Critical mining contributes to economic growth and forest loss in high-corruption settings

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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 9,472 critical mineral and metal mines with geospatial data and leverage exogenous commodity price variations to causally identify local mining impacts. Price booms for critical minerals and metals increase both deforestation and economic activity around mines, revealing an environment-growth tradeoff. 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. These effects are concentrated in areas with high corruption and where mines are operated by firms from poorly governed countries. This suggests that environmental and anti-corruption regulations mitigate deforestation but also limit local economic benefits by constraining operators' responsiveness to price changes. Results underscore trade-offs and distributional consequences involved in expanding critical mineral supply for the clean energy transition.

1 Introduction

Efforts to mitigate global climate change have accelerated the build-out of clean energy technologies, including batteries, wind turbines, solar panels, and electricity transmission infrastructure. Between 2022 and 2023, worldwide solar photovoltaic capacity additions grew by 85%, wind energy capacity additions by 60%, and electric vehicle production by 35% [1]. 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 [2]. 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 [3]. Total demand for major critical minerals and metals is forecast to grow between 68% and 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% [1].[1]

To what extent will the socioeconomic and environmental impacts of critical mineral and metal mining mirror earlier commodity booms? Previous work has documented associations between mining and social conflict [6, 7], corruption [8], deforestation [9–12], air pollution – particularly for coal mining [13–15] – and chemical pollution – particularly mercury exposure from artisanal gold mining [16]. At the same time, resource booms are associated with increased economic activity, wages, and job opportunities in mining areas [17, 18]. von der Goltz and Barnwal [19] 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. [20] 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. [21] 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 [22] 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 [23–25], analyze critical minerals at the country-level [26, 27] or firm-level [28], or describe supply chain issues [29–32]. Carr-Wilson et al. [33] conduct a systematic review of literature on critical mining and identify large gaps in coverage of most critical minerals and world

[1] 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 [4] 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 [5]. 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.

regions. Likewise, Agusdinata et al. [34] 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 descriptive. Owen et al. [35] 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. [36] 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 causal empirical evidence on local critical mining impacts on environmental outcomes and socioeconomic development around nearly all commercial mining sites in the world.

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 often been associated with armed militia conflicts, dangerous working conditions, and environmental damage [37]. 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 [38] and increasing infant mortality by depriving communities of a valuable income source [39]. Careful consideration of what determines the harms and benefits of critical mining is therefore essential for maximizing positive local impacts and minimizing local environmental and social costs – while ensuring reliable access to essential material inputs for the clean energy transition.

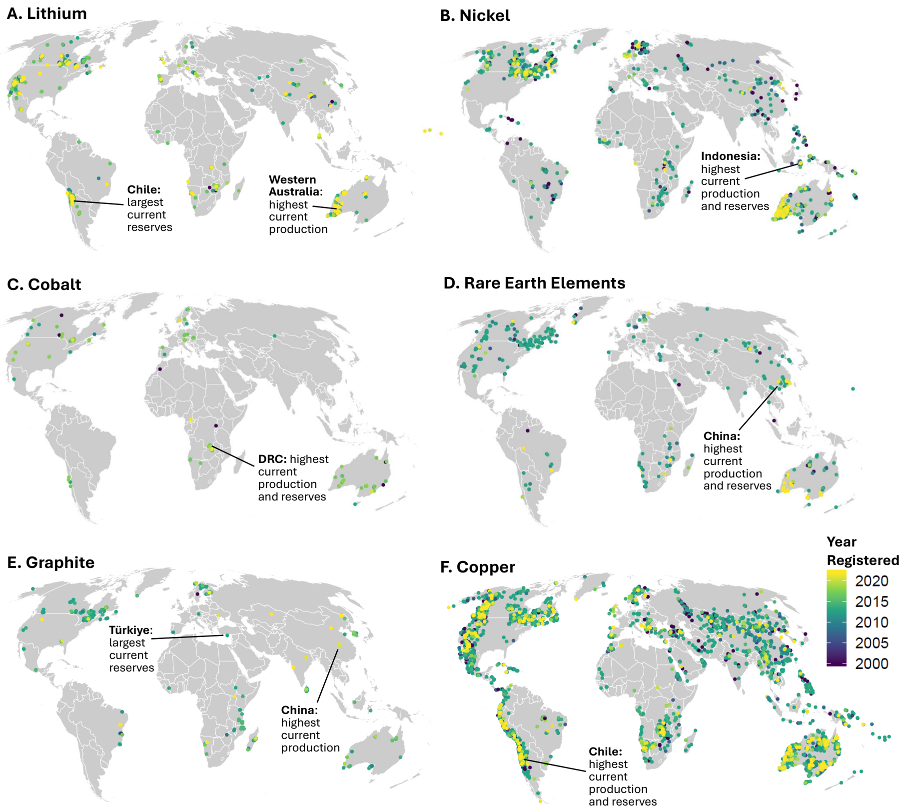
In this paper, we combine a global registry of 35,567 commercial mines (9,472 of which are critical mineral and metal mines) with high-resolution geospatial data on land use changes, economic activity, air pollution, violent conflict, and socioeconomic development indicators between 2000 and 2022 to measure annual local outcomes at varying radii 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. Using new data on subnational corruption [40], we explore heterogeneity in mining impacts by local corruption intensity, as well as by governance conditions in the countries where mine operators are headquartered.

2 Results

2.1 Insights from a Global Database of Critical Mines

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

Fig. 1: Critical mine locations (selected commodities)



Note: Mine locations are drawn from the S&P Global Mining and Metals Database [41]. 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 9,472 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 [42] and USGS Mineral Commodity Summaries [43].

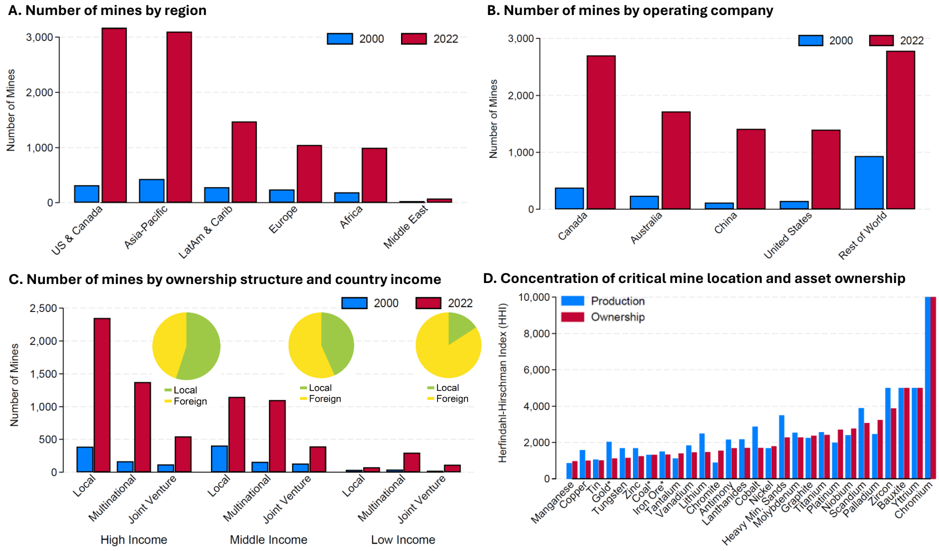
To assess patterns in the growth of critical mines since 2000, Figure 2 reports the number of mines in 2000 and 2022, disaggregated by region of mine location, country of mine ownership, and ownership structure (Figure 2A, 2B, and 2C, respectively). From Figure 2A, it is apparent that there has been massive 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 US and Canada (32.2% of all critical mines in 2022) and the Asia-Pacific (31.5%). Latin America and the Caribbean hosts 14.9%, Europe hosts 10.6%, Africa hosts 10.1%, and the Middle East hosts 0.8%. The US and Canada saw their number of critical mines grow by over 1000% between 2000-2022. 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 27% of all critical mines in 2022. Australian companies held dominant stakes in 17.2% of critical mines, Chinese companies held dominant stakes in 14.1%, and US companies held dominant stakes in 13.9%.

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 (43.4% local ownership) and low-income countries (15.8% 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, while 34.9% were located in middle-income countries and 7.0% were located in low-income countries. This distribution contrasts with the common perception of critical mines predominating in areas with extreme poverty and conflict.

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 [44]. 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.[2] 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 manganese, copper, and tin, have competitive market structures.

[2]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.

Fig. 2: Characteristics of critical mine growth between 2000 and 2022



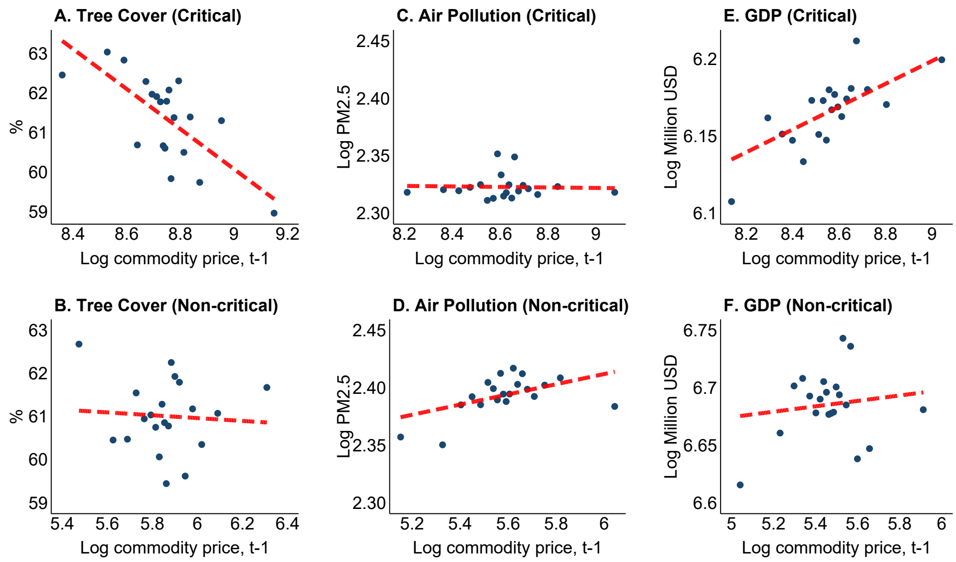
Note: High, middle, and low-income country definitions follow the World Bank classification. Mines are classified as local or multinational based on the headquarters location of the largest operating company. Joint ventures indicate mines that are jointly owned by both local and multinational firms. 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 are denoted with an asterisk.

2.2 Local Impacts of Commodity Price Shocks

Regression analyses (Figure 3) reveal substantial negative environmental externalities of both critical and non-critical mining. Figure 3A plots a linear fit of the relationship between mineral prices and forest cover around critical mines using binned scatter plots, controlling for fixed effects and interacted mine covariates. The regression models show a clear negative relationship: as prices rise, forest cover falls substantially. A similar association holds for non-critical mines, though it is much stronger for critical minerals: a 10% increase in critical mineral prices reduces forest cover by 0.3 p.p. (estimates in Appendix Table A2); the effect is only 0.1 p.p. for non-critical minerals. Appendix Figure A4 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.

The opposite trend is observed for air pollution, where non-critical minerals prices are significantly associated with increased PM2.5 emissions (3D), whereas critical minerals are not (3C). This differential response is likely driven by the composition of non-critical minerals output, which is heavily weighted toward production of pollution-intensive commodities like coal and iron ore [14]. The relationship between non-critical mineral prices and PM2.5, while statistically significant, is quantitatively small, with an elasticity of just 0.05. For critical minerals, the cumulative 102% increase in average commodity prices from 2000-2022 shown in Appendix Figure A2 accounts for a 3.6% loss in baseline pre-mining forest cover in tropical areas around critical mines over this period.

Fig. 3: 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 active mine-years from 2000-2022 for which the outcome variable is non-missing.

Despite the negative environmental externalities of mining, the socioeconomic effects of critical mineral booms are unambiguously positive on average. Figure 3E 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% (estimates in Appendix Table A2). For critical minerals, the cumulative increase in average commodity prices from 2000-2022 shown in Appendix Figure A2 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 (results shown in Appendix Figure A3. The same 10% increase in critical mineral prices increases local population by 2.6% (A3A). 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 [18]. In contrast, no significant local economic effects are observed for non-critical resources (A3B). This aggregate zero likely masks substantial heterogeneity across commodities and locations.

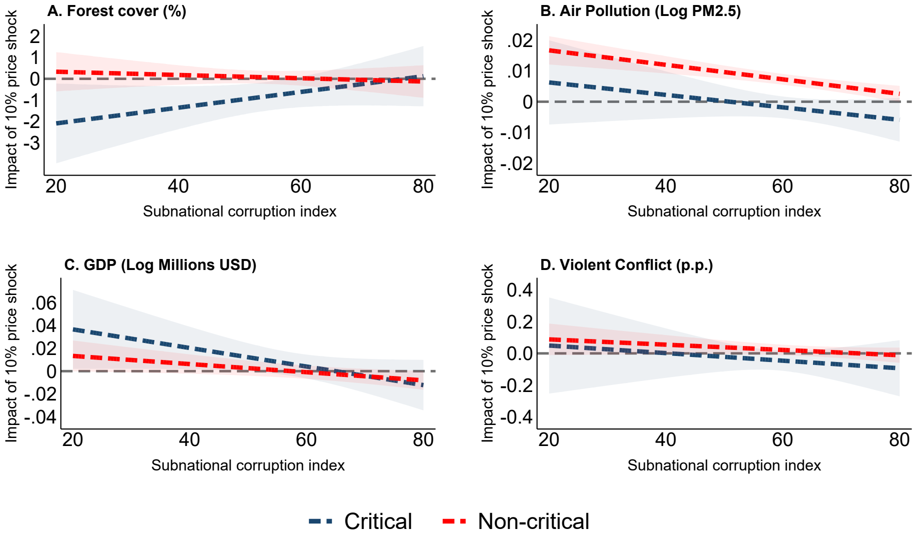
The effect of resource booms on social conflict is theoretically ambiguous. The literature has generally identified two opposite-signed effects [6, 45]. The rapacity effect suggests that as commodity prices rise, the value of the spoils of conflict also rises, incentivizing greater fighting over control 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. Appendix Figures A3C and A3D test the relationship between commodity prices and violent conflict around critical mines and non-critical mines, respectively. Possibly because of offsetting rapacity and opportunity cost effects, there is no significant association between the probability of conflict and mineral prices, consistent with the results of Bazzi and Blattman [46]. However, the relationship is slightly negative for critical mining, perhaps because of the larger local economic benefits from this category.

2.3 Heterogeneity by Local and Investor Governance

The results in Figure 3 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 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) [40] – are added to the main regression specification.

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 A3. 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 production 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. For non-critical mines the relationship between price shocks and deforestation is approximately zero along the entire corruption distribution.

Fig. 4: Local impacts of mineral price shocks by corruption levels

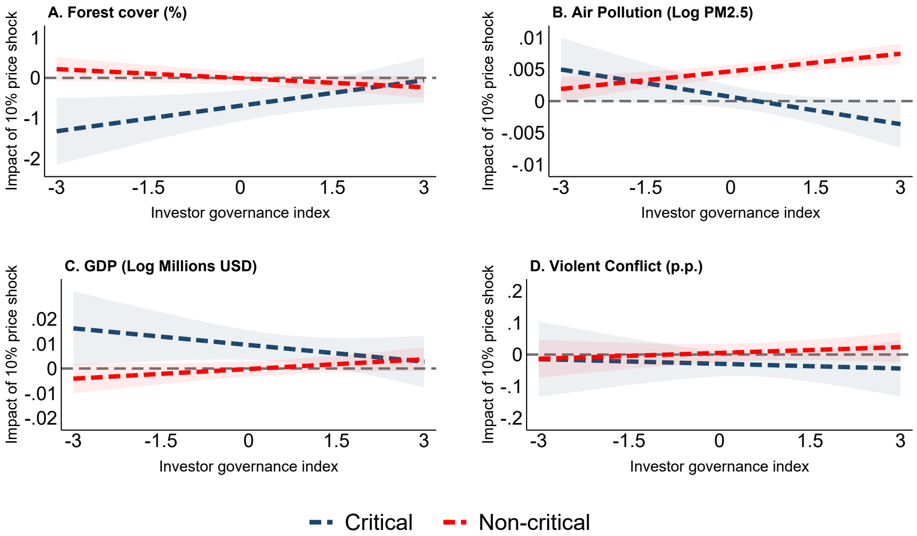


Note: Plots present predicted effects of a 10% price shock from the estimation of equation (2) using OLS, residualizing commodity fixed effects, country-by-year effects, and controls for initial MNC ownership, shareholder HHI, home-country GDP per capita, firm size, mine age, and latitude, interacted 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 active 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 active mine-years from 2000-2022 for which the outcome variable and SCI are non-missing.

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 (Appendix Table A3), 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. Local economic effects of non-critical minerals follow a similar, though somewhat more muted, pattern. Air pollution again follows a very similar pattern for non-critical minerals. There is no significant air pollution effect for critical minerals along the corruption distribution. Finally, for conflict there is essentially no relationship with governance, and the effect is always near-zero, likely reflecting the opposing forces of opportunity costs and rapacity.

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 [47], 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 A5,

Fig. 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 active 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 active mine-years from 2000-2022 for which the outcome variable and SCI are non-missing.

there is a strong 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 [48], 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 price shocks that are more than twice as large as the average effect in Table A2 (linear interaction model estimates are in Appendix Table A4). The distribution of air pollution effects follows a similar pattern, though the response is more muted for critical than non-critical minerals. 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 A4).

2.4 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 might 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 A5 estimates the elasticity of mining output to prices. The 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 somewhat less pronounced for critical than non-critical minerals, and 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. This is particularly true for critical minerals, where the intensive margin effects are not statistically significant while the extensive margin effects are.

Night lights measurement: There are legitimate concerns about using night 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. To address this concern, we document that local night lights-based economic activity around mines is significantly related to several survey-based indicators of wellbeing, including wealth indices and literacy rates (Appendix Figure A6, Table A13). In addition, Appendix Table A14 shows that commodity price shocks are significantly associated with local wealth indices as measured by the Demographic and Health Surveys (DHS) for both critical and non-critical minerals, although this result does not hold for all combinations of fixed effects.

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 A6) and air pollution (Appendix Table A7), 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 A2.

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 A8 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. The effect of price shocks on deforestation for non-critical mines becomes significant when relaxing the restriction of tropical forests and instead considering mines in all areas.

Shock definition: The results are also robust to many different definitions of the price shock, including additional lags (Appendix Table A9) and leads (Appendix Table A10) of prices. Appendix Table A11 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 A12).

3 Discussion

Our database shows that, globally, the number of critical mines grew more than sixfold between 2000 and 2022 – from roughly 1,500 to 9,500 – with the highest growth rates occurring in graphite, lithium, and rare earth metals. The majority of new critical mines are concentrated in North America and Asia and operated by companies based in Canada, Australia, China, and the United States.

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. 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 pattern holds for mines operated by companies based in weak governance countries. There are no measurable effects of price shocks on forest cover or local economic activity for mines in low-corruption places or around mines operated by companies based in low-corruption countries.

Critical mining has the largest economic impacts and largest negative environmental externalities around mines located in poorly-governed regions and operated by firms based in poorly-governed countries. The fact that the costs and benefits of critical mining are concentrated in the same markets and among the same firms suggests a clear mechanism. In weak governance contexts, mining firms are more able to bypass environmental safeguards and local opposition by co-opting local officials. This allows firms to ramp up production rapidly when prices rise, leading to both more economic activity and more pollution and deforestation. Moreover, firms based in countries with weak governance may have a comparative advantage in operating in poor governance settings, possibly because they are unencumbered by home-country anti-corruption statutes [47] or are better able to deploy tacit knowledge on navigating complex political economies. The evidence is consistent with a "greasing the wheels" form of corruption that enables firms to bypass onerous bureaucracy in weak states [47, 49, 50]. Given the central role of critical minerals in the global energy transition, this behavior of corrupt firms and local regulators may increase global welfare by reducing barriers to accessing critical minerals. However, the presence of environmental externalities complicates this efficiency argument and suggests unequal distributional consequences: the poorest, weakest states may capture economic benefits of critical mining but also bear the environmental costs of the clean energy transition.

4 Methods

4.1 Data

We construct a mine-level annual panel dataset ranging from 2000 to 2022 based on a global registry of 35,567 commercial mines (9,472 of which are critical mines) [41], which includes information on each mine's production, location, and ownership.[3] To measure local mining impacts, we intersect mine locations with geospatial data on 300x300m land use classes [52], 1x1km economic activity derived from night-time light intensity [53], socioeconomic indicators based on geo-located Demographic and Health Surveys [54], 1x1km population counts [55], violent conflict incidents [56], and 1x1km particulate matter (PM2.5) air pollution [57].[4] To explore heterogeneity in mining impacts based on governance, we further intersect mine locations with subnational (ADM1-level, i.e. state or province) measures of corruption intensity [40] and intersect mining companies' headquarters locations with country-level indicators of governance quality [48]. We draw annual data on critical mineral and metal commodity prices from the International Monetary Fund [58] and USGS [59]. More detailed descriptions of data sources are provided in Appendix A.1.

4.2 Fixed Effects Regressions Leveraging Commodity Price Shocks

Our empirical strategy leverages variations in global mineral and metal prices to identify local effects of price shocks around mines.[5] Changes in global commodity prices

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[3] 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 low numbers of mines missing from the database, 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 [51]. 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 little environmental or social protections or 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.

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

[5] Critical mineral and metal prices were characterized by substantial growth and high volatility between 2000 and 2022, with some minerals or metals exhibiting 200-750% real price increases and, in other cases, 80% price crashes relative to year 2000 values. Commodity price series are plotted in Appendix Figure A2. In general, prices for battery inputs rose sharply between 2002 and 2012 and again from 2020 to 2022, but

are exogenous to local characteristics, trends, and mining decisions because each individual mine is a price-taker globally. Positive price shocks increase mining profits [60], generating more local economic surplus and incentivizing greater production [61]. This identification strategy follows an extensive literature on mining impacts [6, 62]. For mine i producing commodity m located in country c and observed at time t, we estimate:

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

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. To investigate differences between critical and non-critical mines, the sample is split across this dimension. 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 "active", defined as having submitted ownership data to the S&P Global Mining and Metals Database [41].

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.[6] 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. 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.

fell in 2023 [1]. Prices for renewable energy inputs have increased by approximately 100% in real terms since 2000, with the exception of aluminum.

[6]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 [63].

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. The subnational corruption index (SCI) measures local governance conditions under which the mine's owners operate. 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 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 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. Finally, baseline mine characteristics interacted with time trends reduce the scope for omitted variable bias at the mine level.

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Declarations

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Conflict of interest/Competing interests
The authors declare no competing interests.

Ethics approval and consent to participate
Not applicable. This study did not involve human participants, animals, or sensitive data requiring ethical approval.

Consent for publication
Not applicable. This manuscript does not contain data from individual persons.

Data availability
All shareable datasets analyzed in this study will be made available for download in a public replication repository upon publication.

Materials availability
Not applicable. No new materials or reagents were developed or used in this study beyond publicly available datasets and resources.

Code availability
All code used for data cleaning and analysis will be made available for download in a public replication repository upon publication.

Author contribution
All authors contributed equally to the study conception, design, analysis, and manuscript preparation. All authors read and approved the final manuscript.

Appendix A

A.1 Data Description

Mine Locations and Characteristics: The primary data source for this paper is the S&P Global Mining and Metals Database [41], 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 [4] and [5]. 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 [41], 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. [53]. 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 outcomes 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 [54]. 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 [55]. 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 [52]. 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 [56]. 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. [57]. These authors provide a global, gridded annual panel dataset at the 1x1km resolution covering 1998-2022.

Biodiversity: Shapefiles denoting biodiversity hotspots are drawn from Global Forest Watch [64]. Hotspots are defined as terrestrial areas where at least 1,500 species of vascular plants ($\geq$0.5% of the world's total) are endemic and at least 70% of the original natural vegetation has been lost. Data on the number of threatened bird, amphibian, and mammal species for each 10x10km grid-square of the terrestrial planet are taken from [65].

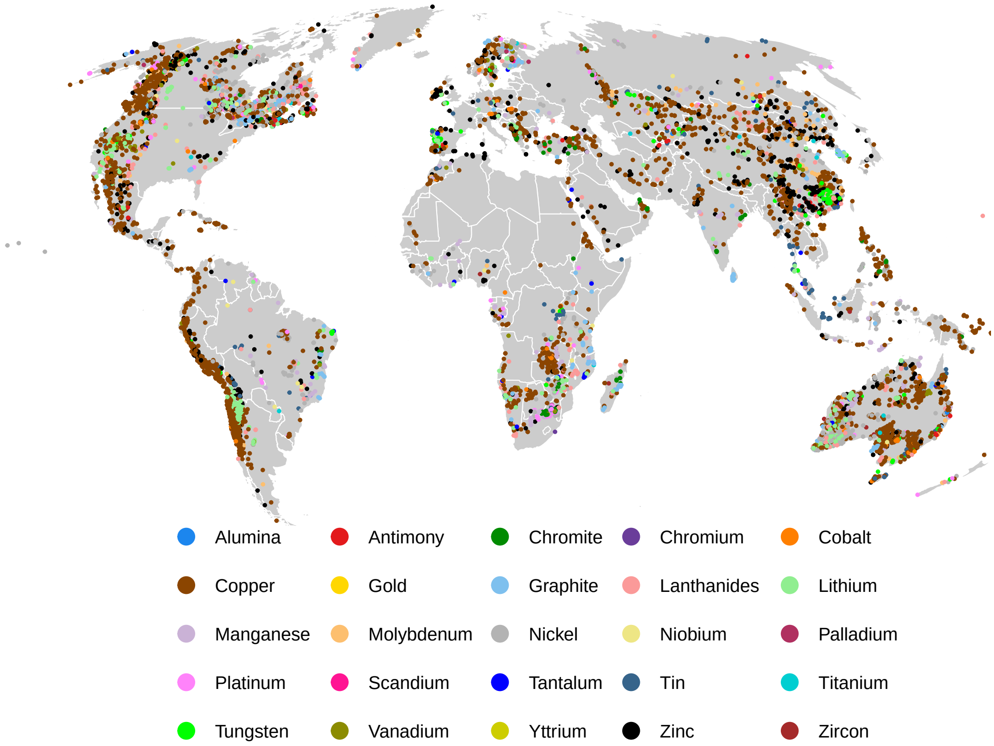
Commodity Prices: Annual data are commodity prices for minerals and metals are drawn from the International Monetary Fund's Primary Commodity Prices Database [58] and the United States Geological Survey's Mineral commodity summaries [59]. Prices are deflated to constant 2010 values using the World Bank 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 [40] 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 [48]. We compute the average of these measures at baseline (2000) to create an aggregate governance index measure for each country.

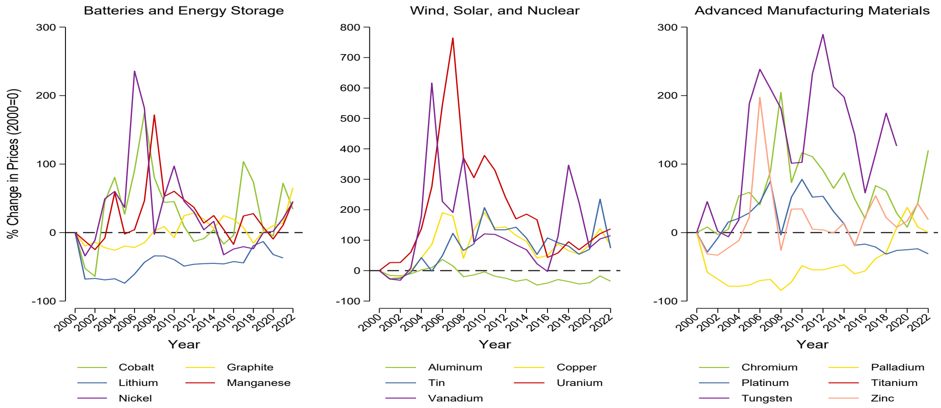
A.2 Appendix Figures

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



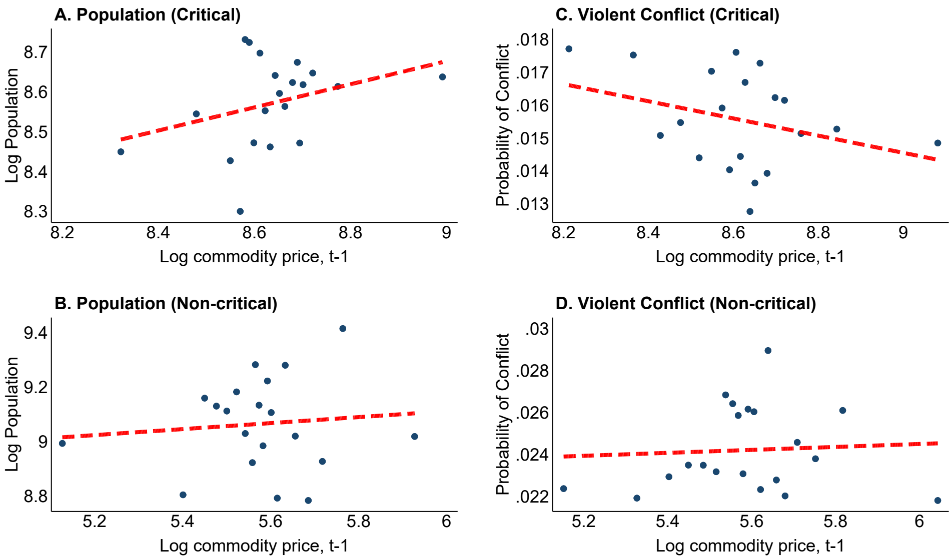
Note: Map shows GPS coordinate locations of all active commercial critical mines from 2000-2022. Critical minerals definition can be found in Appendix A.1. Map locations are drawn from the S&P Global Mining and Metals Database [41].

Fig. A2: Price indices of key critical minerals over time, by usage type



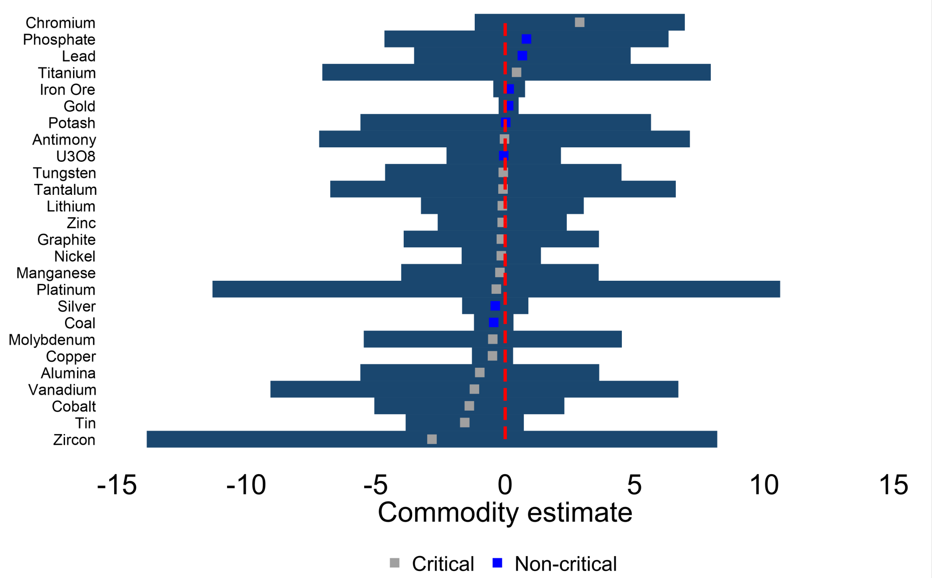
Note: Nominal commodity prices are indexed to base year 2000 = 100 and deflated using the World Bank's world GDP deflator, thus reflecting percentage changes in real prices since 2000. Key commodities are organized by their typical sector of usage. Price data are drawn from International Monetary Fund [58] and USGS [59].

Fig. A3: Additional socioeconomic effects of mineral price shocks



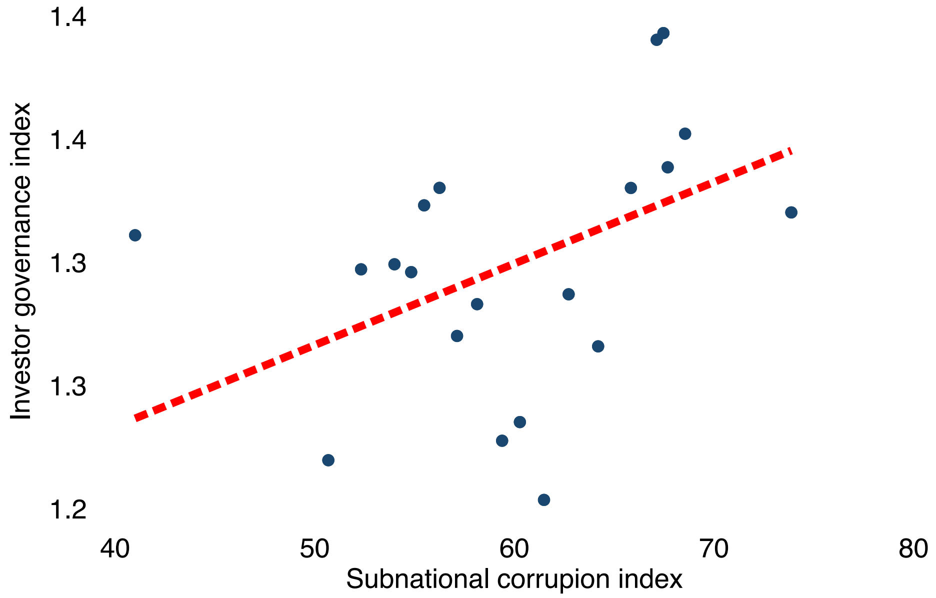
Note: All scatterplots are binned at 20 quantiles of the distribution of log commodity prices, residualizing commodity fixed effects, country-by-year effects, and controls for initial MNC ownership, shareholder HHI, home-country GDP per capita, firm size, mine age, and latitude, interacted with year indicators. 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. Sample is all active mine-years from 2000-2022 for which the outcome variable is non-missing.

Fig. A4: Effects of price shocks on deforestation by critical and non-critical minerals



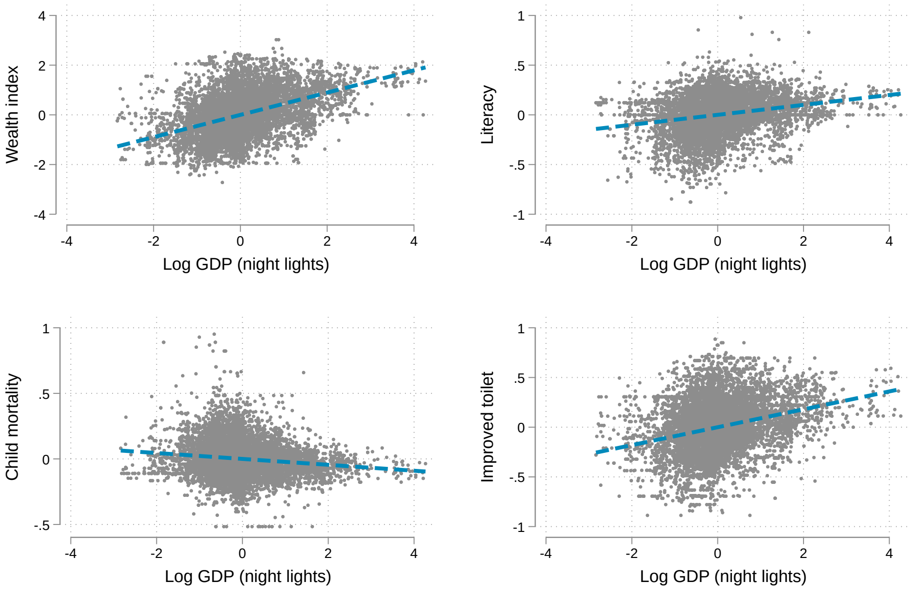
Note: Figure shows estimates from commodity-specific regressions of on forest cover on commodity prices. Bars indicate robust 95% confidence intervals. Sample is all mines in tropical countries with greater than 20% baseline forest cover.

Fig. A5: 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.

Fig. A6: 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 active mine-years from 2000-2019 for which DHS data is available.

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 local environmental and socioeconomic outcomes

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
Log price, $t-1$	-3.262**	-0.001	0.086***	0.260**	-0.002
	(1.641)	(0.008)	(0.024)	(0.110)	(0.002)
Observations	15471	88441	69829	16506	89159
R^2	0.229	0.843	0.587	0.646	0.283
Panel B: Non-critical minerals					
Log price, $t-1$	-1.427*	0.048***	0.026	0.119**	0.003**
	(0.857)	(0.005)	(0.016)	(0.051)	(0.001)
Observations	36918	236700	190271	44189	237168
R^2	0.275	0.865	0.683	0.643	0.346
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 active 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 A3: 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)
Panel A: Critical Minerals					
Log price, $t-1$	-28.722**	0.120	0.518**	1.628***	0.011
	(13.976)	(0.099)	(0.255)	(0.512)	(0.022)
Log price, $t-1$ × Subnational corruption index	0.422*	-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^2	0.329	0.702	0.492	0.561	0.258
Panel B: Non-critical minerals					
Log price, $t-1$	5.843	0.222***	0.231**	2.001***	0.012
	(7.540)	(0.034)	(0.101)	(0.232)	(0.008)
Log price, $t-1$ × Subnational corruption index	-0.098	-0.002***	-0.004**	-0.031***	-0.000
	(0.137)	(0.001)	(0.002)	(0.003)	(0.000)
Observations	10982	75798	61832	14343	75798
R^2	0.259	0.863	0.618	0.591	0.227
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 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 active 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 A4: 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)
Panel A: Critical Minerals					
Log price, $t-1$	-6.914***	0.007	0.095***	0.324***	-0.003
	(1.955)	(0.009)	(0.031)	(0.121)	(0.002)
Log price, $t-1$ × Home governance index	2.112**	-0.014**	-0.022	-0.045	-0.000
	(1.013)	(0.007)	(0.020)	(0.039)	(0.002)
Observations	12196	74689	63112	15196	75296
R^2	0.234	0.842	0.581	0.641	0.262
Panel B: Non-critical minerals					
Log price, $t-1$	-0.070	0.047***	-0.002	0.113**	0.001
	(0.890)	(0.005)	(0.016)	(0.050)	(0.001)
Log price, $t-1$ × Home governance index	-0.754**	0.009***	0.013*	0.011	0.001
	(0.378)	(0.002)	(0.007)	(0.013)	(0.001)
Observations	34717	214851	184199	43740	215270
R^2	0.273	0.865	0.686	0.648	0.317
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 active 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 A5: Impact of price shocks on mine output

Outcome	Log output		Producing		Log output		Producing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Critical Minerals								
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^2	0.940	0.949	0.620	0.665	0.941	0.949	0.626	0.670
Panel B: Non-critical minerals								
Log price, $t-1$	0.099***	0.055	0.083***	0.046***				
	(0.030)	(0.034)	(0.004)	(0.005)				
Log price, $t-2$					0.089***	0.052	0.145***	0.089***
					(0.030)	(0.036)	(0.005)	(0.005)
Observations	38654	38654	266401	266401	36754	36754	261464	261464
R^2	0.901	0.909	0.556	0.615	0.905	0.912	0.566	0.623
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 active 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 local GDP: robustness to distances

Distance (km)	0-5	5-10	10-15	15-20	20-25
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
Log price, $t-1$	0.090***	0.103***	0.089***	0.067***	0.092***
	(0.032)	(0.028)	(0.027)	(0.026)	(0.027)
Observations	69359	69359	69412	69446	69446
R^2	0.461	0.495	0.522	0.536	0.542
Panel B: Non-critical minerals					
Log price, $t-1$	0.024	0.025	0.031*	0.034*	0.021
	(0.021)	(0.019)	(0.018)	(0.018)	(0.017)
Observations	189895	189895	189933	189971	189997
R^2	0.595	0.615	0.632	0.643	0.647
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 active 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 air pollution: robustness to distances

Distance (km)	0-5	5-10	10-15	15-20	20-25
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
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^2	0.837	0.838	0.839	0.841	0.843
Panel B: Non-critical minerals					
Log price, $t-1$	0.048***	0.048***	0.048***	0.048***	0.047***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	236180	236180	236245	236255	236290
R^2	0.863	0.863	0.864	0.865	0.865
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. PM2.5 is measured as log of the total concentration of fine particulate matter, in g/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 active 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 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)
Panel A: Critical Minerals						
Log price, $t-1$	-2.220	-3.261**	-1.219	-1.472*	-2.791***	-2.222***
	(1.523)	(1.632)	(1.817)	(0.775)	(0.682)	(0.610)
Observations	25486	15315	10782	69752	47328	38305
R^2	0.311	0.222	0.230	0.420	0.250	0.176
Panel B: Non-critical minerals						
Log price, $t-1$	-1.931***	-1.427*	-0.637	-3.520***	-1.492***	-0.763*
	(0.649)	(0.856)	(0.878)	(0.470)	(0.468)	(0.418)
Observations	63801	36833	25943	194822	128123	104173
R^2	0.331	0.273	0.232	0.387	0.243	0.139
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × 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 active 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 lags

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
Log price, $t-2$	-3.307**	-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^2	0.229	0.842	0.587	0.646	0.281
Panel B: Non-critical minerals					
Log price, $t-2$	-1.876**	0.055***	0.022	0.106**	0.000
	(0.952)	(0.005)	(0.017)	(0.050)	(0.001)
Observations	36248	231850	185450	44189	232309
R^2	0.275	0.865	0.683	0.643	0.346
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 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 active 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: robustness to leads

Outcome	Forest cover	Log PM2.5	Log GDP	Log Pop	Conflict
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
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^2	0.230	0.843	0.587	0.647	0.284
Panel B: Non-critical minerals					
Log price, t	-0.846	0.003	0.023	0.097**	0.004***
	(0.526)	(0.004)	(0.016)	(0.046)	(0.001)
Observations	37577	241505	195047	48937	241982
R^2	0.275	0.865	0.682	0.647	0.345
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 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 active 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 on outcomes: robustness to shock measurement

Sample	Non-critical				Critical			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Forest cover								
Price shock 0.5SD	-0.281				-0.263			
	(0.229)				(0.254)			
Three-year 0.5SD shock		-0.725***				-0.616**		
		(0.240)				(0.293)		
Price shock 1SD			-0.210				-0.332	
			(0.201)				(0.290)	
Three-year 1SD shock				-0.819***				-0.775**
				(0.271)				(0.336)
Observations	130550	130550	130550	130550	47824	47824	47824	47824
R^2	0.244	0.244	0.244	0.244	0.250	0.250	0.250	0.250
Panel B: Local GDP								
Price shock 0.5SD	-0.005				0.039***			
	(0.007)				(0.009)			
Three-year 0.5SD shock		0.015*				0.051***		
		(0.008)				(0.010)		
Price shock 1SD			-0.021**				0.039***	
			(0.009)				(0.012)	
Three-year 1SD shock				0.009				0.064***
				(0.009)				(0.012)
Observations	194766	194766	194766	194766	70925	70925	70925	70925
R^2	0.682	0.682	0.682	0.682	0.581	0.581	0.581	0.581
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, in parentheses, are clustered at the mine level. Forest cover (Panel A) 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 (Panel B) 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 active 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 A12: Impact of price shocks: pre-period outcomes

Sample	Non-critical		Critical	
Outcome	GDP	Forest	GDP	Forest
	(1)	(2)	(3)	(4)
Log price, $t-1$	-0.011	0.457	-0.024***	1.096
	(0.009)	(0.684)	(0.009)	(0.865)
Commodity FE	Yes	Yes	Yes	Yes
Year × Country FE	Yes	Yes	Yes	Yes
Year × Controls	Yes	Yes	Yes	Yes
Observations	193762	36562	80538	13489
R^2	0.639	0.271	0.612	0.208

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

Outcome	Wealth index		Literacy rate		Child mortality		Improved sanitation	
Critical	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP	0.420***	0.479***	0.041***	0.066***	-0.022***	-0.029***	0.081***	0.111***
	(0.014)	(0.023)	(0.003)	(0.006)	(0.002)	(0.003)	(0.004)	(0.007)
Year × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8063	2698	8063	2698	8063	2698	8063	2698
R^2	0.441	0.582	0.785	0.683	0.484	0.435	0.508	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 active mine-years from 2000-2019 for which DHS data is available. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Impact of price shocks on DHS wealth index

Outcome	DHS Wealth index				
	(1)	(2)	(3)	(4)	(5)
Panel A: Critical Minerals					
Log price, $t-1$	0.140***	0.125***	0.475***	0.355**	0.018
	(0.033)	(0.033)	(0.088)	(0.138)	(0.159)
Observations	1404	1404	1404	1404	1404
R^2	0.020	0.133	0.230	0.281	0.454
Panel B: Non-critical minerals					
Log price, $t-1$	0.059***	0.091***	0.332***	0.358***	0.314***
	(0.014)	(0.016)	(0.047)	(0.093)	(0.108)
Observations	3588	3588	3588	3588	3588
R^2	0.009	0.051	0.072	0.140	0.310
Year FE	No	No	No	Yes	No
Year × Country FE	No	No	No	No	Yes
Commodity FE	No	No	Yes	Yes	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. 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 active mine-years from 2000-2019 for which DHS data is available. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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