Critical Minerals, Geopolitics, and the Green Transition*

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Abstract

The green energy transition will be fueled by the mining and processing of lithium, nickel, and cobalt, which are critical for the production of advanced batteries. These minerals are concentrated geographically but traded globally. We study the geopolitical implications of industrial policy in key mining countries, and we discuss the consequences for green technology adoption worldwide. We highlight how upstream resource concentration and downstream technology choices give rise to supply chain vulnerability, policy spillovers across mineral markets, and the potential for mineral cartels.

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1 Introduction

The global transition toward clean energy calls for the large-scale adoption of advanced battery technology. This green future depends crucially on the extraction, processing, and refining of lithium, nickel, cobalt, and other minerals that are essential inputs for battery technologies. These critical minerals are traded in global markets, but their geological endowments are sharply concentrated: the top three producing countries account for 70 to 85% of world output, far exceeding the concentration observed in fossil fuel markets. As governments pursue ambitious decarbonization targets, the combination of concentrated upstream supply and growing downstream demand makes critical minerals a central bottleneck in the green transition.

This paper studies how concentration in upstream mineral endowments interacts with downstream technology choices. We quantify how mineral endowments, extraction costs, and policy interventions shape mineral prices, battery technology adoption, and the distribution of welfare across producing and consuming countries. We highlight three broad themes. First, because the major minerals used in batteries are jointly demanded and differ across technologies, upstream shocks propagate across markets through both complementarity and substitution. Second, because production is geographically concentrated and supply elasticities are modest, producer countries can meaningfully influence global mineral prices even without explicit coordination. Third, the resulting price movements can either slow or accelerate the green transition depending on how they shift adoption across battery technologies.

Our starting point is that mineral endowments make concentration an intrinsic feature of this setting. Upstream mineral production is dominated by a small number of countries: Australia for lithium, Indonesia for nickel, and the Democratic Republic of the Congo (DRC) for cobalt. Extraction costs vary widely across mines due to differences in ore grade, deposit type, and access to infrastructure, which creates persistent heterogeneity in supply responses. Downstream battery technologies differ sharply in their mineral intensities. We focus on nickel-cobalt-manganese (NMC), nickel-cobalt-aluminum (NCA), and lithium iron phosphate (LFP) battery chemistries, which naturally vary in their use of lithium, nickel, and cobalt. These differences in mineral recipes imply that mineral price shocks change the relative costs of competing battery technologies, creating substitution patterns that can amplify or dampen upstream supply disruptions.

We build a global equilibrium framework that embeds these upstream and downstream elements. On the demand side, we estimate an almost ideal demand system using manufacturer-level data on installations by battery technology around the world. The data span the universe of electric vehicle (EV) models produced between 2018 and 2024. The estimated demand system provides rich substitution patterns across NCA, NMC, and LFP technologies and allows us to discipline how changes in mineral prices reallocate demand across technologies. We find that demand is elastic for all battery technologies, with large cross-price substitution toward LFP when nickel-heavy technologies become more expensive.

On the supply side, we construct a new mine-level panel covering 397 lithium, nickel, and cobalt mines worldwide. These mines account for 92% of world lithium production, 92% of cobalt production, and 80% of nickel production. For each mine, we observe production, capacity, ore grade, and detailed cost breakdowns. We use these data to recover mine-level supply curves, exploiting heterogeneity in ore grade and observed cost structures. We find modest but heterogeneous supply elasticities across countries, reflecting differences in industry costs. These low elasticities imply that price changes translate into large shifts in producer surplus and that even unilateral policy actions can meaningfully move world prices.

We embed our demand and supply estimates in a quantitative model of global trade that links mineral markets to battery technology adoption. This simple equilibrium framework delivers two core insights. First, the sign and magnitude of cross-price spillovers depend on whether minerals are gross complements or substitutes in demand. Consider lithium and nickel. Complementarity arises because lithium and nickel are used jointly in NMC and NCA technologies. But substitutability arises because higher nickel prices shift demand toward LFP, which does not use nickel. Whether complementarity or substitutability dominates is an empirical question. Second, because battery technologies differ in their mineral intensities, upstream shocks can raise or lower aggregate green adoption depending on the relative strength of substitution across technologies.

We use the framework to analyze several policy-relevant counterfactuals. First, we quantify global supply chain vulnerability by removing a major producer from the market: eliminating Australia's lithium supply raises lithium prices dramatically, with large negative impacts on consuming countries. Second, we study the cross-country spillovers from unilateral mineral policy. Indonesian nickel policy, as motivated by existing domestic industrial policy, raises global nickel prices but also reduces NMC and NCA adoption as consumers shift instead toward LFP. Green adoption falls overall because lower adoption of NMC and NCA dominates higher adoption of LFP. Third, we examine the welfare consequences of country-level taxes and find large distributional effects across producers, as well as spillovers onto other minerals through cross-price interactions. With multiple minerals, even a country that succeeds in raising surplus in one market can lose in another.

Taken together, our results show that the geopolitics of critical minerals differ fundamentally from the geopolitics of fossil fuels. In particular, our technology-specific mineral intensities create complementarity – through the joint use of multiple minerals in each battery technology – that has no direct analogue in oil or natural gas markets. This complementarity acts in opposition to the typical substitution across technologies, shaping both the aggregate and distributional impacts of industrial policy in this setting. Policies that unilaterally raise mineral prices can slow green adoption and may also harm other mineral producers.

We build on several bodies of work. First, we contribute to a broad literature on trade and the environment, particularly as it relates to the environmental impacts of unilateral policy (Rauscher 1997, Copeland and Taylor 2003, Kortum and Weisbach 2017, 2023, Copeland et al. 2022, Hsiao 2025). We show that industrial policy in mineral-endowed countries has global implications through trade, and we emphasize high levels of market concentration that lead to strong spillover effects in our setting. This market concentration has geopolitical implications, which relates to a growing literature on geoeconomics (Hirschman 1945, Blackwill and Harris 2016, Mohr and Trebesch 2024, Clayton et al. 2025a,b). We highlight supply chain vulnerability and the potential for cartels in an industry of key importance for global climate targets.

Second, we connect to a literature on market concentration in the fossil fuel sector. We relate most closely to studies that emphasize market power and the Organization of the Petroleum Exporting Countries (OPEC), as well as their implications for the green transition (Asker et al. 2024, De Canniere 2024, Kellogg 2024).[1] Our

[1] More broadly, we relate to prior work that highlights the role of international markets (Farrokhi

emphasis on substitution parallels the margin of substitution toward green energy in this literature: as OPEC exercises market power and drives up oil prices, consumers can respond by substituting toward green energy. Similarly, if Indonesia drives up nickel prices, then consumers can substitute away from nickel-based batteries. We add the novel margin of complementarity: Indonesian nickel policy affects all mineral-producing countries, including that produce lithium and cobalt, because green technology uses all of these minerals jointly. This complementarity creates the potential for otherwise competing countries to form multi-mineral cartels.

Third, we relate to a recent and growing literature on the EV industry (Remmy 2022, Kwon 2023, Allcott et al. 2024, Barwick et al. 2024, Head et al. 2024, Barwick et al. 2025). These studies largely focus on the downstream stages of the supply chain, including the analysis of EV subsidies for the final consumer. We focus instead on mining and processing upstream, and we show how upstream mineral concentration affects downstream EV adoption. A small set of mineral-endowed countries will shape our progress toward a greener future. This paper studies the geopolitics of that green transition.

2 Background and Data

We describe the market for critical minerals, and we discuss our data sources. We present three stylized facts that inform our analysis.

2.1 Institutional details

Critical minerals

While the definition of "critical minerals" varies, many countries identify critical minerals with criteria that capture a combination of supply vulnerability and low demand substitutability. In the United States, the Energy Act of 2020 mandates the Secretary of the Interior, acting through the United States Geological Survey (USGS), to maintain a list of critical minerals that must be updated at least every

2020, Bornstein et al. 2023, Abuin 2024), the impact of sanctions (Johnson et al. 2023a,b, Moll et al. 2023, Bachmann et al. 2024), and the margins of adjustment to scarcity (Popp 2002, Hassler et al. 2021, Alfaro et al. 2025).

Table 1: World mineral demand by end use (2022-2024)

	Lithium	Cobalt	Nickel	Graphite	Copper	Manganese
EV batteries	65%	45%	11%	10%	4%	1%
Non-EV batteries	20%	25%	-	15%	-	-
Ceramics and glass	4%	-	-	-	-	-
Metals/alloys	-	19%	67%	-	-	90%
Wiring/infrastructure	-	-	-	-	92%	-
Refractories	-	-	-	40%	-	-
Other	11%	11%	22%	35%	4%	9%

Values for lithium, cobalt, nickel are from IEA Global EV Outlook (2024). Values for copper, manganese, graphite are from USGS, IRENA, BHP Insights, and Fastmarkets.

three years. Between 2018-2022, the list grew from 35 to 50 minerals. According to USGS, "the Energy Act of 2020 defined critical minerals as those that are essential to the economic or national security of the United States; have a supply chain that is vulnerable to disruption; and serve an essential function in the manufacturing of a product, the absence of which would have significant consequences for the economic or national security of the U.S."

While US criteria focus on a mineral's criticality for economic and national security, other countries such as Canada emphasize a mineral's criticality for the energy transition. Hence, an important distinction is between minerals that are critical for the energy transition and minerals that are critical for national security. In this paper, we focus on the former: battery-specific minerals such as lithium, nickel, and cobalt. We abstract from rare-earth elements since they are more related to national security concerns because of their military applications.

The degree to which mineral demand is driven by the EV battery sector relative to other industrial sectors varies widely across commodities. Table 1 shows the EV battery share of total mineral demand is over 65% for lithium, 45% for cobalt demand, and 11% for nickel. For graphite, copper, and manganese, EV shares are only 10%, 4% and 1%. Given we have rich demand side data from the EV sector but not for all the other industrial sectors, we restrict our set of minerals in this paper to lithium, nickel, and cobalt.[2]

[2] We do not include graphite both because its share of demand accounted for by EV batteries is not very large at 10% and because there are alternatives to natural graphite, called synthetic

Mineral production

Mineral production consists of three broad stages: extraction, processing, and refining. Mines typically handle extraction and processing, while refining is handled by midstream processors. Differences in deposit types creates differences in the production process arises across minerals. Most critical minerals are found in hard-rock deposits. Other critical minerals, including lithium in South America, are found in liquid brine deposits. In the first stage, extraction takes the form of excavation for hard rock and surface pumping for brine deposits. In the second stage, initial processing is also known as "beneficiation." For hard rock, it involves the separation of mineral-bearing ores from waste rock. For brine, the extracted liquid is left to evaporate by sunlight in open-air pools, leaving behind a concentrated solution. Further processing creates the final concentrate, such as spodumene or nickel concentrate. In the third stage, midstream processors refine the concentrate to battery-grade chemical products, such as lithium carbonate or nickel sulfate.

Battery technology

The EV battery market consists of two primary cathode chemistries: nickel-manganese-cobalt (NMC) and lithium-iron-phosphate (LFP). Both use lithium, which moves between the anode and cathode when charging and discharging. In an NMC cathode, nickel provides energy density, and cobalt provides thermal stability. In an LFP cathode, lithium iron phosphate plays both roles. The nickel in NMC batteries is particularly effective at providing high energy density, which allows for longer driving range. NMC batteries are often more expensive and more common in the higher-end vehicles that dominate the North American EV market. At the same time, their high nickel content creates price volatility concerns because of active market intervention and export bans in Indonesia, which is the largest nickel producer. Moreover, their high cobalt content creates ethical sourcing concerns because of the prevalence of informal mining in the DRC, which is the largest cobalt producer.

By contrast, the input materials for LFP batteries – iron sulfates and phosphoric acid – are more widely distributed across the world. LFP batteries are cheaper but have lower energy density, resulting in shorter driving range and making them most

graphite, that are already common and not subject to the same geographic endowments as the minerals that are the focus of this paper.

suitable for the dense urban markets that prevail in China. While LFP is the most prevalent battetry technology in the Chinese EV market, NMC batteries are more common in the European and North American markets (IEA 2024c). Between 2021 and 2023, the LFP share of the EV market grew from 52% to 67% in China, from 4% to 6% in Europe, and from 2% to 7% in the United States (IEA 2024b).

We also consider nickel-cobalt-aluminum (NCA) batteries, for which demand has grown less quickly than for NMC and LFP. NCA batteries have greater nickel content than NMC batteries, thereby amplifying the trade-offs between nickel and lithium batteries. That is, relative to NMC batteries, NCA batteries have even higher cost and less thermal stability, but they also have higher energy density and longer range.

2.2 Data sources

Mineral supply

We obtain mine-level data from three proprietary sources: Global Data, Benchmark Mineral Intelligence, and S&P Global. We combine information across these sources to construct a mine-level panel from 2010 to 2024 for lithium, nickel, and cobalt. Our final sample consists of 397 mines. The mines in our sample account for 92% of world production for lithium, 92% for cobalt, and 80% for nickel. We observe production both in units of processed minerals and crude ore. Other mine characteristics include extraction and production capacity, ore grade, ownership structure, mine type, mining method, and average costs by cost category.[3]

Mineral demand

We construct mineral demand using data on EV battery installations and mineral intensities of each battery technology. Battery installation is observed in EV sales data provided by Rho Motion for 2018-2024. The granularity of the data is at the battery technology-make-model-country level. For example, one observation would be the number of NMC batteries installed in all Tesla Model S units produced in USA and sold in Canada in 2022. We map units of batteries to units of minerals using mineral input recipes for each technology from BatPac (Argonne National Library).

[3] Mine types include underground and aboveground. Mining methods include open pit, stoping, and block caving. Cost categories include mining/extraction costs, processing costs, and royalties.

Prices

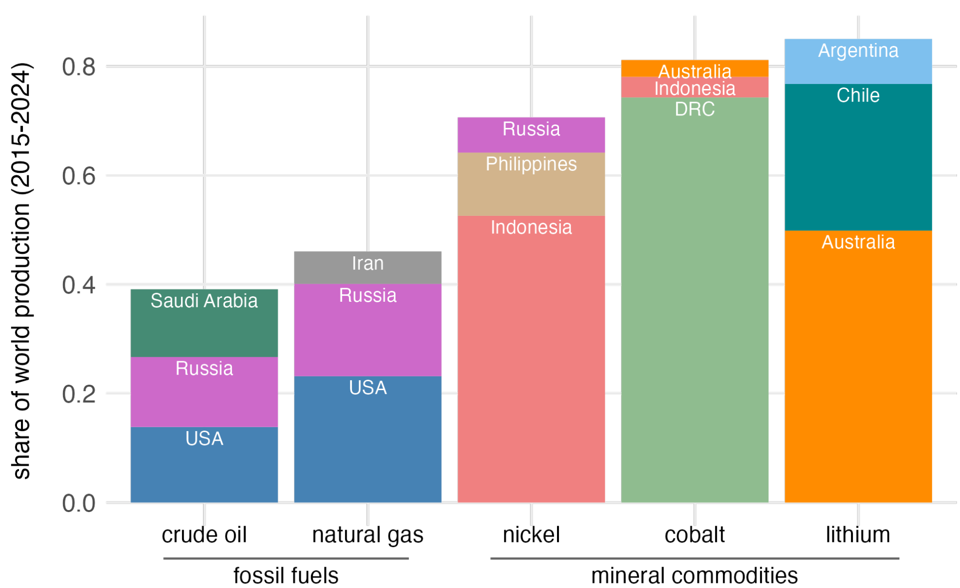
We obtain mineral prices from S&P Global for lithium, nickel, and cobalt for 2010 to 2024 at monthly frequency. Battery prices are from Benchmark Minerals for 2021 to 2024 at monthly frequency. Importantly, prices are reported separately for each battery technology, including NMC, NCA, and LFP.

2.3 Stylized facts

Fact 1: Mineral endowments are geographically concentrated

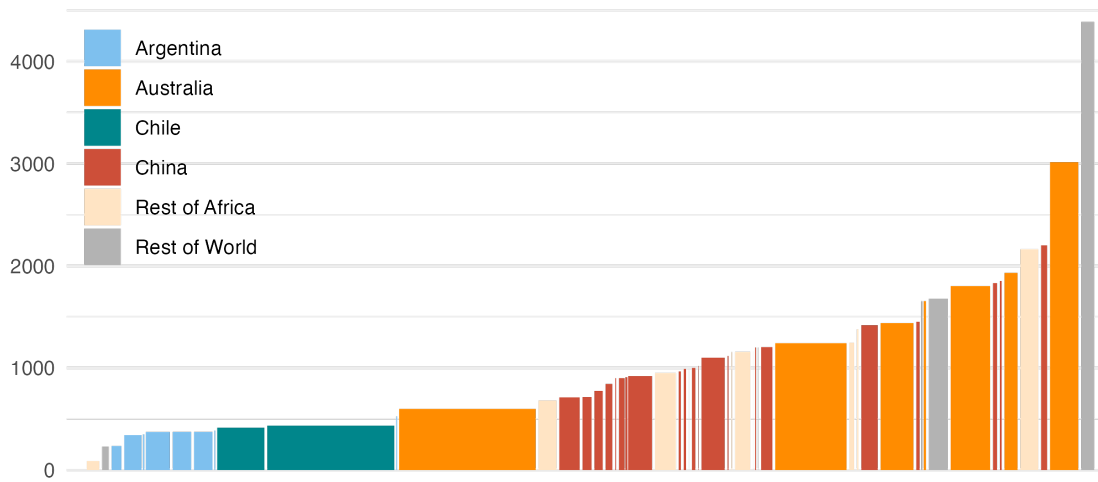
The uneven distribution of geological endowments leads to concentration in production for both minerals and fossil fuels, but minerals markets are especially concentrated. Figure 1 shows that the market share of the top three producing countries ranges from 40 to 50% for fossil fuels, but a substantially higher 70 to 85% for mineral commodities. Concentration is particularly high for lithium and cobalt, which are more nascent markets in which demand is driven primarily by the battery sector. Concentration is somewhat lower for nickel, which is a more mature and general-use

Figure 1: Market concentration in energy and mineral production (2015-2024)



We aggregate production values to the country level from our mine-level data. Crude oil data come from US EIA and include lease condensates. Natural gas data are for 2022 and come from IEA.

Figure 2: Mine-level mining and extraction costs (USD/t LCE, 2024)



The cost values from which this figure is constructed are mine-level microdata from Benchmark Mineral Intelligence for the year 2024. Each vertical bar is a mine, with bar width proportional to mine output. Mining and extractions costs are reported in USD per tonne of lithium carbonate equivalent (LCE). For brine-based operations the extraction costs correspond largely to pumping costs, while for hard-rock operations they correspond to excavation costs.

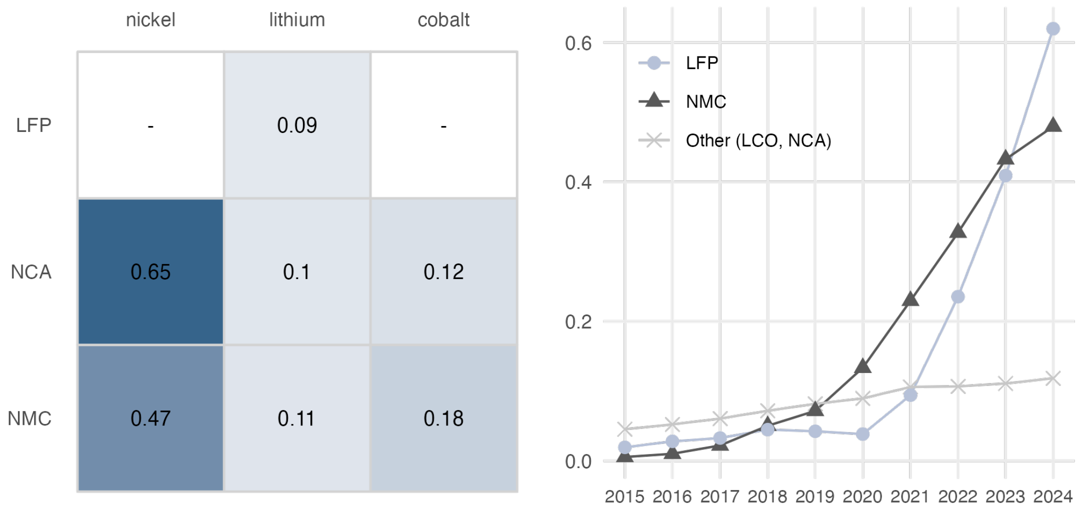
commodity, but concentration remains elevated relative to fossil fuels. Moreover, battery-driven demand growth has also exceeded general-use demand growth in the past decade, as the global adoption of green technology creates strong downstream demand for each of these mineral commodities.

Fact 2. Extraction costs are highly heterogeneous across mines

Our mine-level data reveal substantial heterogeneity in production costs across mines. This heterogeneity reflects large variation in the accessibility and purity of mineral deposits. Across mineral markets, lithium in South America is typically found in underground liquid brine deposits that require capital-intensive pumping to the surface, while cobalt in the DRC can be mined artisanally because it is accessible at surface level. Within mineral markets, geological fundamentals – deposit types and ore grades – drive heterogeneity in costs. Figure 2 shows mine-level extraction costs for lithium in units of USD per ton of lithium-carbonate-equivalent. Brine operations in South America have lower costs because part of the beneficiation process consists of evaporation by natural sunlight, a procedure that is not available for hard-rock operations in Australia. Heterogeneity in ore grade also plays a major role in

Figure 3: Battery-mineral recipes (kg/kWh) and global adoption

(a) Recipes (b) Adoption



On the left, we plot the mineral intensity matrix for selected battery technologies and minerals. NMC values are averaged across all NMC varieties. Appendix A.1 shows the full mineral intensity matrix. On the right, we plot newly installed capacity worldwide for each battery technology with data from Benchmark Mineral Intelligence.

determining cost effectiveness. Ore grades in the DRC average 0.5%, compared to only 0.1% in the rest of the world (Figure A4).

Fact 3. Mineral recipes vary by battery technology

Battery technologies differ significantly in their mineral intensity (Figure 3a). Changes in mineral prices thus have differential impacts on battery prices. Before 2017, price stability for nickel and cobalt facilitated NMC adoption. From 2021, nickel and cobalt prices began to rise faster than lithium prices as NMC demand outpaced supply. It is in this market environment that LFP adoption began to accelerate. The global market share of LFP grew sharply from less than 5% to more than 60% between 2020 and 2024, overtaking NMC by 2024 (Figure 3b). The shift to LFP is expected to create headwinds for nickel and cobalt producers (Fastmarkets).

3 Theory

We present a stylized model with two minerals, which serve as inputs for green technology. We study the impacts of market power at the country level. We characterize patterns of complementarity and substitution among minerals, and we discuss implications for geopolitics and the green transition.

Minerals and technologies

We focus on lithium and nickel. First, we consider two mining countries $m \in \{\ell, n\}$. Country ℓ produces only lithium, while country n produces only nickel. Second, we consider three technologies $j \in \{L, N, T\}$. Green technology L uses lithium and nickel with proportions λ_L and ν_L, respectively, and technology N uses proportions λ_N and ν_N. Lithium and nickel are sole inputs, such that $\lambda_L + \nu_L = \lambda_N + \nu_N = 1$. Green technology L relies more heavily on lithium ($\lambda_L > \lambda_N$), and technology N more heavily on nickel ($\nu_N > \nu_L$). Traditional technology T relies on neither mineral. Our notation uses superscripts to describe upstream minerals m and subscripts to describe downstream technologies j.

Supply and demand

Mining countries supply minerals $m \in \{\ell, n\}$. Country m supplies s^m units of its mineral as a function of world price p^m and its industrial or trade policy τ^m.

$$s^m(p^m + \tau^m), \quad \sigma^m = \frac{\partial s^m}{\partial (p^m + \tau^m)} > 0 \tag{1}$$

We denominate the value of policy in dollars. Supportive policy raises the quantity supplied at any given price, while restrictive policy does the opposite.

Consumers demand technologies $j \in \{L, N, T\}$. Technologies are substitutes, and demand d_j is given by

$$d_j(p_L, p_N, p_T), \quad \delta_{jj} = \frac{\partial d_j}{\partial p_j} < 0, \quad \delta_{jj'} = \frac{\partial d_j}{\partial p_{j'}} > 0 \quad \text{for} \quad j \neq j'. \tag{2}$$

When consumers can switch among technologies, own-price demand elasticities are negative while cross-price demand elasticities are positive. Demand for technology determines demand for minerals.

$$d^\ell = d_L\lambda_L + d_N\lambda_N, \quad d^n = d_L\nu_L + d_N\nu_N$$

We assume that manufacturers of green technologies L and N are perfectly competitive, such that mineral prices pin down green technology prices.

$$p_L = p^\ell\lambda_L + p^n\nu_L, \quad p_N = p^\ell\lambda_N + p^n\nu_N$$

In equilibrium, mineral prices clear markets for minerals.

$$s^\ell(p^\ell + \tau^\ell) = d^\ell(p^\ell, p^n), \quad s^n(p^n + \tau^n) = d^n(p^\ell, p^n) \tag{3}$$

We assume for simplicity that the supply of traditional technology T is perfectly elastic, such that price p_T is fixed.

Complementarity and substitution

We can characterize demand for minerals in terms of demand for technology. These expressions reveal both complementarity and substitution between lithium and nickel. We focus our discussion on lithium, noting analogous expressions for nickel. For $\delta_{jj} < 0$ and $\delta_{jj'} > 0$, the own-price effect of lithium prices is

$$\frac{\partial d^\ell}{\partial p^\ell} = \delta_{LL}\lambda_L^2 + \delta_{NN}\lambda_N^2 + (\delta_{LN} + \delta_{NL})\lambda_L\lambda_N < 0, \tag{4}$$

and the cross-price effect of nickel prices is

$$\frac{\partial d^\ell}{\partial p^n} = \delta_{LL}\lambda_L\nu_L + \delta_{NN}\lambda_N\nu_N + \delta_{LN}\lambda_L\nu_N + \delta_{NL}\lambda_N\nu_L. \tag{5}$$

The own-price effect is negative. Lithium demand falls as lithium prices rise. On the right-hand side of equation 4, the first two terms are negative because $\delta_{LL}, \delta_{NN} < 0$. Higher lithium prices raise prices for both technologies, reducing their demand and thus their use of lithium. The last term is positive because $\delta_{LN}, \delta_{NL} > 0$. Higher lithium prices raise prices most for technology L, which uses more lithium. Demand thus shifts toward technology N, which becomes cheaper in relative terms, thereby raising its use of lithium. This countervailing force mutes the total reduction in lithium demand but does not reverse it. Lithium use still falls on net as consumers shift toward technology N, which is less lithium-intensive than technology L.

The cross-price effect can be negative or positive. Lithium demand can fall or rise as nickel prices rise. That is, lithium and nickel can be either complements or substitutes in demand. On the right-hand side of equation 5, the first two terms are negative because $\delta_{LL}, \delta_{NN} < 0$. These terms capture the complementarity of lithium and nickel through their joint use in both technologies. Higher nickel prices raise prices for both technologies, reducing their demand and thus their use of lithium. The last two terms are positive because $\delta_{LN}, \delta_{NL} > 0$. These terms capture the substitutability of lithium and nickel through consumer switching across technologies. Higher nickel prices raise prices most for technology N, which uses more nickel. Demand thus shifts toward technology L, which becomes cheaper in relative terms, thereby raising its use of lithium. Lithium use rises on net if the shift toward lithium-intensive technology dominates the complementarity from the joint use of lithium and nickel in both technologies.

Geopolitics

We study the global impacts of policy actions τ^m, which countries can implement unilaterally. We again focus our discussion on lithium, noting analogous expressions for nickel. Differentiating equilibrium conditions 3 with respect to τ^ℓ, we obtain the impacts of lithium policy on prices for both minerals. The own-policy effect is negative.[4] Supportive lithium policy raises lithium supply and reduces lithium prices.

$$\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell} = -\frac{\sigma^\ell\left(\sigma^n - \frac{\partial d^n}{\partial p^n}\right)}{\left(\sigma^\ell - \frac{\partial d^\ell}{\partial p^\ell}\right)\left(\sigma^n - \frac{\partial d^n}{\partial p^n}\right) - \frac{\partial d^\ell}{\partial p^n}\frac{\partial d^n}{\partial p^\ell}} < 0$$

[4] The denominator corresponds to the determinant of market-clearing matrix $M(p)$. The determinant is positive under the standard assumptions for equilibrium stability: upward-sloping supply and a negative semidefinite Jacobian for demand.

$$M(p) = \begin{bmatrix} \sigma^\ell & 0 \\ 0 & \sigma^n \end{bmatrix} - \begin{bmatrix} \frac{\partial d^\ell}{\partial p^\ell} & \frac{\partial d^\ell}{\partial p^n} \\ \frac{\partial d^n}{\partial p^\ell} & \frac{\partial d^n}{\partial p^n} \end{bmatrix}$$

Geopolitical implications arise through policy spillovers. That is, lithium policy in country ℓ also affects nickel prices for country n. The impact on nickel prices depends on whether lithium and nickel are gross complements or substitutes.

$$\frac{\mathrm{d}p^n}{\mathrm{d}\tau^\ell} = \left(\frac{\frac{\partial d^n}{\partial p^\ell}}{\sigma^n - \frac{\partial d^n}{\partial p^n}}\right)\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell}$$

If lithium and nickel are complements, then the cross-policy effect is positive because $\frac{\partial d^n}{\partial p^\ell} < 0$. Supportive lithium policy reduces lithium prices, raising nickel demand and nickel prices given the joint use of lithium and nickel. If lithium and nickel are substitutes, then the cross-policy effect is negative because $\frac{\partial d^n}{\partial p^\ell} > 0$. Supportive lithium policy reduces lithium prices, reducing nickel demand and nickel prices as consumers shift toward technology L and away from N.

Green transition

We turn to aggregate implications for the green transition. Countries ℓ and n have different mineral endowments and thus different preferences over technology adoption. But from a climate perspective, technologies L and N are equally effective at reducing carbon emissions relative to traditional technology T. Thus, the green transition depends only on total green adoption

$$d_G = d_L + d_N.$$

Differentiating with respect to lithium policy τ^ℓ,

$$\frac{\mathrm{d}d_G}{\mathrm{d}\tau^\ell} = (\delta_{LL} + \delta_{NL})\left(\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell}\lambda_L + \frac{\mathrm{d}p^n}{\mathrm{d}\tau^\ell}\nu_L\right) + (\delta_{NN} + \delta_{LN})\left(\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell}\lambda_N + \frac{\mathrm{d}p^n}{\mathrm{d}\tau^\ell}\nu_N\right).$$

Own-price demand effects dominate cross-price effects, such that $\delta_{LL} + \delta_{NL} < 0$ and $\delta_{NN} + \delta_{LN} < 0$.

The impact on green adoption again depends on whether lithium and nickel are gross complements or substitutes. If lithium and nickel are complements, then the policy effect is ambiguous because $\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell} < 0$ but $\frac{\mathrm{d}p^n}{\mathrm{d}\tau^\ell} > 0$. On one hand, supportive lithium policy reduces lithium prices and raises lithium adoption. On the other hand, it raises nickel prices and reduces nickel adoption. If lithium and nickel are substitutes, then the policy effect is unambiguously positive because $\frac{dp^\ell}{d\tau^\ell}, \frac{dp^n}{d\tau^\ell} < 0$. Supportive lithium policy reduces both lithium and nickel prices, raising both lithium and nickel adoption. Green adoption rises.

Empirics

Our empirical treatment will work with the same core elements. We model and estimate demand d_j for technologies, as well as supply s^m of minerals. Equilibrium prices (p_j, p^m) clear global markets for technology and minerals, and scientific data on battery-mineral recipes characterize mineral ratios (λ_j, ν_j). Furthermore, we generalize the theory to accommodate many countries, multiple technologies, and multiple minerals. In doing so, we bring the theory to data while also introducing two additional margins of richness. First, heterogeneous endowments across countries allows us to analyze differences in market concentration and the distributional impacts of policy action. Second, heterogeneous policy across countries allows us to compare unilateral and coordinated policy action by mineral-endowed countries.

4 Demand

We model the demand for battery technologies with an almost ideal demand system (Deaton and Muellbauer 1980). We estimate the model with regional panel data on demand by battery technology.

4.1 Model

EV manufacturing

EV manufacturers consume batteries, choosing among available technologies j in region k and period t at global prices p_{jt}. We allow choice sets $\mathcal{J}_{kt}$, which may be subsets of the full set of technologies $\mathcal{J}$, to vary across regions and over time. EV manufacturers allocate budgets X_{kt} across battery technologies taking prices as given. We specify demand in product space with expenditure shares w_{jkt} given by

$$w_{jkt} = \alpha_j + \beta_j \log\left(\frac{X_{kt}}{P_t}\right) + \sum_{j' \in \mathcal{J}} \gamma_{jj'} \log(p_{jt}) + \varepsilon_{jkt}, \tag{6}$$

where price index P_t is of translog form

$$\log(P_t) = \sum_{j \in \mathcal{J}} \alpha_j \log(p_{jt}) + \frac{1}{2} \sum_{jj' \in \mathcal{J}^2} \gamma_{jj'} \log(p_{jt}) \log(p_{j't}). \tag{7}$$

Quality α_j captures product-specific unobservables that affect demand. Income effects β_j allow expenditure shares to respond to changes in budgets X_{kt}, which may increase over time as battery technologies diffuse and adoption rates rise. We deflate these budgets by category price index P_t. Semi-elasticities $\gamma_{jj'}$ govern own- and cross-price elasticities. The main advantage of modeling demand in product space is that these semi-elasticities allow for full flexibility in substitution patterns across products.[5] Finally, we allow for demand shocks ε_{jkt}.

We compute quantities demanded as follows. For technology prices $\boldsymbol{p}_t \equiv \{p_{jt}\}_{j \in \mathcal{J}}$, the quantity demanded d_{jkt} for a battery technology j is

$$d_{jkt}(\boldsymbol{p}_t) = \frac{X_{kt} w_{jkt}(\boldsymbol{p}_t)}{p_{jt}}$$

by definition of expenditure share w_{jkt}. Aggregating across regions $k \in \mathcal{K}$,

$$d_{jt}(\boldsymbol{p}_t) = \sum_{k \in \mathcal{K}} d_{jkt}(\boldsymbol{p}_t).$$

Battery manufacturing

Battery manufacturers produce battery technologies j by combining minerals m from the full set of minerals $\mathcal{M}$ according to recipes r_j^m. That is, producing one unit of battery technology j requires r_j^m units of minerals m, as well as non-mineral inputs. Formally, consider a Leontief production function

$$y_{jt}(\boldsymbol{x}_{jt}, \tilde{x}_{jt}) = \min \left\{ \min_{m \in \mathcal{M}} \left\{ \frac{x_{jt}^m}{r_j^m} \right\}, \frac{\bar{x}_{jt}}{\bar{r}_{jt}} \right\},$$

[5] The full set of semi-elasticities calls for J^2 parameters, which is infeasible with many products. An alternative is to model demand in characteristic space by projecting products onto their observed characteristics, as in Berry (1994) and Berry et al. (1995). This approach restricts the number of parameters but is less flexible in capturing the full range of cross-product substitution patterns.

which includes mineral input $\boldsymbol{x}_{jt} \equiv \{x_{jt}^m\}^{m\in\mathcal{M}}$ and non-mineral input $\bar{x}_{jt}$. To produce one unit of battery technology j, the cost-minimizing quantity of mineral inputs is r_j^m units of each mineral m, noting that battery manufacturers purchase refined minerals at cost $\tilde{p}^{mt}$. The cost-minimizing quantity of non-mineral inputs is $\bar{r}_{jt}$ at constant marginal cost $\bar{c}_{jt}$. We treat battery manufacturers as perfectly competitive, such that the prices of battery technologies are given by

$$p_{jt} = \sum_{m\in\mathcal{M}} r_j^m \tilde{p}^{mt} + \mu_{jt},$$

where $\mu_{jt} = \bar{r}_{jt}\bar{c}_{jt}$ captures non-mineral manufacturing costs. While perfect competition is a strong assumption, we note that the market is indeed relatively unconcentrated with 56 battery manufacturers that we observe in our data.[6]

Mineral refining

Mines produce unrefined minerals m for sale at global prices p^{mt} at time t. Mineral refiners take unrefined minerals as inputs and produce refined minerals at constant marginal cost ρ^{mt}. We treat mineral refiners as perfectly competitive, such that the prices of refined minerals are given by

$$\tilde{p}^{mt} = p^{mt} + \rho^{mt}.$$

It follows that technology prices p_{jt} can be written in terms of (unrefined) mineral prices p^{mt}.

$$p_{jt} = \sum_{m\in\mathcal{M}} r_j^m p^{mt} + \eta_{jt}, \tag{8}$$

where $\eta_{jt} = \sum_m r_j^m \rho^{mt} + \mu_{jt}$ captures both mineral refining costs ρ^{mt} and battery manufacturing costs μ_{jt}.

6 Barwick et al. (2025) explicitly model market power in battery manufacturing, and they estimate limited markups of 11%. In particular, they report battery markups of $142 per kWh relative to baseline total production costs of $1,286 per kWh. The largest battery manufacturer reports average markups of $83 per kWh.

Mineral demand

For mineral prices $\boldsymbol{p}^t \equiv \{p^{mt}\}^{m \in \mathcal{M}}$, the quantity demanded d^{mt} of a mineral m in time period t is

$$d^{mt}(\boldsymbol{p}^t) = \sum_{j \in \mathcal{J}} r_j^m d_{jt}(\boldsymbol{p}_t) + \delta^{mt}. \tag{9}$$

On the right-hand side, the summation term captures battery demand for minerals, summing over battery technologies that use a given mineral. Battery-mineral recipes r_j^m specify the quantity of mineral m used in each unit of technology j. The δ^{mt} term accommodates non-battery demand for minerals.

4.2 Estimation

We estimate the model with iterated linear least squares, as in Blundell and Robin (1999). The challenge for estimation is that the translog price index enters nonlinearly in the expenditure share equation.[7] The iterated approach exploits the expenditure share equation is linear in parameters for a fixed value of price index P_t. We initialize estimation with the Stone price index, which is the average, expenditure-weighted product price, and then we estimate equation 6 by linear regression. We use the resulting parameter estimates to compute an updated price index with equation 7, and we iterate until convergence. We measure battery technology prices in units of USD per MWh of capacity.

We model demand over the full set of technologies $\mathcal{J}$, but we note that not all technologies are available to all regions in all time periods. In estimation, we proceed as in Chaudhuri et al. (2006), solving for "virtual prices" that set expenditure shares to zero for technologies that are excluded from a given choice set. Intuitively, this approach is analogous to setting infinite prices to exclude products from the choice set in a logit demand system. Formally, we solve for prices $\bar{p}_{jkt}$ such that $w_{jkt} = 0$ for all technologies $j \notin \mathcal{J}_{kt}$. Appendix B.1 provides details.

We highlight two sources of identifying variation. First, we draw on variation in prices over time. Price are endogenous because unobserved demand shocks raise demand and thus prices in equilibrium. We address this price endogeneity by in-

[7] For example, on the right-hand side of equation 6, the α_j parameters appears directly in the first term. It also appears indirectly through price index P_t in the second term, where it interacts with the β_j parameters.

Table 2: Estimated demand elasticities

	NCA	NMC	LFP
NCA	-8.50	0.11	7.32
NMC	0.05	-1.89	0.91
LFP	3.33	1.56	-5.98

We compute average global demand elasticities for 2024. We report the percentage change in quantity supplied in response to a one-percent change in price. We show own- and cross-price elasticities for NCA, NMC, and LFP battery technologies.

strumenting with cost shifters in the form of aluminum, copper, phosphoric acid, and manganese prices. These minerals are inputs in battery production, and so their prices are relevant for production costs. At the same time, table 1 shows that demand for these minerals is largely driven by non-EV uses, with only 2% of aluminum, 4% of copper, 3% of phosphoric acid, and 1% of manganese used for EV battery production. It follows that these minerals are plausibly excludable from battery demand.

Second, we draw on variation in choice sets across regions over time. In particular, LFP technology was initially developed in North American and European research institutions but commercially implemented at scale in China. Furthermore, patents prevented the diffusion of LFP technology outside of China until they expired in 2022. This pattern of diffusion generates identifying variation that is akin to difference-in-differences. That is, LFP technology was part of the feasible choice within China both before and after 2022, but it was only widely available outside of China after 2022. Intuitively, the extent of substitution toward LFP after its introduction serves to pin down cross-product substitution patterns.

4.3 Estimates

Table 2 reports our estimated demand elasticities. First, we consider the own-price elasticities. Demand is elastic for all battery technologies, with estimated elasticities that exceed one in magnitude. Demand is least elastic for NMC batteries, for which a 1% increase in price results in a 1.89% decrease in quantity demanded. One potential explanation is that NMC batteries offer an attractive balance of energy density and thermal stability. NCA batteries have higher energy density, which allows for longer driving range than NMC batteries, but this comes at the cost of lower thermal stability. LFP batteries have higher thermal stability, but at the cost of lower energy density and shorter range. To the extent NMC commands higher prices because of its desirable balance of characteristics, its lower price elasticities may reflect the lower price sensitivity of higher-income consumers.

Second, we turn to the cross-price elasticities. We find that substitution occurs primarily between nickel- and lithium-heavy technologies. When NMC prices rise, the bulk of the substitution is toward LFP. Similarly, when NCA prices rise, the substitution toward LFP greatly exceeds that toward NMC. When LFP prices rise, substitution toward NMC and NCA is relatively even because both are nickel-heavy technologies.

5 Supply

We model the supply of minerals as a function of extraction costs, capacity, and quality. We estimate the model with global mine-level data on production by mineral.

5.1 Model

Mineral supply

Mines i produce minerals $m(i)$ in each year t. We observe the universe $\mathcal{I}^{mt}$ of mines that produce each of our minerals of interest. Mines extract raw ore and process it into minerals, which they sell in global markets. The relationship between the raw ore extraction S^{it} and mineral production s^{it} is

$$s^{it} = \gamma^{it} S^{it}, \tag{10}$$

where ore grade γ^{it} is observed and captures the quality of raw ore endowments. High ore grade corresponds to high yields from extraction. For mineral prices p^{mt}, it follows that each ton of raw ore extraction S^{it} yields $\gamma^{it} p^{mt}$ in marginal revenues. We assume that mines are perfectly competitive and take these global prices as given, noting that individual mines are small despite geographic concentration at the country level.

Raw ore extraction also incurs convex costs C^{it}, which we specify as

$$C^{it} = a^{it} S^{it} + \frac{b^{it}}{3(k^i)^2} (S^{it})^3. \tag{11}$$

On the right-hand side, the first term captures linear marginal costs at low levels of capacity utilization, while the second term captures cost convexity as mines approach or potentially exceed their production capacity.[8] Differentiating gives marginal costs.

$$c^{it} = a^{it} + b^{it} \left(\frac{S^{it}}{k^i} \right)^2 \tag{12}$$

We compute quantities supplied as follows. Given mineral prices p^{mt}, perfectly competitive mines i produce to the point that marginal revenues meet marginal costs, such that $\gamma^{it} p^{mt} = c^{it}$. Substituting equations 10 in 12, we can rearrange to obtain

$$s^{it}(p^{mt}) = \gamma^{it} k^i \sqrt{\frac{\gamma^{it} p^{mt} - a^{it}}{b^{it}}}. \tag{13}$$

Aggregating across mines $i \in \mathcal{I}^{mt}$, the quantity supplied s^{mt} of mineral m in year t is

$$s^{mt}(p^{mt}) = \sum_{i \in \mathcal{I}^{mt}} s^{it}(p^{mt}). \tag{14}$$

Equilibrium

Equilibrium is given by market clearing in global mineral markets. In particular, equilibrium mineral prices $\boldsymbol{p}^t = \{p^{mt}\}^{m \in \mathcal{M}}$ satisfy equilibrium conditions

$$d^{mt}(\boldsymbol{p}^t) = s^{mt}(p^{mt}) \quad \forall \; m, t, \tag{15}$$

where mineral demand $d^{mt}(\boldsymbol{p}^t)$ is given by equation 9, while mineral supply $s^{mt}(p^{mt})$ is given by equation 14. Demand depends on the prices of all minerals because minerals are used jointly in battery technologies and because battery consumers can switch across technologies. Supply depends only on the price of the mineral of interest

[8] The cubic functional form approximates a "hockey-stick" shape for marginal costs, as is typical in modeling industrial processes with soft capacity constraints (Ryan 2012, Reguant 2014, Fowlie et al. 2016).

because mines are endowed with specific minerals. By equation 8, mineral prices $\boldsymbol{p}^t$ also pin down technology prices $\boldsymbol{p}_t = \{p_{jt}\}_{j\in\mathcal{J}}$ in equilibrium.

5.2 Estimation

We estimate the model with our mine-level data. First, we note that estimation is possible without measures of costs. This more typical approach relies on firm optimization. Setting marginal revenue equal to marginal costs, as we did to derive equation 13, we can rearrange to obtain a linear estimating equation.

$$\left(\frac{S^{it}}{k^i}\right)^2 = \frac{\gamma^{it}p^{mt}}{b^{it}} - \frac{a^{it}}{b^{it}} \tag{16}$$

On the left-hand side, we observe extraction quantities S^{it} and capacities k^i at the mine level. On the right-hand side, we observe ore grades γ^{it} and mineral prices p^{mt}. From the data, we therefore obtain one equation but two unknowns (a^{it}, b^{it}) for each mine i in each year t. We thus require additional restrictions for identification. Imposing homogeneity in the form of $b^{it} = b^m$ and $a^{it} = a^m + e^{it}$ reduces the parameter space. The estimating equation then takes the form of a linear fixed effects regression.

$$\left(\frac{S^{it}}{k^i}\right)^2 = \frac{\gamma^{it}p^{mt}}{b^m} - \frac{a^m}{b^m} - \frac{e^{it}}{b^m}$$

Prices may be correlated with aggregate supply shocks, but fixed effects a^m control for such shocks. Identification thus relies instead on the interaction of price variation over time and ore-grade variation across mines, where ore grade is a geological fundamental.[9]

Second, we highlight the value of our cost data. Equation 11 describes total costs, which yield average costs

$$\frac{C^{it}}{S^{it}} = a^{it} + \frac{b^{it}}{3}\left(\frac{S^{it}}{k^i}\right)^2. \tag{17}$$

[9] Intuitively, if supply is inelastic, then mines respond similarly to price increases regardless of ore grade. If supply is elastic, then mines with high ore grade respond more strongly to price increases than mines with low ore grade. The reason is that higher prices lead to scarcely higher revenues when ore grade is especially low. Thus, the relative responses of high- and low-grade mines identify the elasticity of supply and, correspondingly, semi-elasticities b^m.

We observe the left-hand side as data because we observe the average costs of extraction. On the right-hand side, we again observe extraction quantities S^{it} and capacities k^i. Between equations 16 and 17, our mine-level data deliver two equations for each of the two unknowns (a^{it}, b^{it}) that we seek to identify. We can therefore invert the model to obtain our parameters of interest. Solving the system of two equations,

$$a^{it} = \frac{1}{2}\left(\frac{3C^{it}}{S^{it}} - \gamma^{it} p^{mt}\right), \quad b^{it} = \frac{3}{2}\left(\gamma^{it} p^{mt} - \frac{C^{it}}{S^{it}}\right)\left(\frac{k^i}{S^{it}}\right)^2.$$

For both equations, the left-hand side terms are the parameters of interest, and the right-hand side terms can be computed from data. Variation in ore grade γ^{it} remains an important source of heterogeneity across mines, although the model inversion holds even without this heterogeneity. The crucial component is the cost data, which has two advantages: allowing full flexibility in the parameter space, and allowing model inversion that avoids the need for estimation.[10]

5.3 Estimates

Table 3 reports our estimated supply elasticities. We focus on the major producers of nickel, lithium, and cobalt, which we list in order of their rank as global producers. We estimate supply elasticities that are positive but modest in magnitude relative to existing literature (Fally and Sayre 2018), such that changes in world prices lead to large impacts on producer surplus.

These elasticities nonetheless vary meaningfully across countries. For nickel, Indonesia is the largest producer, but it is also the least price-responsive, with a supply elasticity of only 0.16 relative to 0.63 for the Philippines and 0.37 for Russia. Indonesia has large installed capacity and substantial sunk investments in downstream processing, which limit short-run flexibility. Moreover, Indonesia's notoriously active policy interventions in the nickel market could be preventing price signals from being fully perceived by producers.

For lithium, Australia, Chile, and Argentina have similar supply elasticities de-

[10] We also draw a contrast to other approaches for leveraging cost data. Asker et al. (2019) and Clausing et al. (2025) read the cost structure of production from the data by assuming constant marginal costs, such that the average costs in the data are direct measures of the marginal costs in the model. We do not impose constant marginal costs.

Table 3: Estimated supply elasticities

Mineral	Country	Elasticity
Nickel	Indonesia	0.16
	Philippines	0.63
	Russia	0.37
Lithium	Australia	0.44
	Chile	0.42
	Argentina	0.41
Cobalt	DRC	0.29
	Indonesia	0.02
	Australia	0.52

We compute supply elasticities for 2024. We report the percentage change in quantity supplied in response to a one-percent change in price. Within each mineral, countries are ordered by their rank as world producers.

spite differences in deposit types, with hard rock in Australia and brine in Chile and Argentina. All three producers rely on well-established operations with extensive experience in navigating technological and regulatory constraints. For cobalt, we estimate particularly heterogeneous elasticities. Indonesia is especially inelastic at 0.02, likely due to its cobalt output being largely a byproduct of nickel mining, which is the primary focus of national policy. The DRC is the dominant global producer with a moderate elasticity of 0.29. Its higher elasticities are possibly driven by its artisanal mining sector, which due to its low capital intensity can come quickly online when world prices surge.

5.4 Dynamics

We can extend the model to incorporate dynamics. Consider ore grade γ^{it} that evolves as a function of extraction and reserves.

$$\gamma^{it} = g^i \left(1 - \frac{\sum_{t'<t} s^{it'}}{r^i}\right)^{\lambda} \exp\left(\omega^{it}\right).$$

Mines i are characterized by baseline ore grade g^i, cumulative extraction $\sum_{t'<t} s^{it'}$ until time t, reserves r^i, and shocks ω^{it}. Parameter λ governs the extent to which ore

grade decays as a mine exhausts its reserves. We log-linearize to obtain

$$\log\left(\gamma^{it}\right) = \log\left(g^{i}\right) + \lambda \log\left(1 - \frac{\sum_{t'<t} s^{it}}{r^{i}}\right) + \omega^{it},$$

which we can estimate offline with a linear fixed-effects regression. On the right-hand side, the challenge is that cumulative extraction $\sum_{t'<t} s^{it}$ is mechanically correlated with shock ω^{it} because, by equation 13, extraction s^{it} is increasing in contemporaneous ore grade γ^{it}. We can therefore instrument with lagged cumulative extraction, which is correlated with contemporaneous cumulative extraction.[11] Assuming that mines form expectations given by $\mathbb{E}^{it'}[\omega^{it}] = 0$ for $t' < t$, the instrument is also uncorrelated with contemporaneous shock ω^{it}.[12]

6 Counterfactuals

We use our model to perform three counterfactual exercises. First, we quantify supply chain vulnerability by removing the largest producer of each mineral and evaluating the impact on mineral and battery markets. Second, we simulate policies that restrict supply to exercise country-level market power. We show how such policies have spillovers on other countries and battery adoption. Third, we discuss implications of our results for mineral cartels.

6.1 Supply chain vulnerability

We first explore how vulnerable battery supply chains are to production disruptions in specific countries. Since mineral endowments are geographically concentrated, shocks in an individual country can substantially raise the cost of minerals and batteries worldwide. We quantify supply chain vulnerability by simulating an extreme case where the top-producing country of a mineral is fully removed from global supply. We consider the separate cases in which Australia is removed from lithium supply, Indonesia from nickel supply, and the DRC from cobalt supply. These three countries

[11] For cumulative extraction $\bar{s}^{it} = \sum_{t'<t} s^{it}$, $\bar{s}^{it} = \bar{s}^{it-1} + s^{it}$ yields $1 - \frac{\bar{s}^{it}}{r^{i}} = 1 - \frac{\bar{s}^{it-1}}{r^{i}} - \frac{s^{it}}{r^{i}}$.

[12] Aguirregabiria and Luengo (2016) propose a dynamic structural model of copper mining that takes this endogenous evolution of ore grade seriously, while also highlighting similar themes of heterogeneity across mines and market concentration more broadly.

made up 44%, 35%, and 71% of the supply of their respective minerals in 2021.

Table 4: Impact of removing top producers on equilibrium prices and quantities.

Country	Baseline share	Outcome	Mineral	LFP	NCA	NMC
Australia (Li)	44 %	Price	240.5	22.9	22.7	20.9
		Quantity	-7.3	-22.5	-17.4	-16.0
Indonesia (Ni)	35 %	Price	67.2	-0.4	8.6	6.5
		Quantity	-0.6	13.0	55.1	-7.8
DRC (Co)	71 %	Price	774.0	-1.6	54.3	52.4
		Quantity	-13.9	77.0	194.6	-42.7

Baseline share is the country's share of global production of the mineral at baseline. Price and quantity impacts of removing each country are reported as percentage point changes. Percentage changes in battery quantities are computed using changes in battery capacity (not battery units).

Table 4 presents the equilibrium effects of removing individual producers on mineral and battery market outcomes. The impacts on mineral prices and quantities are substantial. Upon removing the top producing country – whose mines tend to have lower production costs and higher capacity – production shifts to countries with higher-cost mines. Such mines have higher costs because of an extensive margin (they have lower ore grades) and an intensive margin (they increase their capacity utilization rates). Overall, higher mining costs due to production reallocation cause mineral prices rise. While this is true for all minerals, this impact is particularly stark for cobalt. The removal of the DRC results in prices increasing approximately 8-fold. This is because, as depicted in appendix figure A4, ore grades of cobalt mines in the DRC are dramatically higher than in the rest of the world, resulting in substantially lower costs in the DRC.

Battery prices increase for technologies that use the affected mineral most intensively because their mineral input costs disproportionately rise. As for technologies that are less exposed to the affected mineral, their battery prices may rise or fall. On the one hand, their prices rise because they face a surge in demand that is shifting away from the exposed technology. On the other hand, their prices fall because of a drop in demand from the exposed technology for minerals that are complementary to the affected one, thus reducing overall mineral costs. For example, when removing

DRC, NCA and NCM demand drops because of rising cobalt prices, thus reducing demand for complementary lithium. Hence, LFP technology prices can fall because of cheaper lithium. As illustrated in our theory model (section 3), this can yield lower or higher prices depending on how strong substitution patterns are. We explore these spillovers in the following section.

6.2 National mineral policy

6.2.1 Cross-country spillovers

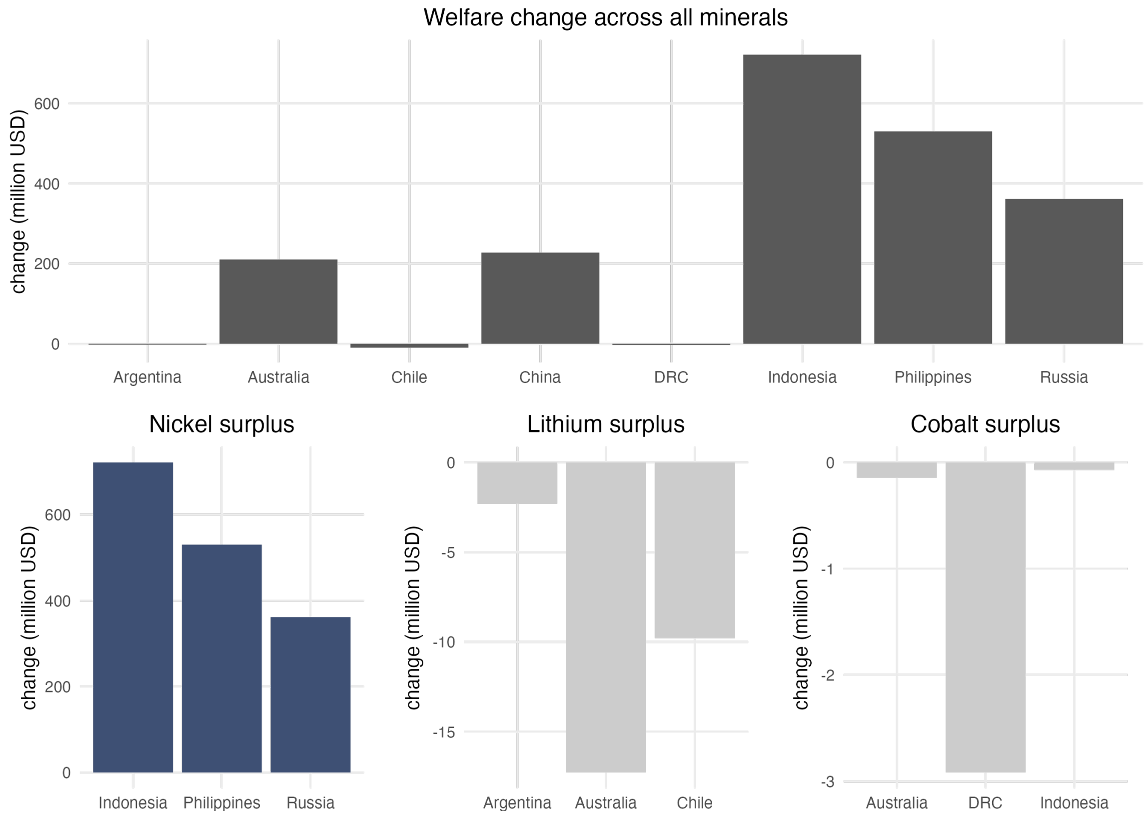
In this section we consider a scenario in which an individual country exercises its market power and restricts supply to raise prices of a specific mineral. We implement this in our model by having the country choose a tax on its mines that maximizes the sum of producer surplus and government revenue. The rationale for the tax is that the government uses it to coordinate a supply restriction among its mines.[13] This exercise is motivated by recent export restrictions imposed by Indonesia and DRC on their nickel and cobalt producers. In the case of DRC, the government explicitly stated the reason for the restriction is to support global cobalt prices (Fastmarkets).

To isolate the role of demand switching across battery technologies, we report results for our baseline as well as a case where there is no switching, as in our theory model in section 3. In our main analysis we simulate a policy scenario where Indonesia restricts its nickel supply optimally. Analogous exercises for lithium and cobalt supply restrictions by the largest producers are located in section C of the appendix.

Figure 4 shows the welfare impact of an Indonesian supply cut. The bottom panel shows that other nickel producers derive positive surplus: their nickel is substitutable with Indonesia's so they free ride on the supply cut. In stark contrast, lithium and cobalt surplus falls because of their complementarity with nickel. The total welfare change for a country is obtained by aggregating mineral-specific surplus across the minerals it produces. The results of this calculation are in the top panel of 4. Notice Australia produces all three minerals, so even though it loses cobalt and lithium surplus, it is more than compensated by gains from nickel.

[13] We report welfare numbers that are the sum of producer surplus and government revenues and do not take a stand on how the tax revenue is used.

Figure 4: Welfare impacts of an Indonesian nickel policy



Welfare is defined as the sum of producer surplus and government revenue. The top panel plots welfare across minerals (since some countries produce multiple minerals). Only countries with large welfare changes are plotted. The bottom panel shows welfare changes attributed to each mineral.

6.2.2 Green adoption

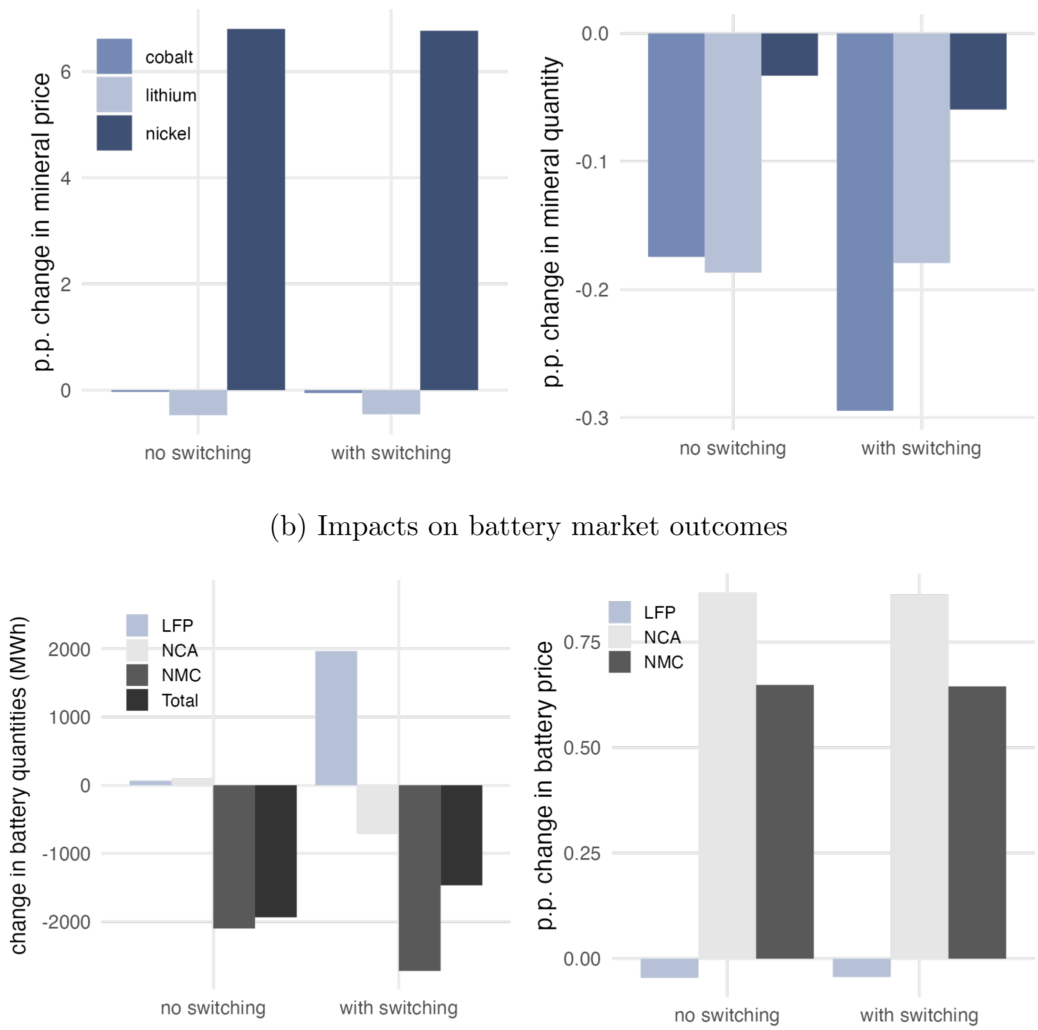
Figure 5a shows the impact of a production cut of Indonesian nickel on mineral market outcomes. Results are displayed under our default assumption where consumers can switch across battery technologies, as well as a "no-switching" case. Prices of nickel rise and quantities fall. Quantities of cobalt and lithium also fall (and their prices drop) because of their complementarity with nickel.

Figure 5b shows impacts on battery market outcomes. Higher nickel prices lead to higher battery prices for the nickel-intensive battery technologies (NMC, NCA). Quantities of these technologies fall while demand for LFP rises. The increase in LFP is significantly larger when we allow for demand switching. However, in all cases total battery adoption falls because the decline in nickel-intensive battery technologies is

Figure 5: Market impacts of an Indonesian nickel supply cuts

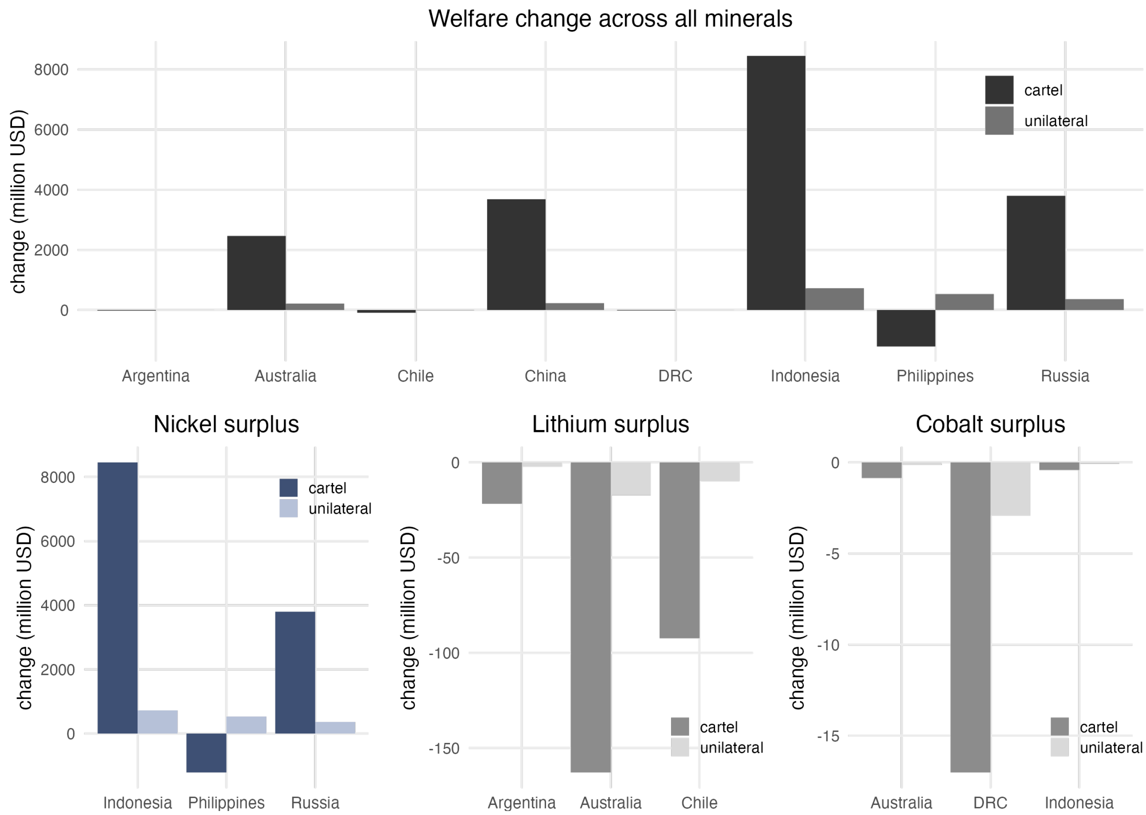
(a) Impacts on mineral market outcomes

(b) Impacts on battery market outcomes



larger than the increase in LFP. It is worth noting that we could have obtained a qualitatively different result with alternative demand estimates – a strong enough LFP increase that total battery adoption rises. Hence, our framework with complementarity is flexible enough to allow the effects of mineral scarcity on green adoption to go in either direction.

Figure 6: Welfare impacts of a nickel cartel (Indonesia, Philippines, Russia)



Welfare is defined as the sum of producer surplus and government revenue. The top panel plots welfare across minerals (since some countries produce multiple minerals). Only countries with large welfare changes are plotted. The bottom panel shows welfare changes attributable to each mineral. Bar colors compare cartel impacts to those of a unilateral cut by the top producer (Indonesia).

6.3 Mineral cartels

We next turn to policies set by coalitions of countries forming a cartel. Some energy commodities with concentrated production are organized through producer cartels, such as crude oil under OPEC. Many studies on oil markets often implement a single-commodity analysis where the only margin of product differentiation is the source of production (e.g., Russian oil versus Saudi oil), typically delivering high substitutability across producers. Our setting differs because it involves multiple commodities, thus allowing for standard substitution forces while also introducing a novel complementarity mechanism. In such a setting, what impact could a potential mineral cartel have on the full set of minerals relevant for renewable energy adoption?

We consider coalitions of all subsets of the top three producers within each mineral market, as well as multi-mineral coalitions of top producers across different minerals. Cartel members restrain supply with the objective of maximizing cartel surplus.[14] Our full set of results for both single- and multi-mineral cartels are displayed in Appendix Table C1. A few themes emerge from this exercise. First, even the largest producers can gain substantially by being part of the cartel. Second, countries in coalitions have incentives to deviate. The three largest producers of lithium, Australia, Chile, and Argentina, have substantial pricing power collectively; however, Argentina can gain substantially by exiting a coalition and free-riding off of Australia and Chile's actions. Even more starkly, some countries are better off in a laissez-faire baseline where a cartel does not exist than in being part of a cartel that forces them to hold back their output. This is the case with the Philippines being part of a potential nickel cartel with Indonesia and Russia (Figure 6). Third, coalitions can exacerbate the cross-country and cross-mineral spillover effects that were the focus of section 6.2.1. However, there are multi-mineral coalitions that restrict the supply of all minerals and leave mineral-producing countries with positive payoffs.

7 Conclusion

This paper argues that the upstream structure of critical mineral markets fundamentally shapes the pace and incidence of the global green transition. We show that concentrated mineral endowments, modest supply elasticities, and cross-technology substitution create strong spillovers across minerals and across countries. Unilateral industrial policy by major producers can meaningfully move world prices, reallocate adoption across battery technologies, generate sizable distributional effects, and either accelerate or slow the green transition. Our climate progress will depend on these critical mineral markets.

[14] We implement this as a jointly applied tax on coalition members, thus mimicking a joint decision to restrain supply. Thus, cartel surplus consists of producer surplus and tax revenue of all members.

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APPENDIX

A Data

A.1 Battery recipes

Battery recipes come from BatPaC (Knehr et al. 2024), developed by Argonne National Laboratory. Their lithium-ion battery cost model includes the mineral intensities of commodities for a large number of battery technologies (chemistries) in use in EV batteries. Figure A1 summarizes the recipes for each technology. While many values are pulled directly from the BatPaC model, a few require additional explanation. Aluminum exists in batteries both because it may be part of the cathode active material (in NCA batteries) and because it is part of a current collector foil in all batteries. We use the sum of aluminum from both of these sources. We additionally convert iron phosphate ($FePO_4$) quantities to quantities of phosphoric acid (H_3PO_4), a precursor to iron phosphate, based on stoichiometric conversions. The chemical reaction to iron phosphate is $Fe_2O_3 + 2\,H_3PO_4 \longrightarrow 2\,FePO_4 + 3\,H_2O$, and since $FePO_4$ is 150.8 g/mol and H_3PO_4 is 98.0 g/mol, one tonne of iron phosphate requires 98.0/150.8 tonnes of phosphoric acid. Additionally, we aggregate NMC chemistries to a representative category that we call NMC by averaging over the recipes, weighted by aggregate market shares.

A.2 Harmonization of mine-level datasets

We combine data from three proprietary sources (Global Data, Benchmark Mineral Intelligence, S&P Global) to create a harmonized mine-level panel for lithium, nickel, and cobalt from 2010 to 2024. Given there are no common identifiers across datasets and mine names are not always standardized, this exercise consists of verifying each individual mine is correctly matched across data sources. To do so we use a variety of variables that appear across datasets (names, location, ownership information, production and capacity volumes). Our final panel consists of 397 mines that produce lithium, cobalt, or nickel.

We perform several validation exercises to gauge the coverage and representativeness of our harmonized panel. We use USGS values for 2020 to 2024 as reference

Figure A1: Mineral intensities (kg/kWh) across battery technologies

	LFP	NCA	NMC-111	NMC-523	NMC-622	NMC-811
phosphorus	0.38	-	-	-	-	-
phosphoric acid	1.43	-	-	-	-	-
nickel	-	0.65	0.32	0.43	0.51	0.61
manganese	-	-	0.3	0.24	0.16	0.07
lithium	0.09	0.1	0.12	0.11	0.1	0.09
iron phosphate	2.2	-	-	-	-	-
iron	0.68	-	-	-	-	-
graphite	0.95	0.85	0.84	0.84	0.85	0.85
fluorine	0.09	0.06	0.07	0.06	0.06	0.06
copper	0.62	0.33	0.39	0.36	0.36	0.32
cobalt	-	0.12	0.32	0.17	0.17	0.08
aluminum	0.24	0.14	0.15	0.14	0.13	0.12

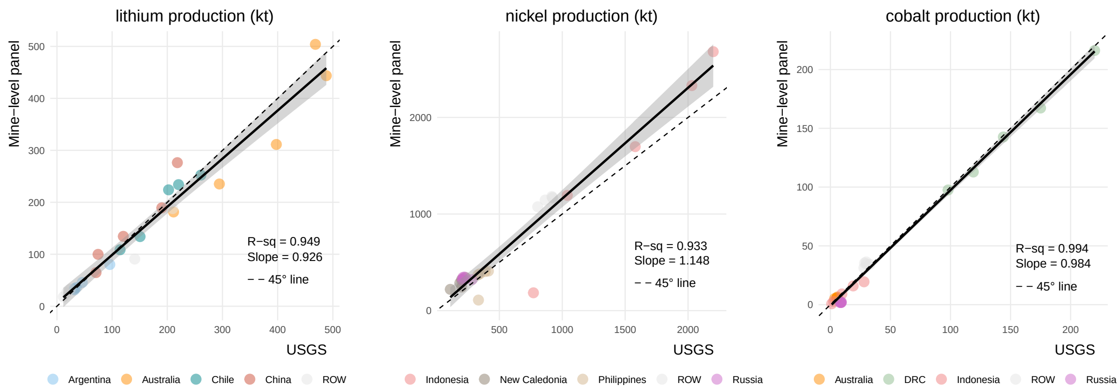
Mineral intensities are obtained from the battery technology data described in section 2.2.

values for world and country-level production. First, our mines cover 92% of world production for lithium, 92% for cobalt, and 80% for nickel. Second, we aggregate our mine-level data up to the country-level and compare production values to USGS (which does not report production below the country-level). Figure A2 shows our country-level aggregates are highly correlated with USGS values. Country-level correlation coefficients are above 0.93 for lithium, nickel, and cobalt.

A.3 Mine development

Time lags from first discovery to first production are measured in decades in the mining sector. Lead times in most countries range between 15 and 25 years (Mohsen Bonakdarpour and Rajan 2024). The United States has an average lead time of 29 years, the world's second-longest after Zambia (at 34 years), partly due

Figure A2: Validation of mine-level panel against USGS production values

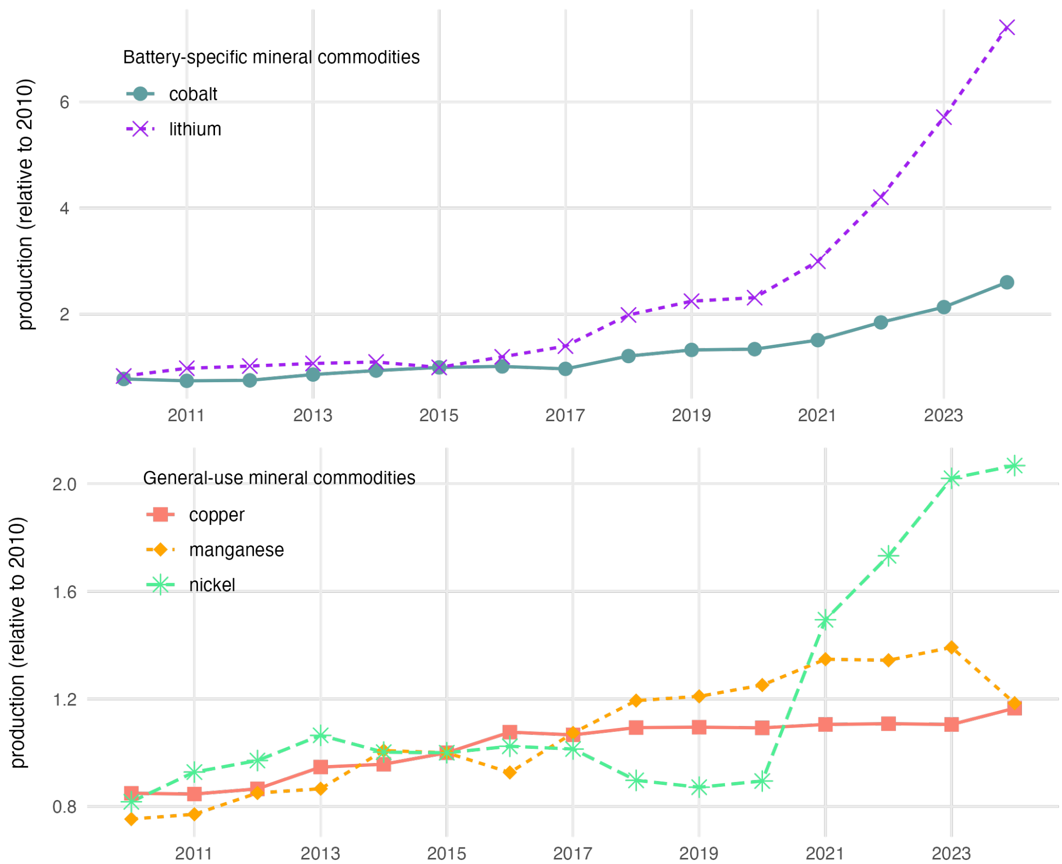


The vertical axes display country-level production values aggregated from our mine-level data. The horizontal axes show country-level production values reported by USGS for 2020 to 2024.

to uncoordinated and overlapping regulatory jurisdictions on the federal lands where most mining resources are located. By contrast, lead times for conventional oil wells are shorter, on the order of 5 years (Wachtmeister and Höök 2020). There are a variety of reasons why mining projects have notoriously long development times. Mining is inherently more environmentally disruptive than other extractive activities given it requires stripping open entire swathes of land, in contrast to drilling operations that can take place mostly underground or entirely offshore. As a consequence, mining projects are subject to extensive exploration and feasibility studies, lengthy permitting processes, and higher litigation risk from local opposition. Nevertheless, there has been significant growth in mining production over the past decade, especially minerals whose demand primarily stems from the battery sector, such as lithium and cobalt (Figure A3).

Boom-and-bust price dynamics are common in industries with time-to-build and demand uncertainty, and the mining industry is no exception. These volatile dynamics are exacerbated among the more nascent mineral markets, such as lithium and cobalt, relative to the more established metal commodities (bottom panel of Figure A5). Following capacity additions, prices do tend to fall. This has been especially evident post 2022 as the market entered a supply glut, a persistent trend that has been at the center of recent market commentary (IEA 2024c). Moving beyond price cycles to price trends, growth rates differ substantially between minerals whose demand stems primarily from the growing EV sector, as opposed to traditional demand sources. For

Figure A3: World production of mineral commodities (2010-2024)



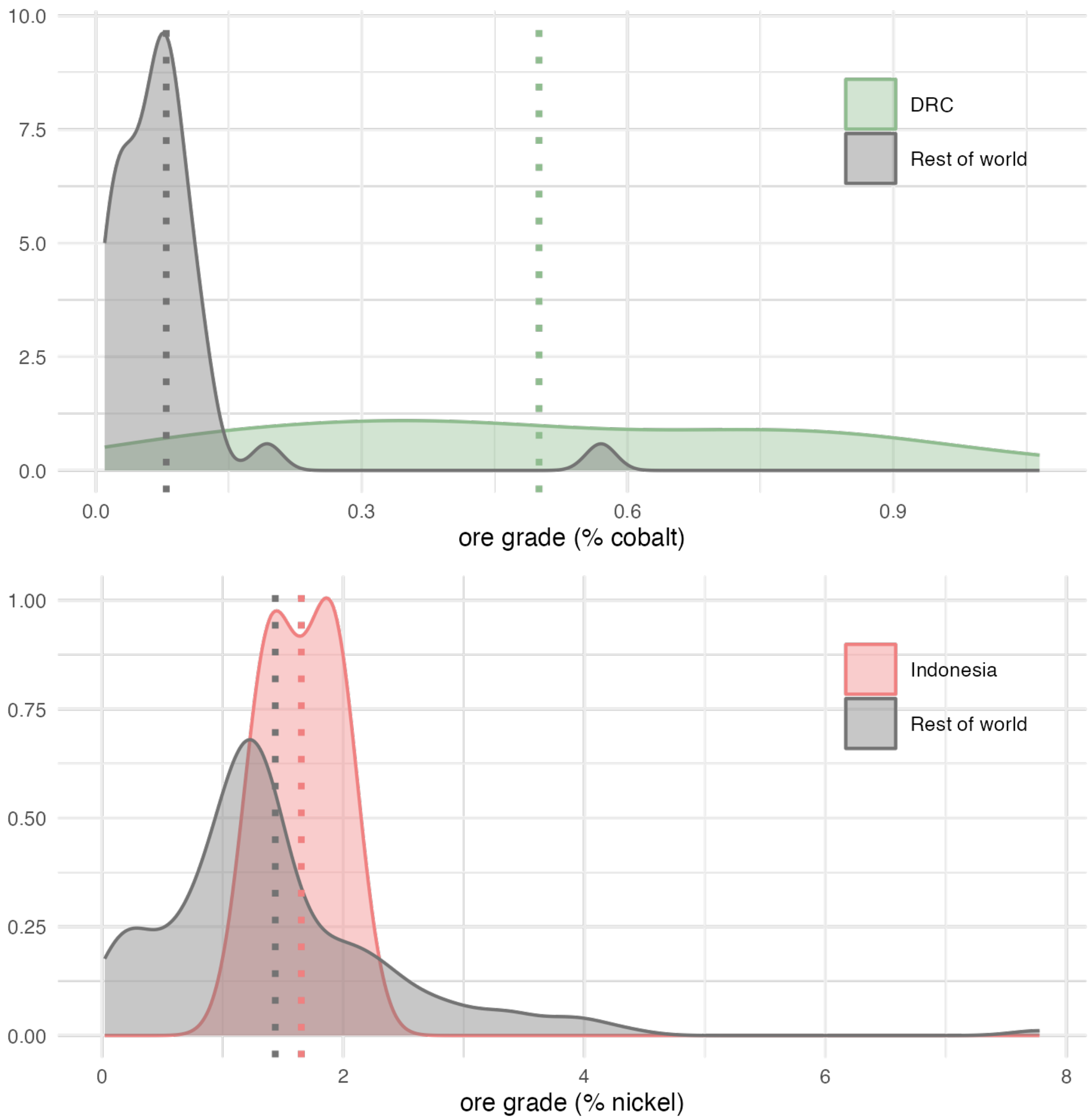
Values are constructed from mine-level production data described in section 2.2. Categorization of mineral commodities into battery-specific versus general-use minerals is based on demand composition values from Table 1.

example, lithium prices have risen systematically over the past 15 years, while prices of the other commodities have been flat on average (top panel of Figure A5).

A.4 Mine heterogeneity

Ore grade. Ore grade is a major determinant of a mine's profitability and explains why some countries dominate specific mineral markets. Figure A4 shows the distribution of ore grades across all the mines in our data, separately for those located in the top producing country of each mineral and in the rest of the world. While Indonesian nickel grades are higher than in the rest of the world, the gap is not as large as the case of DRC and cobalt. The DRC's significantly higher-grade cobalt deposits are a

Figure A4: Distribution of ore grade across mines



The figure above shows density plots constructed from mine-level ore grade data described in section 2.2. The distribution of mines from the top producer of each mineral is compared to mines in the rest of the world. Vertical lines show the average ore grade within each region.

major reason why it dominates the global cobalt market.

A.5 Recent market trends

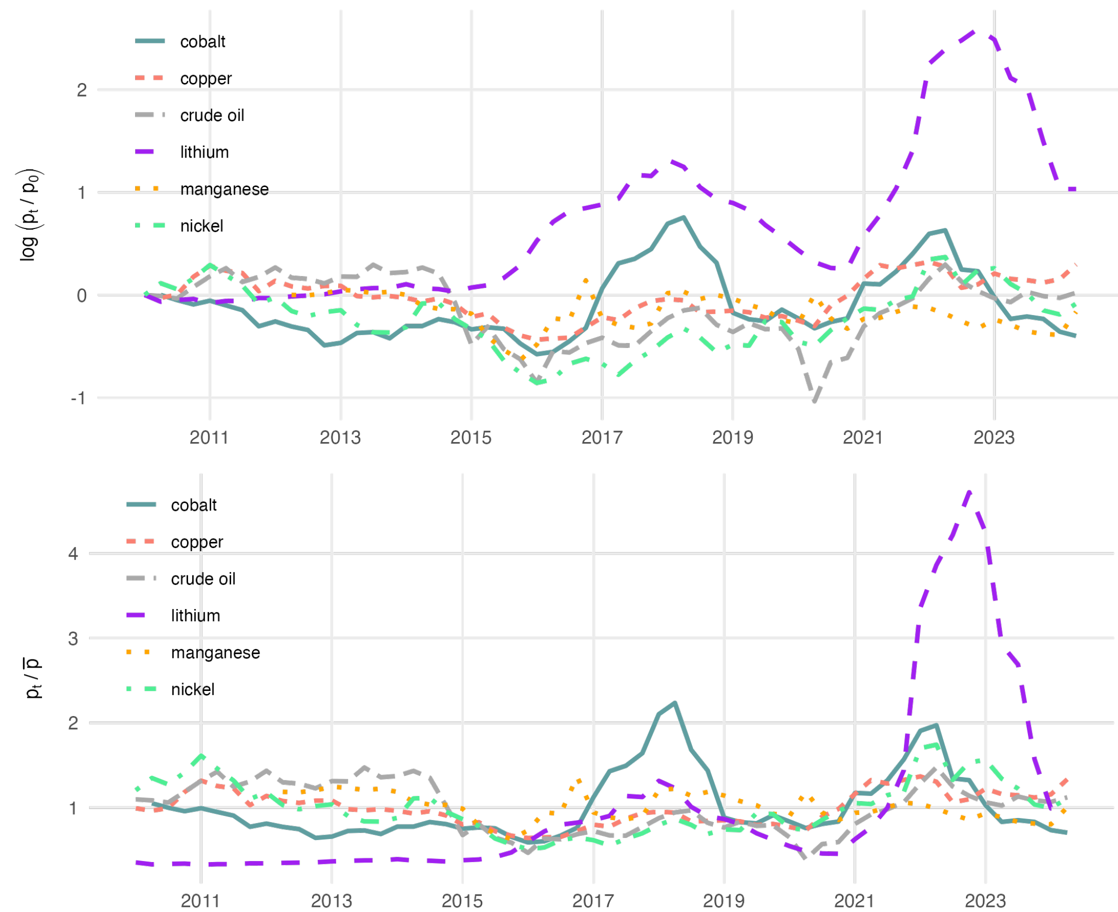
A.5.1 Mineral markets

Between 2017-2022 demand from the energy sector was the main factor behind a tripling in global production of lithium and a 70% jump for cobalt. Short-term pressures weakened with the contraction in demand caused by Covid-19. After 2021 production of all minerals grew rapidly as the global economy recovered and many countries boosted efforts to accelerate the energy transition. Between 2017-2022, the EV share of mineral demand for lithium, cobalt, and nickel grew from 15% to 60%, 15% to 30%, and 2% to 10% (IEA 2024a). The supply response to the increase in demand eventually led to oversupply, which most market commentary attributes as the cause of the main driver of the post-2023 price drop.

Cobalt market. Between 2015-2022, the EV and grid storage share of cobalt demand increased from 5 percent to almost 25 percent. Such rapid growth partly explains the rise in cobalt prices between 2016 and early 2018. Disruptions by major suppliers also fueled fear of material security. Relatedly, NMC chemistries began shifting to lower-cobalt ratios (from NMC333, NMC111 to NMC622, NMC811) in response to cobalt price spikes and ethical sourcing concerns (IEA 2024a). Such shifts contributed to the price decline after 2018. Towards 2022, Indonesia tightened export regulations for nickel-cobalt intermediate products. Since nickel mining also produces cobalt as a byproduct, this impacted cobalt supply and added upward pressure to prices.

Nickel market. In 2014 Indonesia implemented a ban on unprocessed nickel ore exports to encourage domestic smelting. Prices initially rose but gradually fell in 2015-2016 as alternative production sources and Indonesian domestic smelters took off. Since 2022, Indonesia has progressively banned the export of nickel ore to encourage domestic processing (IEA). Following Russia's invasion of Ukraine in February 2022, fears of sanctions on Russian nickel also led to a price increase. Additionally, in March 2022 a short squeeze on the London Metal Exchange caused nickel prices to surge (Reuters). As a result, in 2022 the price of nickel reached a peak twice as high as its 2015-2020 average. This added incentives to use battery technologies that were less reliant on nickel, such as LFP, despite their lower energy density. Hence, demand substitution contributed to nickel prices slowly dropping from their 2022 peaks.

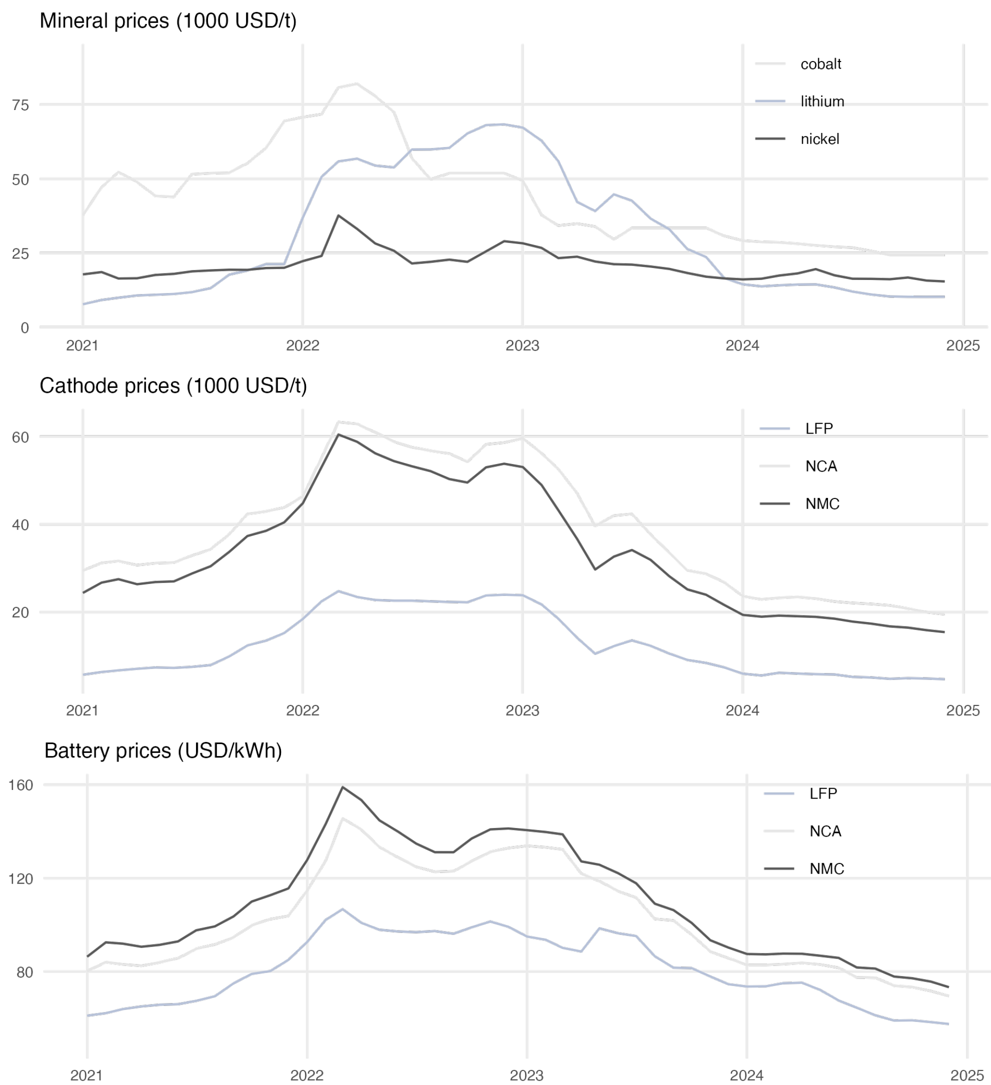
Figure A5: Mineral price trends and cycles (2010-2024)



The two panels show the price of each commodity normalized by (i) its price at the start of the sample, and (ii) its average value across the sample period. Nominal values from which this figure is constructed are quarterly-averaged prices from SP Global. Cobalt, nickel, and copper prices are based on over-the-counter (OTC) and contract for difference (CFD) financial instruments, primarily from the LME. Crude oil prices are WTI futures. Lithium prices are spot prices for lithium carbonate (battery grade, 99.5%) traded in China. Manganese prices are based on Tianjin port prices.

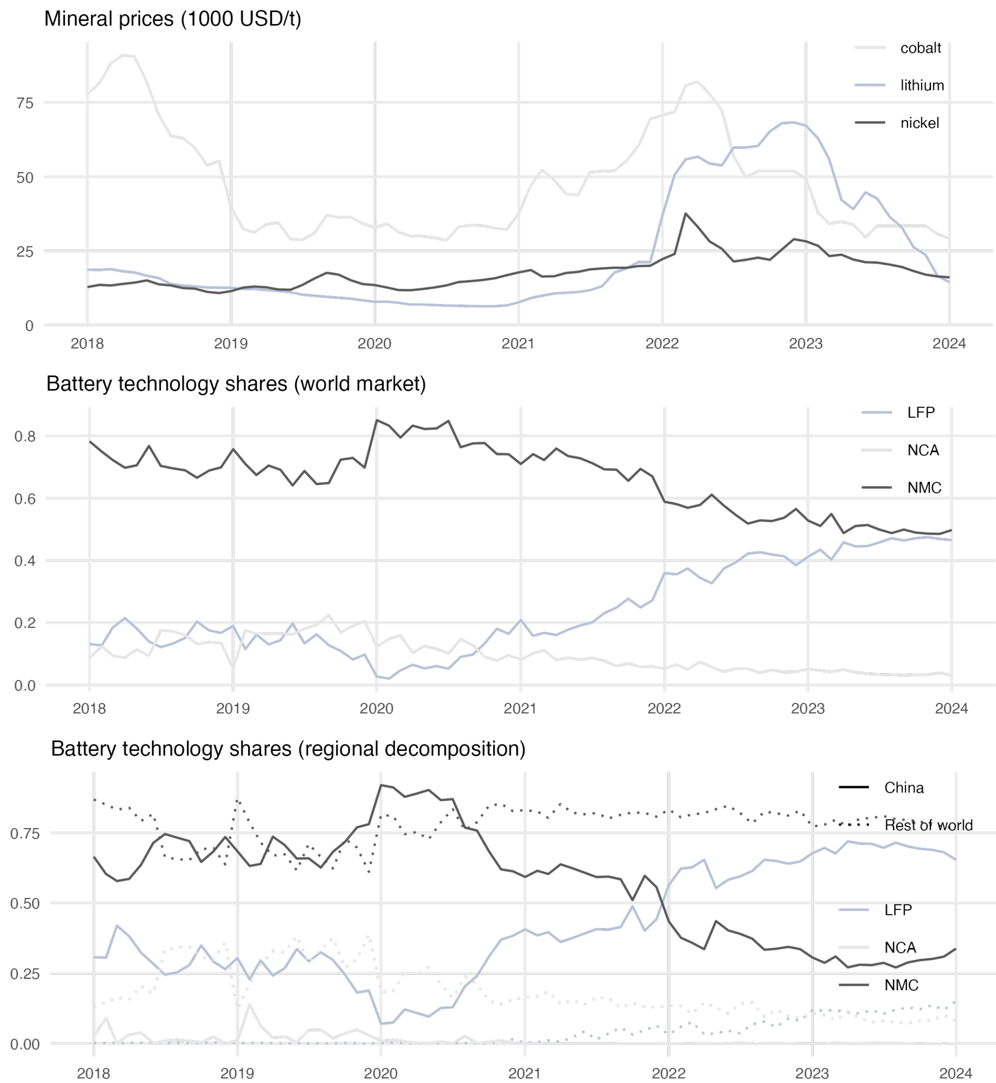
Lithium market. The increase in EV demand drove lithium prices to rise towards 2017. In response to high prices, new lithium mines in Australia, Argentina, and Chile expanded production, alleviating upward price pressure around 2019. Yet by 2022 lithium prices stood six times above their average over the 2015-2020 period. Similar to nickel and cobalt, one key reason for the price increase was supply lagging behind the post-2021 demand surge. Supply eventually did respond in Australia, Chile, Argentina, and China, so that by late 2023 lithium prices receded 20 percent, returning to their 2021 levels. Since then, increased lithium production has led to a supply glut. Additionally, many automakers shifted to LFP chemistries, which require less lithium (IEA 2024a).

Figure A6: Mineral, cathode material, and battery prices (2021-2024)



Mineral prices are monthly-averaged prices from SP Global. Cathode and battery prices are at monthly frequency from Benchmark Mineral Intelligence.

Figure A7: Mineral prices and battery technology adoption



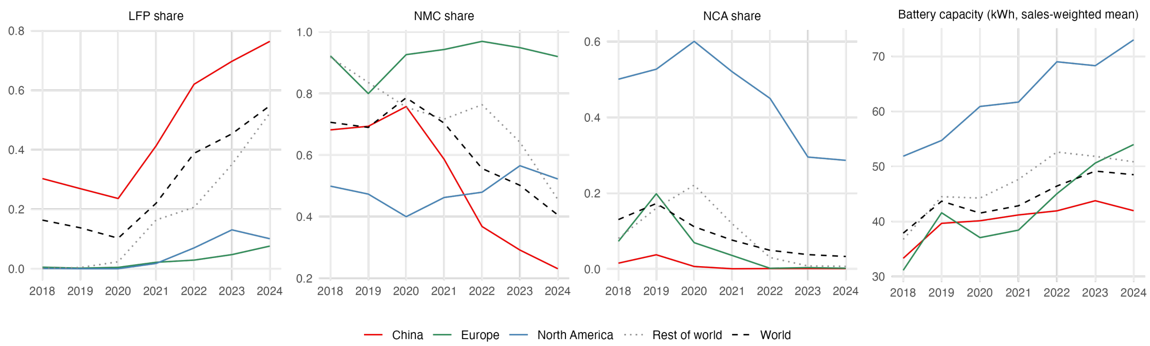
Mineral prices are monthly-averaged prices from SP Global. Battery technology market shares constructed from units sold, using monthly EV sales data from Benchmark Mineral Intelligence.

A.5.2 Battery markets

Figure A8 shows the evolution of EV battery technologies worldwide and across four consumer regions: China, Europe, North America and the rest of the world. As of 2024, consumers in China accounted for over 60% of global EV sales, while Europe and North America represented 20% and 10% of the market.

Beginning in 2018, every region had positive NMC and NCA shares, while LFP

Figure A8: Regional market shares of EV battery technologies

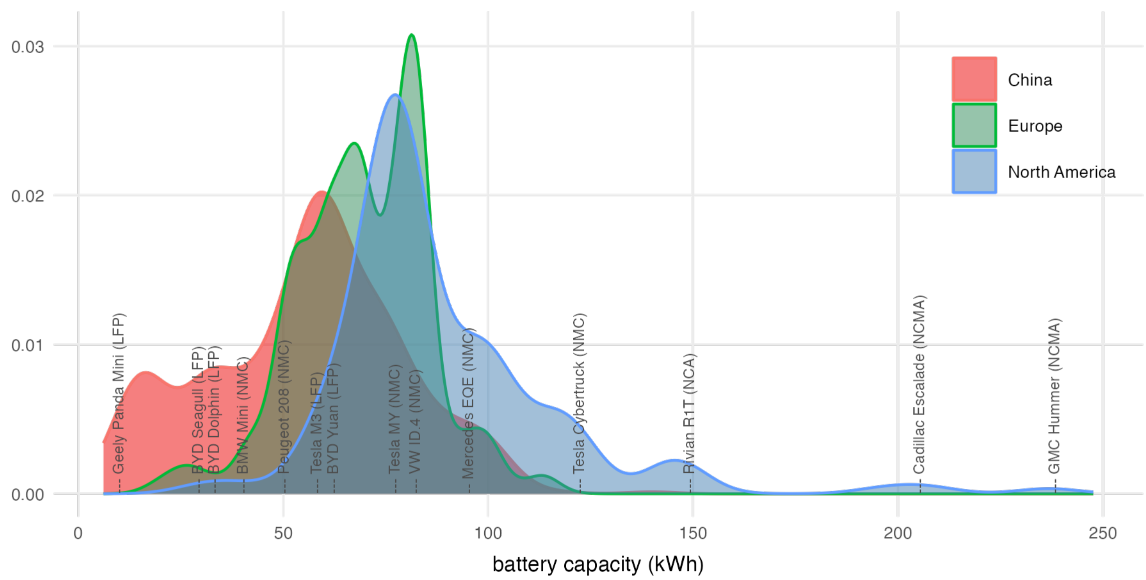


Market shares constructed from units sold, using EV sales data from Benchmark Mineral Intelligence.

was less than 1% everywhere except China. Since then, LFP has increased its market share everywhere, but especially in China and the rest of Asia, primarily at the expense of NMC. In Europe and North America, NMC still remains the main cathode technology. NCA has fallen to near zero market share in all regions except North America, where it is still highly demanded for its higher energy density in premium brands (e.g., Rivian). The far right panel of Figure A8 plots the average battery capacity of EV sales in each region. North American consumers purchase vehicles with significantly higher battery capacities than Chinese or European consumers.

Going beyond regional averages, Figure A9 shows the distribution of battery capacities of vehicles purchased in each region. Again, North American consumers buy vehicles with significantly higher capacities than Chinese or European consumers. These models tend to use NMC and NCA cathodes. Moreover, the North American distribution also holds a right tail of very heavy vehicles that use NCMA cathodes (e.g., GMC Hummer, Cadillac Escalade). Since NCMA accounts for less than 1% of the global battery market we exclude it from our main analysis.

Figure A9: Distribution of battery capacity across consumer regions



Plots are constructed from EV sales data from Benchmark Mineral Intelligence for 2024 BEV models.

B Model

Table B1: Notation

Symbol	Description
i	indexes mines
j	indexes battery technologies
k	indexes regions
m	indexes minerals
t	indexes years
p_{jt}	price per MWh of battery technology j in year t
P_t	price index of batteries in year t
X_{kt}	battery budget in region k and year t
w_{jt}	expenditure share of budget spent on battery technology j in year t
d_{jt}	quantity demanded (in MWh) of battery technology j in year t
r_j^m	tonnes of mineral m per MWh of battery technology j
η_{jt}	technology j mineral refining and battery manufacturing costs in year t
p^{mt}	price per tonne of mineral m in year t
d^{mt}	quantity demanded (in tonnes) of mineral m in year t
δ^{mt}	non-EV battery demand for mineral m in year t
S^{it}	crude ore quantity supplied (in tonnes) by mine i in year t
γ^{it}	ore grade of mine i in year t
s^{it}	mineral quantity supplied (in tonnes) by mine i in year t
$C^{it}(\cdot)$	total cost function of mine i in year t
k^i	capacity of mine i (in tonnes/year)
r^i	reserves of mine i (in tonnes)
g^i	baseline ore grade of mine i

B.1 Demand

Table B2 presents our algorithm for demand estimation. We build on Blundell and Robin (1999), which estimates demand parameters through the standard almost ideal demand system regression (Deaton and Muellbauer 1980) for a given price index and iterates on the price index until convergence. Our framework differs with variation across markets in choice sets. We remove products from choice sets using the procedure described in Chaudhuri et al. (2006), solving for virtual prices $\bar{p}_{jkt}$ that set respective expenditure shares to zero.

$$w_{jkt}\left(\boldsymbol{p}_t, \bar{\boldsymbol{p}}_t\right) = 0 \quad \text{for all } j \notin \mathcal{J}_{kt},$$

where $\boldsymbol{p}$ is the vector of prices of products in the choice set and $\bar{\boldsymbol{p}}$ is the vector of virtual prices of products not in the choice set. These virtual prices are a function of demand parameters, and hence we must iterate over virtual prices alongside the price indices.

Table B2: Demand estimation

Algorithm 1: Iterated AIDS with Choice Set Variation

Input : $\mathbf{w}$, $\mathbf{p}$, $\mathbf{z}$, $\{\mathcal{J}_{kt}\}_{k,t}$
Output : Estimates $\hat{\boldsymbol{\alpha}}$, $\hat{\boldsymbol{\beta}}$, $\hat{\boldsymbol{\gamma}}$
Initialize: $P_{kt}^{(0)}$ for all k, t;
virtual prices $\bar{p}_{jkt}^{(0)}$ for all $j \notin \mathcal{J}_{kt}$, all k, t;
$max\_diff \leftarrow \infty$;
while $max\_diff > threshold$ **do**
    $(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}}) \leftarrow$ AIDS regression using $(\mathbf{p} \cup \bar{\mathbf{p}}^{(0)})$ and $\mathbf{P}^{(0)}$;
    $\mathbf{P}^{(1)} \leftarrow \mathbf{P}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}}, \mathbf{p} \cup \bar{\mathbf{p}}^{(0)})$; $\bar{\mathbf{p}}^{(1)} \leftarrow \bar{\mathbf{p}}(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}}, \mathbf{p} \cup \bar{\mathbf{p}}^{(0)}, \mathbf{P}^{(0)})$;
    $max\_diff \leftarrow \max\{\max\{|\mathbf{P}^{(1)} - \mathbf{P}^{(0)}|\}, \max\{|\bar{\mathbf{p}}^{(1)} - \bar{\mathbf{p}}^{(0)}|\}\}$;
    $\mathbf{P}^{(0)} \leftarrow \mathbf{P}^{(1)}$; $\bar{\mathbf{p}}^{(0)} \leftarrow \bar{\mathbf{p}}^{(1)}$;
return $(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}})$;

C Counterfactuals

Figure C1: Market impacts of supply cuts (unilateral vs cartel)

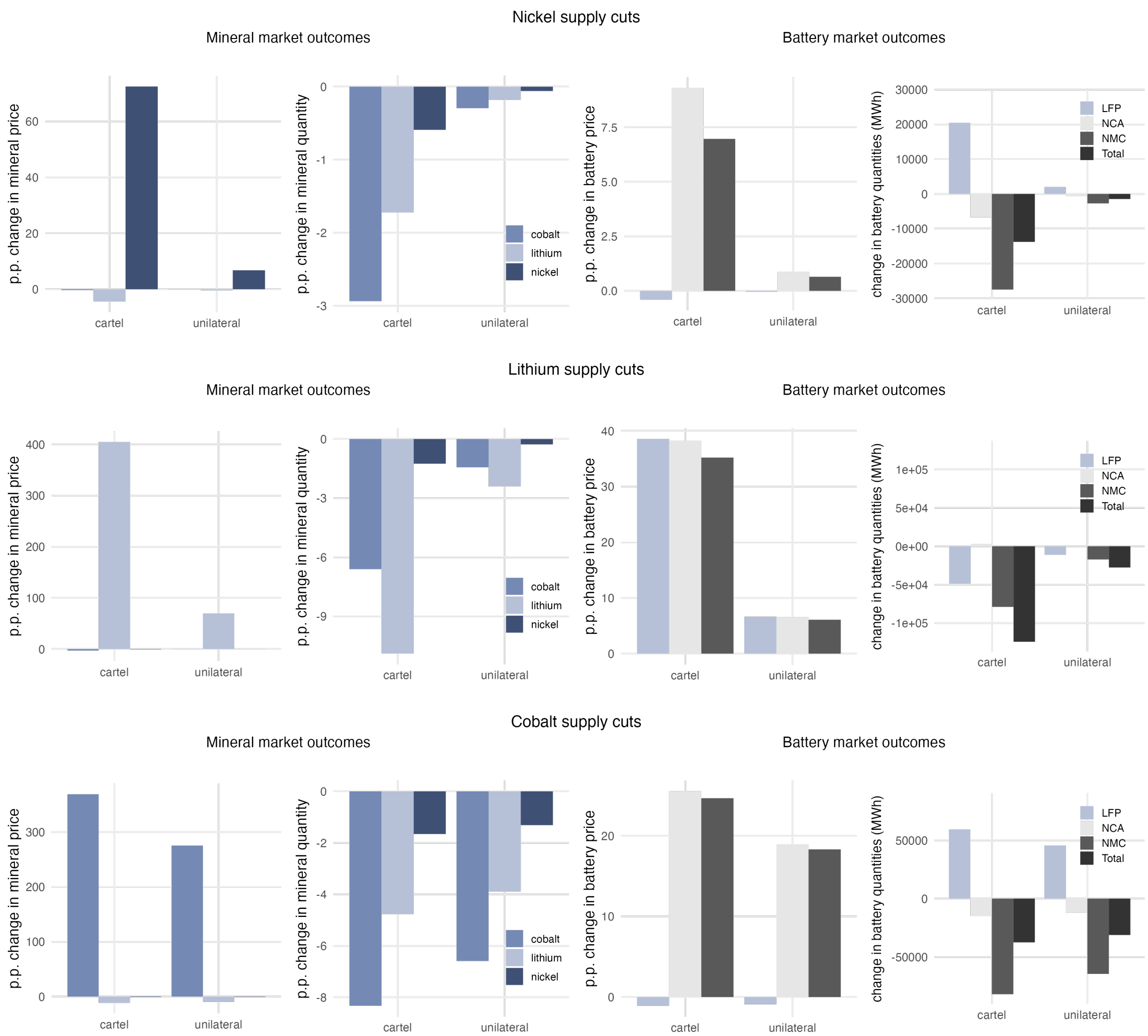
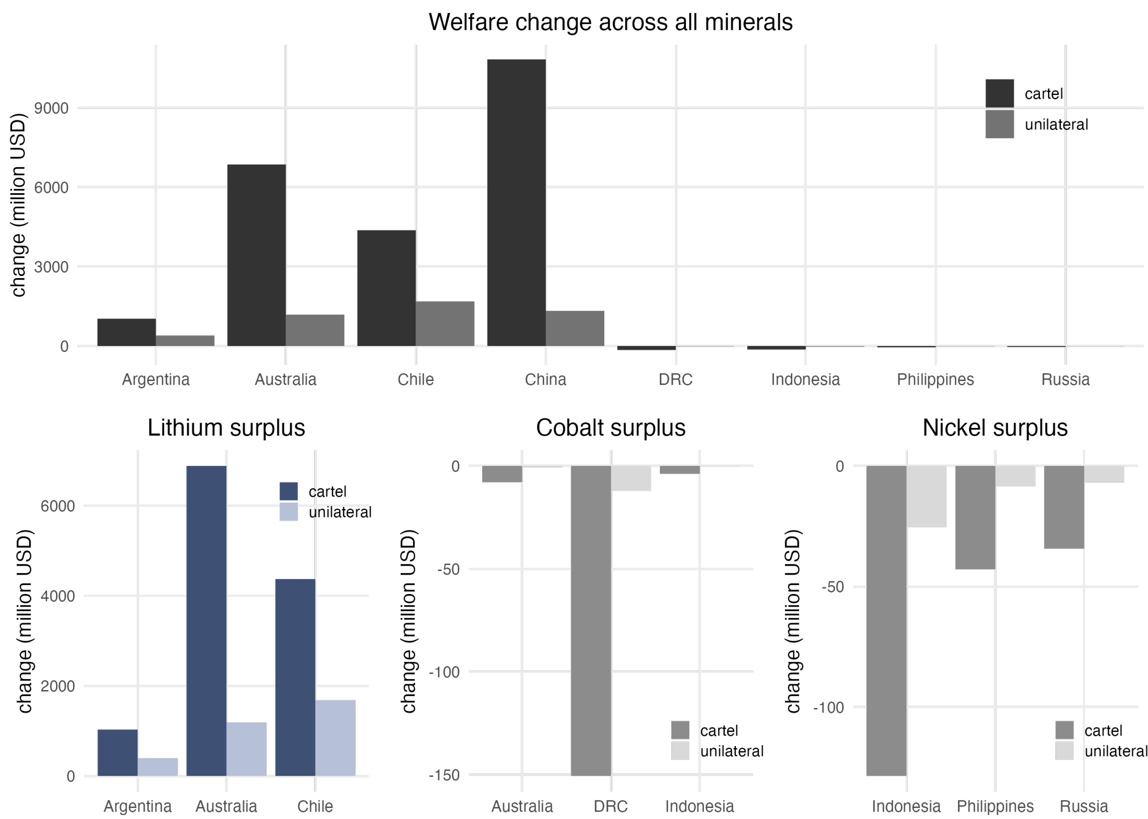
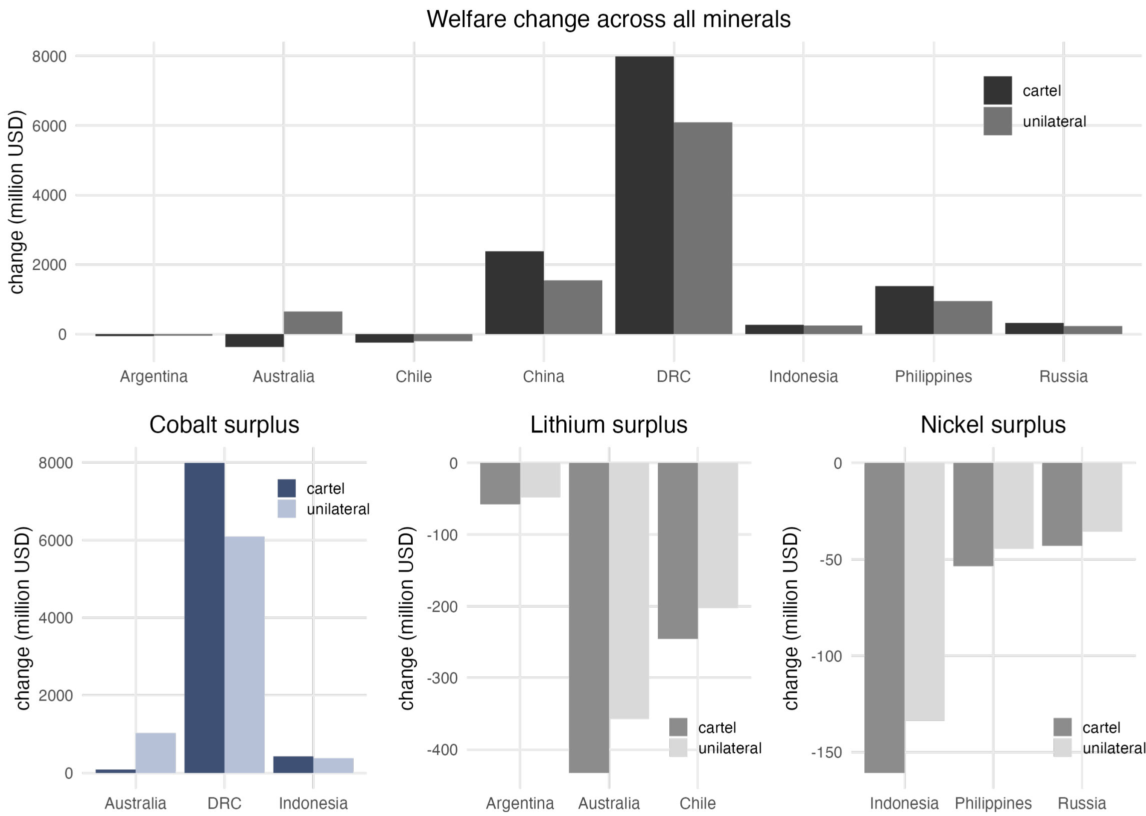


Figure C2: Welfare impacts of a lithium cartel (Australia-Chile-Argentina)



Welfare is defined as the sum of producer surplus and government revenue. The top panel plots welfare across minerals (since some countries produce multiple minerals). Only countries with large welfare changes are plotted. The bottom panel shows welfare changes attributable to each mineral. Bar colors compare cartel impacts to those of a unilateral cut by the top producer (Australia).

Figure C3: Welfare impacts of a cobalt cartel (Australia-DRC-Indonesia)



Welfare is defined as the sum of producer surplus and government revenue. The top panel plots welfare across minerals (since some countries produce multiple minerals). Only countries with large welfare changes are plotted. The bottom panel shows welfare changes attributable to each mineral. Bar colors compare cartel impacts to those of a unilateral cut by the top producer (Australia).

Table C1: Welfare impacts of taxes on lithium, nickel, and cobalt mining (millions of USD relative to baseline)

Policy	Tax ($/t)	Aus. Li	Chl. Li	Arg. Li	Ind. Ni	Phl. Ni	Rus. Ni	DRC Co	Aus. Co	Ind. Co
Lithium policies										
Aus.	21,775	1,188.49	1,682.64	395.44	-25.44	-8.52	-6.74	-11.95	-0.60	-0.29
Chl.	9,678	595.18	155.43	79.14	-4.72	-1.59	-1.25	-3.22	-0.16	-0.08
Arg.	2,117	27.32	15.48	1.77	-0.26	-0.09	-0.07	-0.16	-0.01	-0.00
Aus. & Chl.	63,965	4,784.95	3,150.07	2,398.17	-110.55	-36.87	-29.45	-109.48	-5.70	-2.78
Aus. & Arg.	27,370	1,653.06	2,514.64	246.15	-37.98	-12.71	-10.07	-14.95	-0.75	-0.36
Chl. & Arg.	12,551	994.66	251.46	59.23	-8.47	-2.85	-2.24	-5.09	-0.25	-0.12
Aus., Chl. & Arg.	75,457	6,882.22	4,370.44	1,029.55	-128.60	-42.86	-34.31	-150.56	-7.89	-3.85
Nickel policies										
Ind.	6,443	-17.27	-9.79	-2.30	721.63	530.23	361.52	-2.92	-0.15	-0.07
Phl.	1,526	-5.47	-3.10	-0.73	436.71	61.22	113.36	-0.94	-0.05	-0.02
Rus.	678	-0.00	-0.00	-0.00	0.32	0.11	0.04	-0.00	-0.00	-0.00
Ind. & Phl.	22,721	-133.29	-75.57	-17.76	7,591.39	-89.25	3,088.74	-16.18	-0.81	-0.40
Ind. & Rus.	8,647	-19.43	-11.02	-2.59	710.17	605.33	400.59	-3.27	-0.16	-0.08
Phl. & Rus.	3,052	-8.85	-5.02	-1.18	716.29	22.00	183.26	-1.52	-0.08	-0.04
Ind., Phl. & Rus.	29,842	-162.81	-92.33	-21.70	8,452.29	-1,213.18	3,798.11	-17.02	-0.86	-0.42
Cobalt policies										
DRC	182,574	-357.24	-202.72	-47.65	-133.71	-44.55	-35.68	6,089.25	1,028.13	380.37
Aus.	472	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.15	0.00	0.00
Ind.	-0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DRC & Aus.	218,429	-418.46	-237.52	-55.83	-155.43	-51.74	-41.55	7,839.18	85.61	491.05
DRC & Ind.	191,066	-370.86	-210.46	-49.47	-138.50	-46.14	-36.98	6,197.70	1,099.74	335.84
Aus. & Ind.	472	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	0.16	0.00	0.00
Aus., DRC & Ind.	228,808	-432.74	-245.64	-57.74	-160.80	-53.52	-43.01	7,987.61	88.48	427.16
Li & Ni policies										
Li: Aus.; Ni: Ind.	$\begin{bmatrix}21,341\\7,692\end{bmatrix}$	1,162.67	1,627.62	382.51	822.87	622.88	418.29	-13.54	-0.68	-0.33
Li & Co policies										
Li: Aus.; Co: DRC	$\begin{bmatrix}18,293\\214,011\end{bmatrix}$	639.12	1,098.46	258.16	-160.77	-53.51	-43.00	7,647.98	81.08	477.44
Ni & Co policies										
Ni: Ind.; Co: DRC	$\begin{bmatrix}5,983\\187,854\end{bmatrix}$	-372.54	-211.42	-49.70	443.05	380.66	266.80	6,152.58	1,072.21	329.32
Li, Ni & Co policies										
Li: Aus.; Ni: Ind.; Co: DRC	$\begin{bmatrix}18,293\\6,837\\218,767\end{bmatrix}$	621.31	1,089.97	256.17	506.43	435.55	302.04	7,748.48	83.33	405.21

Values reported in millions of USD relative to baseline with no policy intervention. Welfare values are the sum of mine-level producer surplus within a country and commodity and government revenue from the tax.