirectly through increased demand for inputs, as well as local goods and services (Allcott and Keniston, 2018). As such, we might expect both rising wages as well as a shift in employment activity away from low-productivity agriculture to the types of goods and services demanded by firms and workers in the mining sector. Though we lack geographically disaggregated wage data, we can test for shifts in employment composition. Columns (5)-(8) of Table 2 estimate the impact of commodity prices on the employment share of the non-agricultural sector in the DHS sample. The results indicate anywhere between a 0.3 -1.2 p.p. (0.3-1.6% of the sample mean) increase in the share of workers employed outside agriculture due to a 10% increase in prices. These estimates suggest mining booms can boost off-farm labor demand, triggering structural change and driving increasing economic activity and well-being.

5.4 Robustness Checks and Extensions

Production effects: There are two mechanisms by which price shocks affect environmental and socioeconomic outcomes. First, price shocks increase the value of production at a fixed level of output. This could affect conflict by raising the value of attacking mining sites, or increase local wages through rent sharing. Second, higher prices also incentivize greater production – both on the extensive and intensive margins – leading to greater deforestation and increased PM2.5. Socioeconmic impacts likely operate via both mechanisms, while environmental consequences depend primarily on the expansion of output. It is therefore important to verify whether price shocks increase output. Appendix Table A4 estimates the elasticity of mining output to prices. Estimates reveal a small but meaningful and statistically significant elasticity on both the intensive and extensive margins: a 10% increase in commodity prices is associated with a 0.4% increase in output and a 0.32 percentage point (2.5%) increase in the probability of production. These effects are larger for longer lags of prices, suggesting that firms face adjustment costs to ramping up production. The fact that extensive margin effects are larger than intensive margin may also explain why the effects of mineral price shocks are more pronounced for deforestation than air pollution.

Outcome radius: Results might also be sensitive to the geographic radius around the mine used to define outcomes. This is particularly important for local economic activity (Appendix Table A5) and air pollution (Appendix Table A6), for which impacts might reasonably be expected to materialize further out from the precise location of the mine. The results for local economic activity and air pollution for different distance rings (0-5, 5-10, 10-15, 15-20, and 20-25) are broadly similar to the main regression results in Appendix Table 1.

Baseline forest cover: Main specifications analyzing forest cover throughout this study restrict the sample to only mines located in tropical forests with a baseline forest cover of 20% or more. Appendix Table A7 investigates the sensitivity of the results to this restriction. For critical minerals, results remain negative and significant for thresholds of 0, 20, and 40% and in both the sample of only tropical forests and all forests – though effects are largest at the 20% threshold.

Shock definition: The results are also robust to many different definitions of the price shock, including additional lags (Appendix Table A8) and leads (Appendix Table A9) of prices. Appendix Table A10 defines positive price shocks as years (or consecutive three-year periods) in which commodity prices are more than 0.5 or 1 standard deviations above the average for the sample period. The results remain broadly unchanged.

Placebo test: Concerns about omitted variables may remain even after conditioning on fixed effects. These concerns are allayed with a placebo test that estimates the main models in the period before a mine opened. There is no evidence of meaningful effects of price shocks on GDP or forest cover in this pre-opening period (Appendix Table A11).

Sample selection: In the data, it is only possible to observe the year in which a mine registered in S&P, but not it's precise activity status over time. The main sample throughout this paper takes all mines in all years after their first year of registration. This may create concerns that inactive mines contaminate the main sample. Appendix Table A12 subsets the sample to only mines that were listed as active as of 2022.[11] The main results remain broadly unchanged

[11] Note that this restriction may introduce other biases, because *i*) mine activity status is plausibly an outcome of prices, and *ii*) activity status is not time varying, so there is a risk of excluding mines that were active during the earlier years in the sample, but not in 2022.

in magnitudes, though the coefficient on deforestation for critical minerals loses significance because of the smaller sample.

6 Discussion and Policy Implications

Our results reveal that mines located in high-corruption regions and operated by firms based in weak-governance jurisdictions exhibit the strongest economic impacts and steepest declines in forest cover during commodity price booms. In line with "greasing-the-wheels" corruption mechanisms, this pattern suggests that when rules are pliable and enforcement is weak, mining companies can accelerate permitting, development, and production quickly in response to price shocks, amplifying both local economic activity and environmental damage.

Given the central role of critical minerals in the global energy transition, "greasing the wheels" corruption may increase global welfare by reducing barriers to production, allowing critical mineral supply to respond more rapidly to demand shocks and attenuating global price volatility in critical sectors. However, the presence of environmental externalities suggests highly unequal distributional effects: the poorest, weakest states may capture economic benefits of critical mining but also bear the environmental costs of the clean energy transition. Even worse, the volatile boom-bust nature of extractive sectors suggests these short-term economic gains may not translate into long-run development—especially when weighed against largely irreversible forest loss (Luckeneder et al., 2025; van der Ploeg and Poelhekke, 2009).

Our findings yield several policy implications. First, in *high-income countries*—where a large share of the social gains from critical minerals accrue downstream of extraction—policymakers should accelerate permitting and production timelines, adopt precision mining practices that minimize environmental impacts, and prioritize the least environmentally vulnerable sites, even if doing so reduces local economic spillovers. Fiscal transfers and place-based policies can partly offset such trade-offs. Because so many recent critical mining projects are concentrated in high-income settings, fast-tracking sustainable extraction in these jurisdictions is likely to have disproportionate effects on global supply while also addressing concerns over de-risking and on-shoring of supply chains (Arezki and van der Ploeg, 2023).

In *low and middle-income countries*—where generating local economic impacts from extraction is a higher priority—policymakers should focus on converting short-run economic gains from mining booms into sustainable long-run development. How to do so effectively remains an active and high-priority area for research. Outstanding questions include how best to collect and allocate mining revenues between infrastructure, public goods provision, environmental conservation, or poverty alleviation (van Krevel, 2025; Murillo and Sardon, 2024), and how to design local content and local ownership policies to promote human capital accumulation, development of upstream and downstream industries, and sustainable extraction (Chang, 2025; Rexer, 2024; Cust and Zeufack, 2023).

Finally, *traceability and sustainable supply chain initiatives* can be used to align firms' private incentives with environmental and social performance (Lambin et al., 2018). The same tools employed in our analysis—tracking mine ownership and measuring impacts around each mine—can inform procurement and licensing decisions based on observed environmental and socioeconomic outcomes. Such practices raise the cost of environmentally damaging "greasing-the-wheels" strategies and increase returns from sustainable extraction. Home-country regulations can bind firms to higher standards abroad, and mineral importers can leverage their purchasing power to encourage compliance, especially as improved monitoring based on remote sensing data reduces reliance on local enforcement capacity (Mendonca Severiano et al., 2024).

This study has several limitations. First, governance is inherently multidimensional and difficult to measure. Our use of the Subnational Corruption Index and Worldwide Governance Indicators provides global coverage but inevitably embeds measurement error and conceptual choices about what constitutes "good governance." Second, while remote-sensing datasets enable global-scale analyses, they do not capture all impact channels (e.g., groundwater depletion, biodiversity loss, or social or cultural harms). Thus, our global estimates should be seen as complementary to detailed country or site studies. Third, mine start-up dates in the S&P database are imperfect, leading us to analyze within-mine responses to commodity price movements rather than using event study designs around mine openings. Finally, our empirical strategy measures short-to-medium term impacts of commodity price shocks, rather than long-run impacts of exposure to mining. Credibly identifying long-run impacts would require quasi-experimental variation in mine placement or credible counterfactual locations, which is challenging at a global scale. Each of these limitations suggests avenues for future work.

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ONLINE APPENDIX

A Appendix

A.1 Data Description

Mine Locations and Characteristics: The primary data source for this paper is the S&P Global Mining and Metals Database (2023), covering nearly all (35,567) commercial mines in the world annually between 2000-2022. Information reported in this database includes mine locations, primary commodity produced, and production volume. Production data are only available for 6,170 mines covering 122 countries (46,252 mine-years). Primary commodities produced are used to classify mines as "critical" or "non-critical." Critical minerals and metals include alumina, antimony, bauxite, chromite, chromium, cobalt, copper, graphite, heavy mineral sands, ilmenite, lanthanides, lithium, manganese, molybdenum, nickel, niobium, palladium, platinum, rutile, scandium, tantalum, tin, titanium, tungsten, vanadium, yttrium, zinc, and zircon following classifications discussed in (IEA, 2022) and (Cossins-Smith, 2023). There are a very small number of ferrochrome and ferronickel mines (23 each) in the dataset, which we classify as non-critical. Changing the classification of these commodities to critical does not alter the results.

Mine Ownership and Company Characteristics: Time-varying ownership data are available for 96.5% of mines in the S&P Global Mining and Metals Database (2023), including each firms' percentage participation share in each mine, firm names and ID numbers, and firms' country and city headquarters for 16,805 unique mining firms. Firm ownership structures are reconstructed up to one level above immediate mine operators, thus identifying all parent companies (and their characteristics) for wholly or partially owned subsidiary firms.

Economic Activity: Annual 1x1km gridded GDP levels inferred from night-time light intensity are from Chen et al. (2022). Average GDP levels within 5, 10, 15, 20, and 25km of mine locations are measured each year to assess the level of economic activity. GDP is measured in millions of real USD.

Demographic and Health Surveys: To validate the relationship between GDP from night lights and household-level socioeconomic development outcomes, as well as to assess socioeconomic impacts around mine locations, mine locations are intersected with the universe of Demographic and Health Surveys (DHS) collected between 2000 and 2022 within 20km of those locations (Demographic and Health Surveys Program, 2024). Overall, we are able to match just 1,191 critical mines, or 12% of the total sample. DHS surveys covered over 90 low and middle-income countries during this period. DHS data were shared with the authors by the World Bank Planet Vice Presidency Unit.

Population: Population comes from satellite-derived data from NASA's Gridded Population of the World (Version 4) database, which provides 1x1km population estimates for the years 2000, 2005, 2010, and 2015 (NASA, 2023). Population levels are interpolated between these years.

Land Use: Measurement of land use change draws on satellite-derived data from the Copernicus Land Monitoring Service (2024), an initiative of the European Union, which uses satellite images and machine learning algorithms to predict global, gridded land cover categories at 300x300m resolution across 23 land-use classes from 1992-2023 (Copernicus Land Monitoring Service, 2024). We aggregate natural vegetation classes into our primary land-use outcome (tree cover).

Conflict: Data on conflict are drawn from the Uppsala Conflict Data Program (UCDP), which compiles the universe of geolocated conflict events between 1975-2023 (Uppsala Conflict Data Program, 2023). Each event includes information on the parties involved and the number of civilian deaths. The variables of interest are the sum of total conflict events and conflict-related civilian deaths registered each year within 5, 10, 15, 20, and 25km of each mine location.

Air Pollution: Concentrations of fine particulate matter air pollution (PM2.5) can be inferred from satellite data. Satellite-predicted data on hyper-local PM2.5 concentrations come from Shen et al. (2024). These authors provide a global, gridded annual panel dataset at the 1x1km resolution covering 1998-2022.

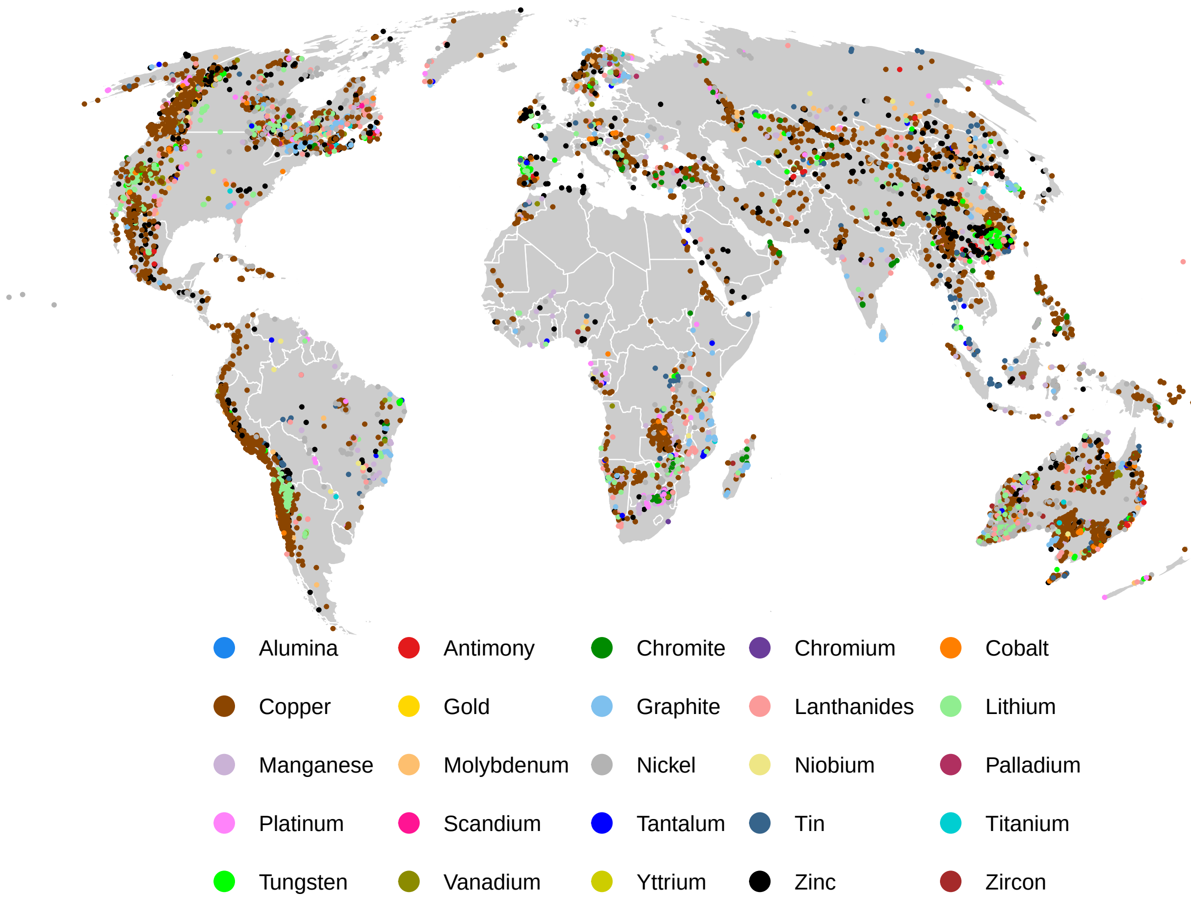
Commodity Prices: Annual data are commodity prices for minerals and metals are drawn from the International Monetary Fund's Primary Commodity Prices Database (International Monetary Fund, 2024) and the United States Geological Survey's Mineral commodity summaries (USGS, 2024). Prices are deflated to constant 2010 values using the World Bank GDP deflator.

Subnational Corruption Index: Subnational data on annual grand and petty corruption in 1,473 regions (ADM1-level) of 178 countries between 1995-2022 are drawn from the Subnational Corruption Database, developed by Crombach and Smits (2024) and made available by the Global Data Lab in the Nijmegen School of Management of Radboud University. This dataset compiles data from 807 surveys covering 1,326,656 respondents to develop a comprehensive corruption measure for each region, as well as separate measures for grand and petty corruption.

Worldwide Governance Indicators: The World Bank combines data from over thirty sources into annual measures of governance along the dimensions of voice and accountability, regulatory quality, political stability, rule of law, government effectiveness, and control of corruption (World Bank, 2024). We compute the average of these measures at baseline (2000) to create an aggregate governance index measure for each country.

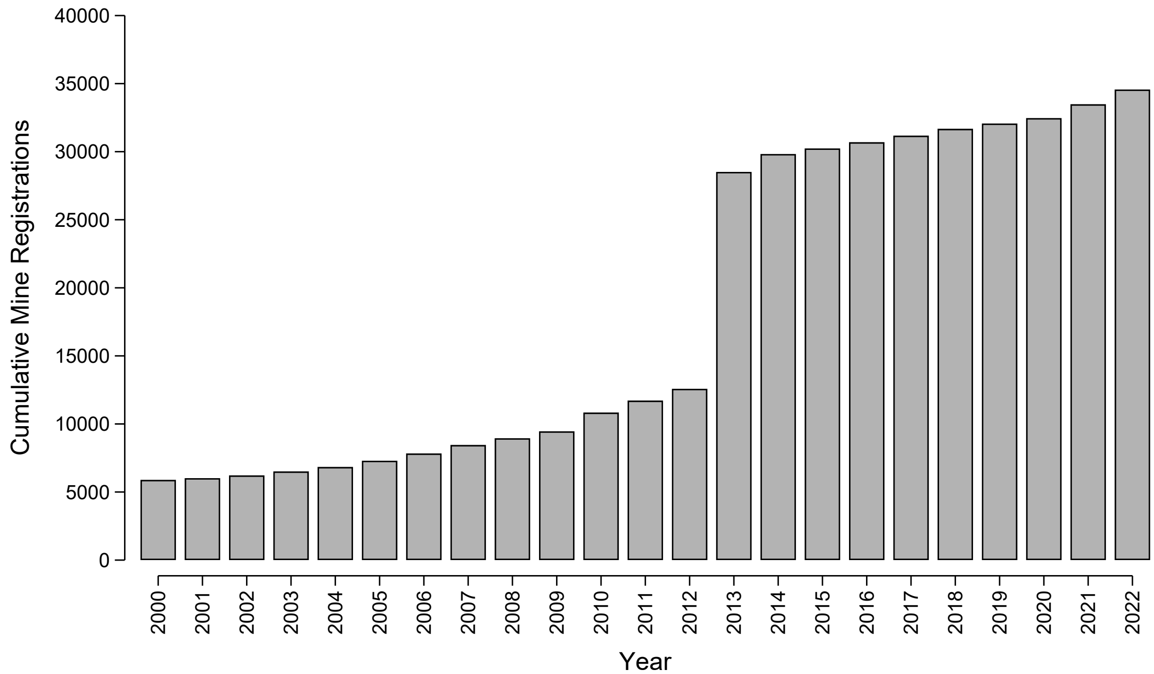
A.2 Appendix Figures

Figure A1: Critical Mines Around the World (All Critical Minerals and Metals)



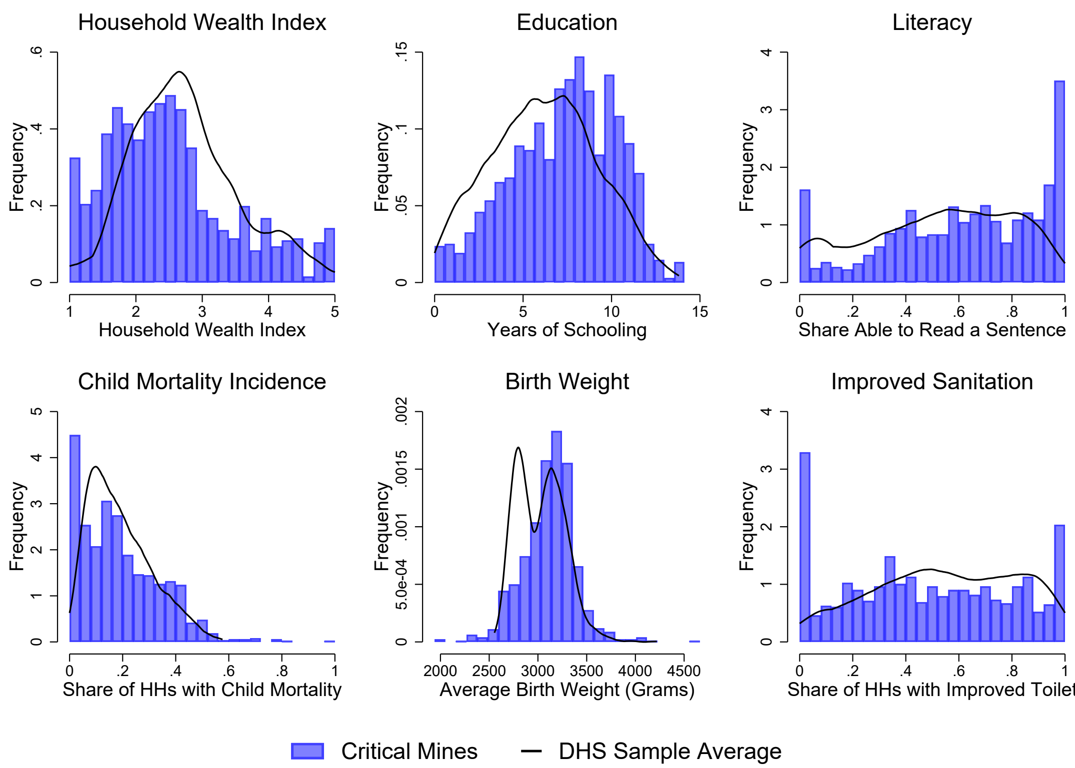
Note: Map shows GPS coordinate locations of all registered commercial critical mines from 2000-2022. Critical minerals definition can be found in Appendix A.1. Map locations are drawn from the S&P Global Mining and Metals Database (2023).

Figure A2: Cumulative Number of Mines (Critical and Non-Critical) Registered in S&P Global Database



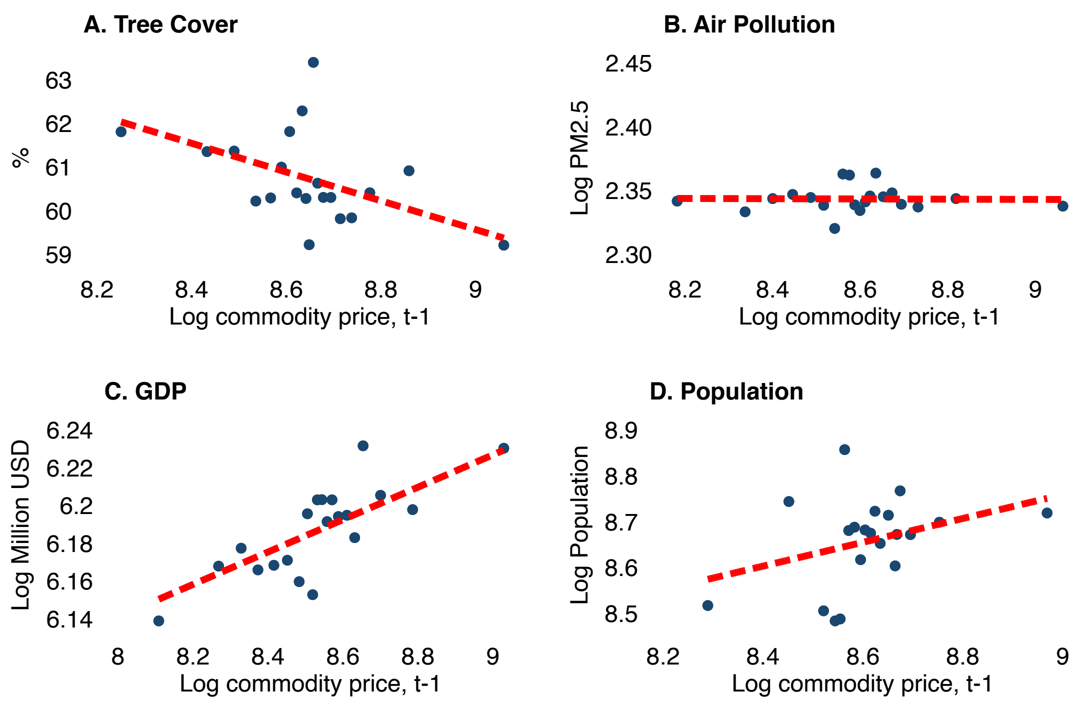
Note: The large increase in mine registrations in 2013 likely reflects major data acquisitions by S&P Global, suggesting mines registered in this year could potentially have been present prior to 2000. Mine registrations in other years appear more steady and organic, allowing us to infer that they most likely reflect real-time updates in mine presence. Exact dates of mine opening or production start date are not consistently available in the database.

Figure A3: Socioeconomic development indicators around mines



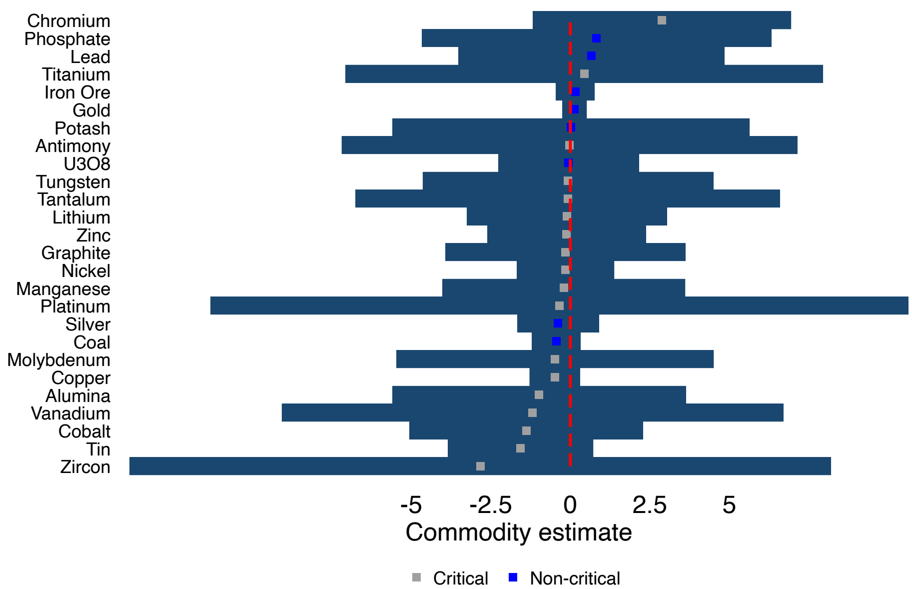
Note: Data are from S&P Global Mining and Metals Database (2023) and the universe of Demographic and Health Surveys Program (2024) between 2000-2021; authors' calculations. Values corresponding with critical mines are averaged across all surveys completed within 20km of critical mine locations. DHS sample average distributions reflect the distribution across all DHS surveys, which are representative of the low- and middle-income countries covered by DHS. Household wealth index ranges from 1 (poorest) to 5 (wealthiest). Share of households with child mortality measures the share of households within a 20km circle around the mine that experienced one or more child mortality events during the sample period.

Figure A4: Local environmental and economic effects of mineral price shocks



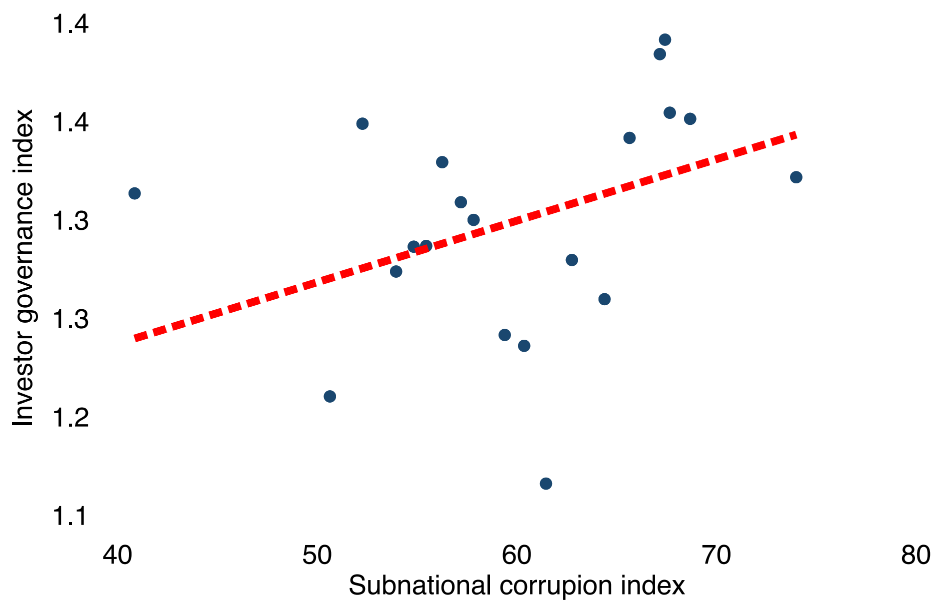
Note: All scatterplots are binned at 20 quantiles of the distribution of log commodity prices, residualizing commodity fixed effects, country-by-year fixed effects, and controls for initial MNC ownership, operator HHI, controlling operators' home-country GDP per capita, firm size, mine age, and latitude, interacted with year indicators. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical forest and mines with baseline forest cover greater than 20%. Local GDP is measured as the log of total night lights-predicted GDP, in millions of USD, within 25 kilometers of the mine. Sample is all registered mine-years from 2000-2022 for which the outcome variable is non-missing.

Figure A5: Effects of price shocks on deforestation by critical and non-critical minerals



Note: Figure shows estimates from commodity-specific regressions of on forest cover on commodity prices. Bars indicate robust 95% confidence intervals. Sample is all mines in tropical countries with greater than 20% baseline forest cover.

Figure A6: Subnational corruption and foreign investor governance



Note: All scatterplots are binned at 20 quantiles of the distribution of subnational corruption, residualizing commodity-by-year fixed effects. Investor governance index is the country-level average of all Worldwide Governance Indicators (WGI) sub-indices for the country in which the largest mine shareholder is headquartered, with larger numbers indicating better governance. The subnational corruption index (SCI) is defined at the ADM1 level, with larger numbers indicating less corruption.

A.3 Appendix Tables

Table A1: Socioeconomic and Environmental Indicators Around Critical Mines

	Critical Mines	Other Mines	World Average
Socioeconomic Development Indicators			
Population, thousands (2020)	75.8	112.2	66.3
Percent change in population since 2000	34.8	24.2	27.3
GDP per capita, thousands (2019)	76.0	74.0	11.338
Percent change in GDP p.c. since 2000	28.2	29.5	205.5
Urban Land-Use (2020)	1.5	2.4	0.7
Percent change in urban land-use since 2000	137.7	103.0	50.0
Number of Violent Conflicts (2020)	0.21	0.12	0.11
Percent change in violent conflicts since 2000	246.3	-14.0	235.9
Conflict Deaths per 100k people (2020)	2.6	1.2	1.12
Percent change in conflict deaths/100k since 2000	205.1	84.5	-6.8
Subnational Corruption Index (2020)	59.7	61.2	60.65
Environmental Sustainability Indicators			
Forest Cover (2020)	39.2	38.8	31.2
Located within Tropical Forest	9.3	9.9	14.2
Located within Biodiversity Hotspot	20.3	17.3	2.5
Percent change in forest cover since 2000	-0.7	-0.4	-2.4
Percent change in tropical forest cover since 2000	-0.9	0.9	-8.7
Air Pollution (2020)	11.9	13.3	17.9
Percent change in air pollution since 2000	-0.7	-3.7	0.6
Threatened Vertebrate Species in Area (2020)	6.4	6.8	10.4

Note: Values reported are sample means with the exception of GDP per capita, which reports medians to reduce the influence of extreme outliers. World averages refer to a representative similarly-sized circle drawn randomly from the earth's terrestrial area.

Table A2: Impact of price shocks on outcomes, by subnational corruption

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	-28.690**	0.120	0.517**	1.628***	0.011
	(13.940)	(0.099)	(0.255)	(0.512)	(0.022)
Log price, $t-1$ × Subnational corruption index	0.421*	-0.002	-0.007*	-0.023***	-0.000
	(0.252)	(0.002)	(0.004)	(0.008)	(0.000)
Observations	3551	16094	12551	3130	16094
R-squared	0.329	0.702	0.492	0.561	0.258
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μ g/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Subnational corruption index comes from Crombach and Smits (2024) and is defined at the ADM1 level, with larger values indicating less corruption. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable, mineral prices, and the SCI are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Impact of price shocks on outcomes, by investor country governance

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	-4.066**	0.004	0.098***	0.306***	-0.002
	(1.825)	(0.009)	(0.029)	(0.114)	(0.002)
Log price, $t-1$ × Home governance index	1.203	-0.011	-0.016	-0.037	-0.000
	(0.918)	(0.007)	(0.019)	(0.037)	(0.002)
Observations	13816	78638	66463	16004	79245
R-squared	0.223	0.843	0.584	0.646	0.253
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Home governance index is the average value of the World Governance Index for the home country of the mine's largest shareholder. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable, prices, and investor governance are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Impact of price shocks on mine output

Outcome	Log output		Producing		Log output		Producing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log price, $t-1$	-0.089**	0.036	0.033***	0.014*				
	(0.044)	(0.055)	(0.008)	(0.008)				
Log price, $t-2$					-0.029	0.081	0.049***	0.031***
					(0.047)	(0.056)	(0.008)	(0.008)
Observations	9570	9570	98613	98613	9260	9260	97338	97338
R-squared	0.940	0.949	0.620	0.665	0.941	0.949	0.626	0.670
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year × Country FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Producing is defined as an indicator variable if no output is reported but the mine has reported ownership data to S&P. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Impact of price shocks on local GDP: robustness to distances

Distance (km)	0-5	5-10	10-15	15-20	20-25
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	0.090***	0.103***	0.088***	0.067***	0.092***
	(0.032)	(0.028)	(0.027)	(0.026)	(0.027)
Observations	69359	69359	69412	69446	69446
R-squared	0.461	0.495	0.522	0.536	0.542
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within k kilometers of the mine, from Chen et al. (2022), where k is given in the table header. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Impact of price shocks on air pollution: robustness to distances

Distance (km)	0-5	5-10	10-15	15-20	20-25
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	-0.002	-0.001	-0.001	-0.001	-0.000
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	87949	87949	87956	87956	88004
R-squared	0.837	0.838	0.839	0.841	0.843
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year $\times$ Country FE	Yes	Yes	Yes	Yes	Yes
Year $\times$ Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within k kilometers of the mine, where k is given in the table header. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Impact of price shocks on forest cover: robustness to baseline cover

Sample	Tropical countries			All mines		
Threshold (%)	0	20	40	0	20	40
	(1)	(2)	(3)	(4)	(5)	(6)
Log price, $t-1$	-2.220	-3.261**	-1.219	-1.472*	-2.791***	-2.215***
	(1.523)	(1.632)	(1.817)	(0.775)	(0.682)	(0.610)
Observations	25486	15315	10782	69752	47328	38305
R-squared	0.311	0.222	0.230	0.420	0.250	0.176
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is given in table header: either all countries with tropical rainforest (columns 1-3) or the full sample of mines (columns 4-6), where with baseline forest cover threshold varies from 0 to 40%. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Impact of price shocks: robustness to lags

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, $t-2$	-3.308**	-0.004	0.072***	0.110*	-0.002
	(1.564)	(0.007)	(0.024)	(0.067)	(0.002)
Observations	15211	87180	68296	16506	87881
R-squared	0.229	0.842	0.587	0.646	0.281
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μ g/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Impact of price shocks: robustness to leads

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, t	-2.406	-0.004	0.089***	0.071	-0.005***
	(1.642)	(0.008)	(0.025)	(0.084)	(0.001)
Observations	15682	89325	71335	17865	90061
R-squared	0.230	0.843	0.587	0.647	0.284
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Impact of price shocks on outcomes: robustness to shock measurement

Outcome	Forest cover				Log GDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price shock 0.5SD	-0.263				0.039***			
	(0.254)				(0.009)			
Three-year 0.5SD shock		-0.616**				0.051***		
		(0.293)				(0.010)		
Price shock 1SD			-0.332				0.039***	
			(0.290)				(0.012)	
Three-year 1SD shock				-0.775**				0.064***
				(0.336)				(0.012)
Observations	47824	47824	47824	47824	70925	70925	70925	70925
R-squared	0.250	0.250	0.250	0.250	0.581	0.581	0.581	0.581
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all mines with baseline forest cover greater than 20%. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). "Price shock" is measured as an indicator for years in which the commodity price is 0.5 or 1 SD greater than its average over the sample period. "Three-year shock" is measured as an indicator for periods in which the commodity price has been 0.5 or 1 SD greater than its average over the sample period for the past three consecutive years. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2022 for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Impact of price shocks: pre-period outcomes

Sample	Non-critical		Critical	
Outcome	GDP	Forest	GDP	Forest
	(1)	(2)	(3)	(4)
Log price, $t-1$	-0.013	0.746	-0.025***	1.076
	(0.010)	(0.807)	(0.009)	(0.803)
Commodity FE	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes
Observations	190943	35189	83347	14852
R-squared	0.638	0.268	0.613	0.209

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all mine-years before the mine entered the S&P database, for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Impact of price shocks on local environmental and socioeconomic outcomes, currently active sample

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Log price, $t-1$	-2.334	0.002	0.094***	0.469***	0.002
	(2.297)	(0.010)	(0.031)	(0.149)	(0.002)
Observations	7854	43754	33433	8145	44126
R-squared	0.294	0.846	0.589	0.657	0.300
Commodity FE	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover is measured as the share of pixels within 5 kilometers of the mine that are classified as tree cover. Forest cover sample is all countries with tropical rainforest (see Appendix B) and mines with baseline forest cover greater than 20%. PM2.5 is measured as log of the total concentration of fine particulate matter, in μg/m3, within 25 kilometers of the mine. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Population is measured as log of the total population living within 25 kilometers of the mine, derived from GPW estimates. Conflict is an indicator variable if there was any conflict within 25 kilometers if the mine in a given mine-year. Controls are initial MNC ownership, shareholder HHI, home-country GDP per capita, and firm size, as well as mine age and latitude. Critical minerals definition can be found in Appendix A. Sample is all mine-years from 2000-2022 indicated as active in 2022, for which the outcome variable and prices are non-missing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Correlation between night lights-predicted GDP and DHS outcomes

Outcome	Wealth	Literacy	Child mort.	Sanitation
	(1)	(2)	(3)	(4)
Log GDP	0.479***	0.066***	-0.029***	0.111***
	(0.023)	(0.006)	(0.003)	(0.007)
Year × Country FE	Yes	Yes	Yes	Yes
Observations	2698	2698	2698	2698
R-squared	0.582	0.683	0.435	0.521

Note: Standard errors, in parentheses, are clustered at the mine level. Local GDP is measured as the log of total night lights-predicted GDP, in USD, within 25 kilometers of the mine, from Chen et al. (2022). Wealth index is measured as the standardized DHS asset index. Literacy is the share of the adult population that is literate. Child mortality is the share of births in which the child died before their 5th birthday. Improved sanitation measures the share of households in the DHS sample with. All mine-level DHS estimates use survey weights and are defined within 20 kilometers of the mine. Critical minerals definition can be found in Appendix A. Sample is all registered mine-years from 2000-2019 for which DHS data is available. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.