Critical Minerals, Geopolitics, and the Green Transition*

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Abstract

The green energy transition will be powered 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 active policy intervention 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, creating 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 dynamic equilibrium framework that embeds these upstream and downstream elements. On the demand side, we estimate an almost ideal demand system using electric vehicle (EV) manufacturer-level data on battery installations by technology around the world. The data span the universe of EV models produced between 2018-2024. The estimated demand system provides rich substitution patterns and allows us to discipline how changes in mineral prices reallocate demand across battery technologies. We find demand is elastic for all technologies, with significant substitution toward LFP when nickel-heavy technologies become more expensive.

On the supply side, we estimate a dynamic mining model using a new mine-level panel dataset 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 data. We develop a general framework that leverages cost data for dynamic supply estimation, allowing for cost convexity and addressing the typical endogeneity issue that arises from unobserved cost shocks. We recover mine-level supply curves, and we find modest but heterogeneous supply elasticities across countries. These 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 an equilibrium model that links global 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 export restrictions, raises global nickel prices and reduces NMC and NCA adoption as consumers shift toward LFP. Green adoption falls overall because lower adoption of NMC and NCA dominates higher adoption of LFP. Third, we examine the welfare impacts of market power among key producers, finding significant spillovers across mineral markets through cross-price interactions. As one country restricts the supply of a specific mineral to raise its price, other countries producing that same mineral free ride and win, while countries producing complementary minerals lose.

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 standard substitution forces, shaping both the aggregate and distributional impacts of policy interventions. One of our main insights is that the formation of a cartel among producers of multiple complementary minerals can lead to *lower* mineral prices, *lower* battery prices, and *more* green adoption. The logic is the same as double marginalization. When producers of complementary minerals separately exercise their market power, they do not internalize that by raising the price of their own mineral they are lowering demand for the other minerals. A multi-mineral merger internalizes this effect, leading to lower prices and higher output. This stands in stark contrast to a merger among producers of a single mineral, which leads to higher prices and less output because of the commodity's substitutability across suppliers (e.g., an oil cartel).

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 upstream policies of mineral-endowed countries have 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 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-intense batteries. We add the novel margin of complementarity: Indonesian nickel policy affects all mineral-producing countries, including those producing 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 impact of EV subsidies on final consumers. We focus instead on mining and processing upstream, showing how upstream 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

2.1 Institutional details

Critical minerals

While the definition of "critical minerals" varies, many countries identify them using criteria that capture a combination of supply vulnerability and low demand

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

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 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]

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 operators. Differences in deposit types create differences in the production process across minerals. Most minerals are found in hard-rock deposits. Others, including lithium in South America, are found in liquid brine deposits. In the first

[2] We do not include graphite because its share of demand accounted for by the EV sector is not very large and because there are alternatives to natural graphite, such as synthetic graphite, that are already common and not subject to the same geographic endowments as the minerals that are the focus of this paper.

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.

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 is dominated by 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 phosphate 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 suitable for the dense urban markets that prevail in China. While LFP is the most prevalent battety 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, 94% 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

[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.

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).

Prices

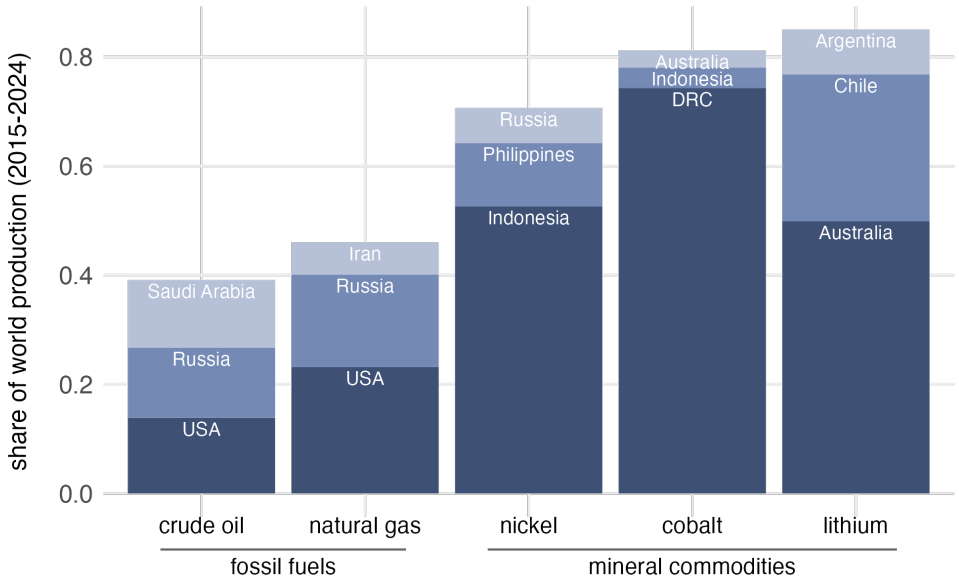
We obtain mineral prices from S&P Global for lithium, nickel, and cobalt for 2010 to 2024 at monthly frequency. Battery prices are from Benchmark Minerals for 2021 to 2024 at monthly frequency. Importantly, prices are reported separately for each battery technology, including NMC, NCA, and LFP.

2.3 Stylized facts

Fact 1: Mineral endowments are geographically concentrated

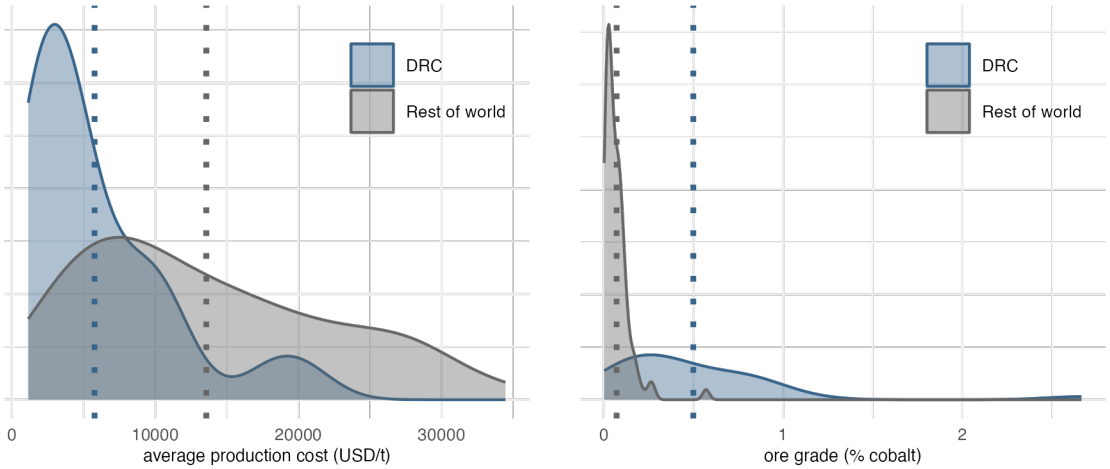
The uneven distribution of geological endowments leads to concentration in production for both minerals and fossil fuels, but minerals markets are especially concentrated. Figure 1 shows that the market share of the top three producing countries ranges from 40 to 50% for fossil fuels, but a substantially higher 70 to 85% for min-

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: Distribution of production costs and ore grade across mines (cobalt)



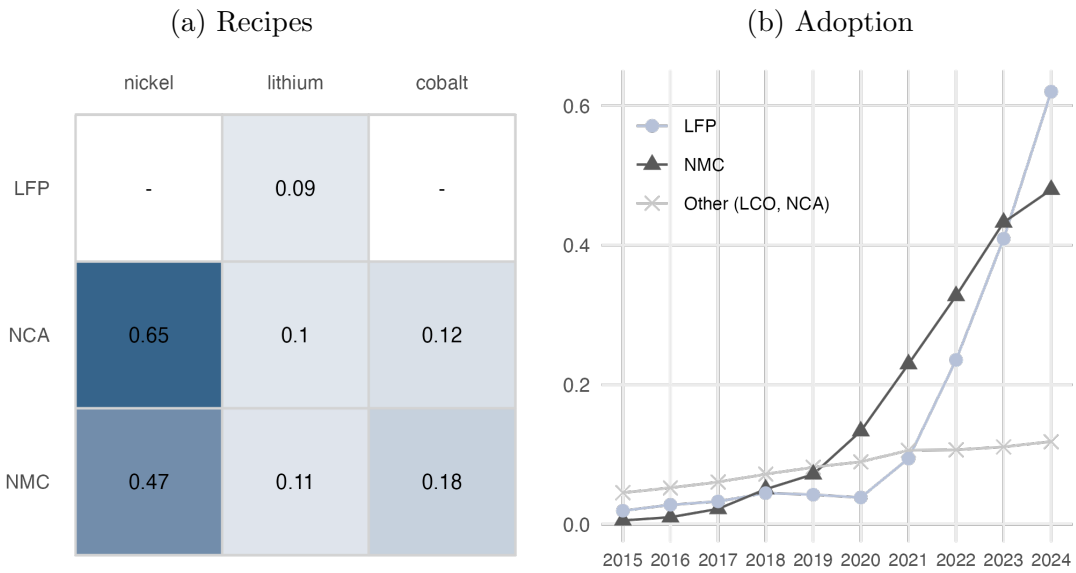
The panel on the left is a density plot of mine-level production costs (USD/t cobalt, averaged over time for each mine). The panel on the right is a density plot of mine-level ore grade (% cobalt, averaged over time for each mine).

eral 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 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. Mining costs are highly heterogeneous

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 production costs. Figure 2 shows this heterogeneity for the case of cobalt. Ore grades in the DRC average 0.5% compared to only 0.1% in the rest of the world, thus conferring it a significant cost advantage.

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

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 com-

petitive, 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.

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

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.

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

[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.

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

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 $\frac{\mathrm{d}p^\ell}{\mathrm{d}\tau^\ell}, \frac{\mathrm{d}p^n}{\mathrm{d}\tau^\ell} < 0$. 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 battery technologies used by EV manufacturers.

4.1 Model

EV manufacturing

In each region k and period t, EV manufacturers chooses among battery technologies $j \in \mathcal{J}$. They do so by allocating a battery budget X_{kt} across individual technologies taking global prices p_{jt} as given. We specify their demand in product space with expenditure shares w_{jkt} given by

$$w_{jkt} = \alpha_{jt} + \beta_j \log\left(\frac{X_{kt}}{P_t}\right) + \sum_{j' \in \mathcal{J}} \gamma_{jj'} \log(p_{j't}) + \varepsilon_{jkt}, \tag{6}$$

where the battery price index P_t is of translog form

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

Quality α_{jt} captures product-time varying unobservables that affect demand. Income effects β_j allow expenditure shares to respond heterogeneously to changes in budgets, which may increase over time as battery technologies diffuse and adoption rates rise. We deflate these budgets by the price index P_t.[5] Semi-elasticities $\gamma_{jj'}$ govern own- and cross-price elasticities. The main advantage of modeling demand in product space is that the semi-elasticities allow for full flexibility in substitution patterns across products.[6] Finally, unobserved demand shocks are denoted 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 in region k is

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

by definition of expenditure share w_{jkt}. Global demand is obtained by aggregating across regions $k \in \mathcal{K}$,

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

Battery manufacturing

A battery manufacturer produces a technology j by combining minerals $m \in \mathcal{M}$ using a recipe r_j^m. Producing one unit of technology j requires r_j^m units of mineral m, as well as non-mineral inputs. Formally, consider a Leontief production function

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

where y_{jt} is battery output, $\boldsymbol{x}_{jt} \equiv \{x_{jt}^m\}^{m \in \mathcal{M}}$ is the mineral input, and $\bar{x}_{jt}$ is a non-mineral input. To produce one unit of technology j, the cost-minimizing quantity of each mineral input m is r_j^m, which battery manufacturers purchase at the refined mineral price $\tilde{p}^{mt}$. The cost-minimizing quantity of non-mineral inputs is $\bar{r}_{jt}$ at constant

[5] Factors affecting the extensive margin between EV and ICE vehicles among final consumers, such as fossil fuel prices, are picked up by the variation in X_{kt} observed in the data. Namely, the battery budgets chosen by EV manufacturers summarize their view of relative EV-ICE demand conditions.

[6] 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.

marginal cost $\bar{c}_{jt}$. We treat battery manufacturers as perfectly competitive, such that the prices of battery technologies are given by

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

where $\bar{\mu}_{jt} = \bar{r}_{jt}\bar{c}_{jt}$ 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.[7]

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} as

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

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

Mineral demand

Given mineral prices $\boldsymbol{p}^t \equiv \{p^{mt}\}^{m \in \mathcal{M}}$, the demand for mineral m in period t is

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

The summation on the right hand side captures the the mineral demand implied by the battery demand across all technologies. The $\widetilde{d}^{mt}$ term accommodates non-battery

[7] 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.

demand for minerals.

4.2 Estimation

We estimate the model with iterated linear least squares (ILLS), as in Blundell and Robin (1999). The first estimation challenge is that the translog price index contains the parameters of interest and enters nonlinearly in the expenditure share equation. The iterated approach exploits the expenditure share equation is linear in parameters for a fixed value of P_t. We initialize estimation with the Stone price index, which is the expenditure-weighted average product price, and then we estimate 6 by linear regression. We use the resulting parameter estimates to compute an updated price index with equation 7 and iterate until convergence. Throughout, we impose the standard restrictions in AIDS estimation: adding-up, homogeneity, and symmetry.

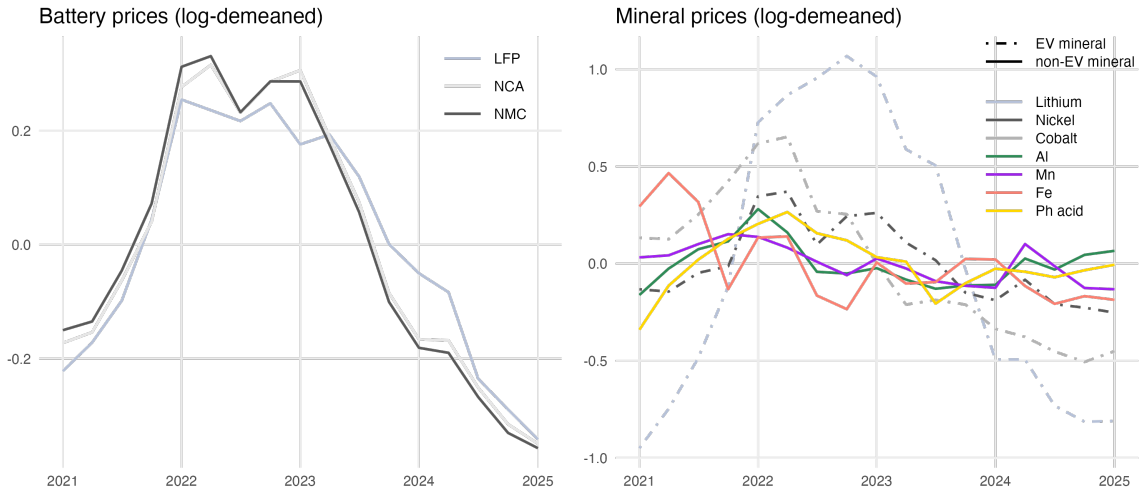
The second estimation challenge is that battery prices are endogenous because they are correlated with unobserved demand shocks. We address this by instrumenting with cost shifters in the form of aluminum, phosphoric acid, iron, and manganese prices. These minerals are inputs in battery production, so their prices are relevant for determining battery prices. At the same time, their demand is primarily driven by non-EV uses, such as steel production. The battery share of global demand for any of these minerals is less than 3%. It follows that their prices are plausibly excludable from battery demand. We denote this subset of minerals $\mathcal{M}_{non-EV} \subset \mathcal{M}$. Figure 4 confirms the prices in this subset co-vary with battery prices, but less strongly than those of core EV minerals (lithium, nickel, cobalt) given their distinct demand sources. To conclude, we construct the instrument for each endogenous price p_{jt} as

$$z_{jt} = \sum_{m \in \mathcal{M}_{non-EV}} r_j^m p^{mt}. \tag{10}$$

4.3 Results

Our final estimation sample is a quarterly panel from 2021 Q1 to 2025 Q1 with four regions of EV manufacturers: China, North America, Europe, and Asia ex-China. We define the set of battery technologies available to EV manufacturers as consisting of two options. Option L consists of LFP and option N is a nickel-cobalt aggregate

Figure 4: Prices of battery technologies and minerals



Mineral prices are from SP Global. Battery prices are from Benchmark Mineral Intelligence. All prices are averaged at the quarterly level and log de-meaned.

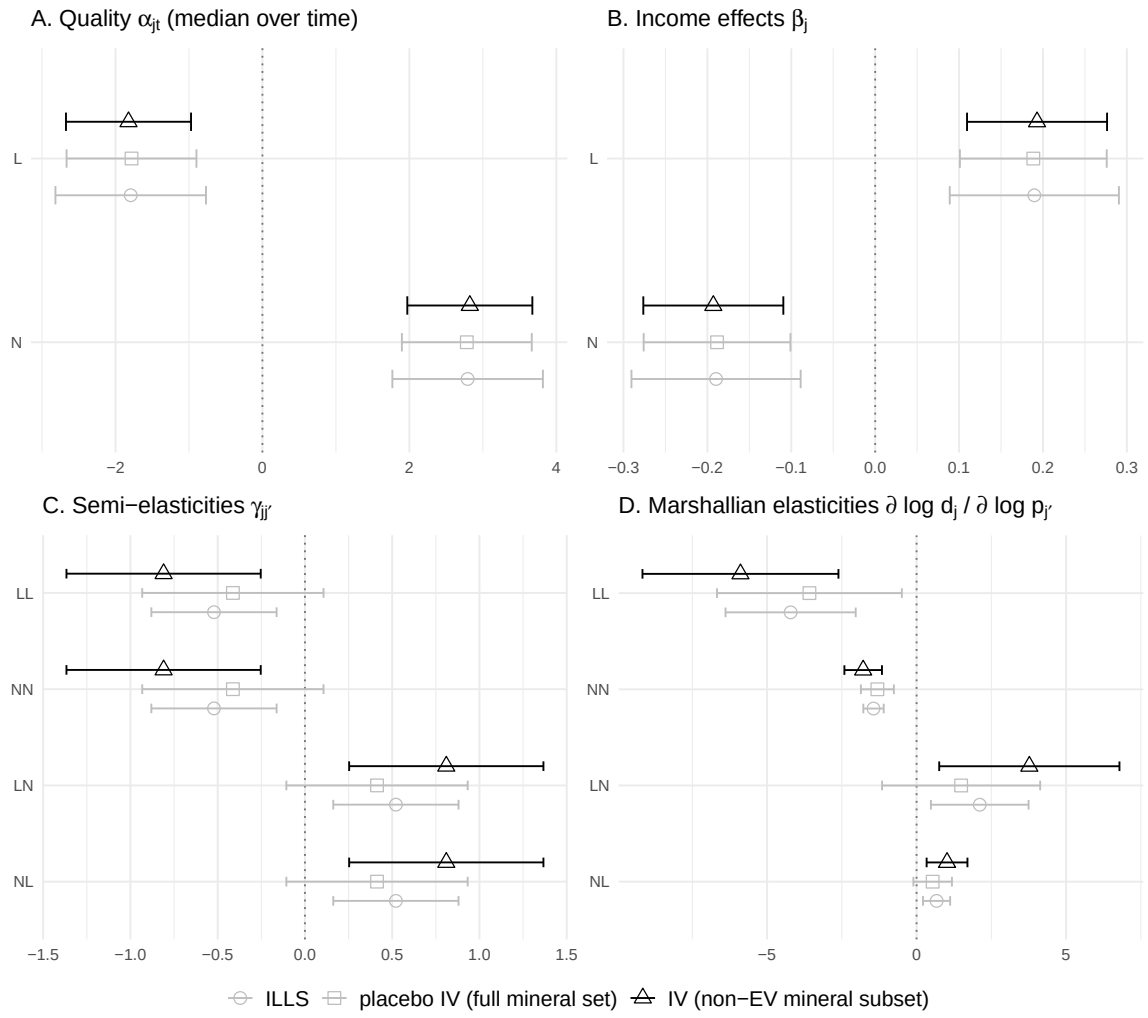
that includes NMC and NCA. We aggregate NMC and NCA because their mineral intensities and prices are highly correlated, as shown in Figure 4.[8] Battery technology prices are measured in units of USD per MWh of capacity.

Figure 5 reports estimates of the demand parameters and the implied elasticities under three specifications: un-instrumented ILLS, our main IV approach defined in equation 10, and a placebo IV that uses the full set of minerals $\mathcal{M}$ instead of the subset $\mathcal{M}_{non-EV}$. Further implementation details can be found in Appendix B.1.

We begin by interpreting the results from our main IV. First, panel A of Figure 5 shows that estimates of the quality term α_{jt} are on average lower for technology L. The fact that technology L has systematically lower prices *and* lower shares is rationalized by its lower quality. This is consistent with LFP-equipped vehicles catering to the lower-end of the consumer market due to their shorter driving ranges. Second, panel B shows income effects β_j are larger for L, likely due to the fact that aggregate battery expenditure rises during our sample period and coincides with sharp

[8] Keeping NMC and NCA separate to gain heterogeneity within the nickel-intense varieties comes at the cost of noisy estimation results. Moreover, the key margin of heterogeneity observed in the industry's stylized facts is the distinction between LFP and nickel-intense technologies, not the heterogeneity within the nickel-intense varieties.

Figure 5: Demand estimation results



The vertical axis of each panel labels the sub-indices of each parameter. Marshallian elasticities are computed as $\frac{\partial \log d_j}{\partial \log p_{j'}} = \frac{1}{\overline{w}_j}\left[\gamma_{jj'} - \beta_j \overline{w}_{j'}\right] - 1_{j=j'}$ where $\overline{w}_j$ is the technology-j expenditure share worldwide and averaged over time. Standard errors are clustered by regional market. Standard errors for Marshallian elasticities are computed using the delta method.

growth in L. Third, panel C shows own-price semi-elasticities γ_{jj} are negative while the cross-price terms $\gamma_{jj'}$ are positive. These qualitative patterns carry over to the Marshallian elasticities in panel D since they are a function of the semi-elasticities. Panel D shows demand is elastic for all technologies, as own-price elasticities exceed one in magnitude. The own-price elasticity of L being larger than N is consistent with the fact that LFP tends to be used in lower-end vehicles for which consumer

demand is likely more price-sensitive.

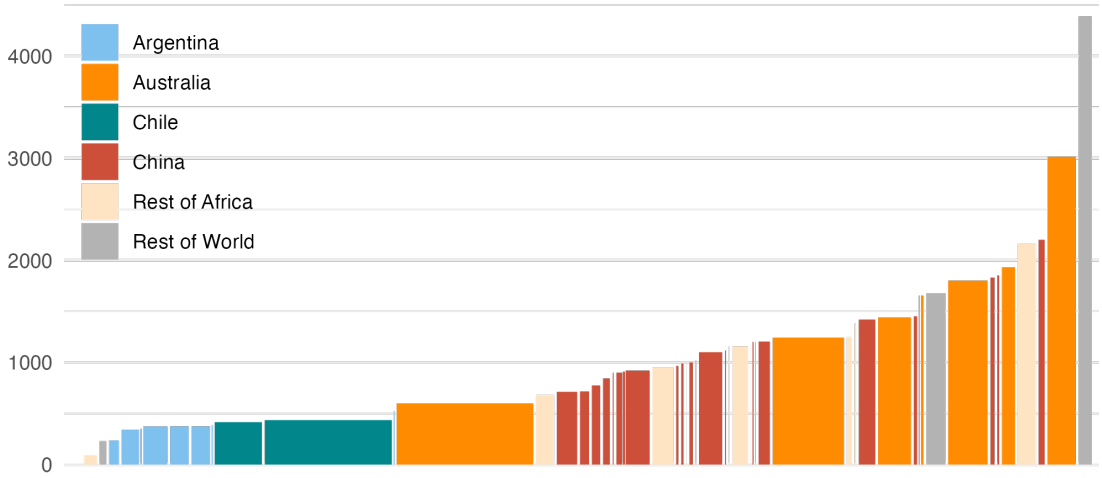
Finally, we discuss the performance of our IV strategy in terms of relevance and exclusion restrictions. Relevance is testable and is not a concern given our first stage F-statistics exceed conventional thresholds for weak instruments. Turning to the exclusion restriction, we compare the un-instrumented ILLS estimates to our main IV and the placebo IV. The placebo uses the full set of minerals $\mathcal{M}$ so we expect it to fail the exclusion restriction because demand shocks ε_{jkt} are likely driving the prices of the EV-specific minerals in $\mathcal{M}$, such as lithium. Indeed, panels C-D of Figure 5 show the placebo IV delivers results that are very similar to the un-instrumented ILLS estimates, consistent with the notion it is not correcting endogeneity. By contrast, restricting the set of minerals to $\mathcal{M}_{non-EV}$ changes the estimates substantially, suggesting that the subset restriction is stripping away price endogeneity. Moreover, panels C-D of Figure 5 show the semi-elasticities move away from zero—consistent with correcting simultaneity bias—and they nearly double in magnitude. Recall that under simultaneity bias the demand shocks ε_{jkt} push up shares w_{jkt} and prices p_{jt}, so an un-instrumented regression will tend to infer they are positively related. If the true price coefficient is negative, then its un-instrumented estimate will be pushed up towards zero. An IV that satisfies the exclusion restriction should deliver estimates that are further away from zero, as is the case with our main IV specification.

5 Supply

Our objective is to construct mineral supply curves that allow for rich heterogeneity across mines. We leverage our mine-level data on realized costs as a starting point and complement it with a dynamic extraction model.

A straightforward approach to construct an industry supply curve is to use the realized average costs of firms. The result is an empirical step function, shown in Figure 6 for the case of lithium. This purely data-driven approach is successful at capturing first-order drivers of mine-level heterogeneity, such as geological fundamentals. For example, brine-based lithium mines in South America have lower average costs because their beneficiation process consists of evaporation by natural sunlight, a low-cost procedure that is not available for hard-rock mines in Australia.

Figure 6: Realized average costs across mines (USD/t LCE, 2024)



The average 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 height indicating its average cost (USD per tonne of lithium carbonate equivalent, LCE) and bar width proportional to its production level. For brine-based operations the extraction costs correspond largely to pumping costs, while for hard-rock operations they correspond to excavation costs.

However, the empirical step function can only be interpreted as a supply curve under two restrictive assumptions. First, average costs need to equal marginal costs, which only holds for a linear cost function. Linearity is a strong assumption if mines actually face capacity constraints that lead to cost convexities. Second, the empirical step function depends only on the current mineral price, which implicitly assumes mines are myopic. Myopia is a strong assumption given the non-renewable nature of the resource being extracted. The purpose of our model is to relax these two assumptions by allowing for non-linear costs and forward-looking mines.

5.1 Model

We propose a model of mineral supply with forward-looking mines facing non-linear extraction costs. The model-implied extraction path provides the econometric restrictions from which we estimate the extent of cost non-linearities. We estimate the model at annual frequency using mine-level data on extraction volume, capacity, average costs, and ore grade.

Mineral supply

In each period t a mine i extracts raw ore x^{it} by solving a dynamic problem. The mine produces mineral $m(i)$ by processing the extracted ore x^{it} into mineral supply

$$s^{it} = g^{it} x^{it}, \tag{11}$$

where g^{it} is the grade of the mineral $m(i)$ contained in the ore. Given mineral prices p^{mt}, each tonne of raw ore delivers marginal revenue given by

$$mr^{it} = p^{mt} g^{it}. \tag{12}$$

Dynamics (depletion and degradation)

The mine's optimal extraction problem is subject to two dynamic forces: reserve *depletion* and ore *degradation*. First, because of the non-renewable nature of the resource, mines internalize how current extraction x^{it} depletes future reserves R^{it+1}

$$R^{it+1} = R^{it} - x^{it} \geq 0. \tag{13}$$

Second, because ore grade varies within a mine and the highest-grade deposits are extracted first, current production affects future grade,

$$\log\left(g^{it+1}\right) = \log\left(g^{it}\right) - \delta \log\left(s^{it}\right). \tag{14}$$

The $\delta > 0$ term is defined as the ore degradation elasticity, which we estimate separately for each mineral using equation 14 (see Appendix B.2.1). It will be useful to define mc_d^{it+1} as the marginal degradation cost: the impact of period t extraction on period $t+1$ revenue due to future degradation,

$$mc_d^{it+1} \equiv -\frac{\partial g^{it+1}}{\partial x^{it}} p^{mt+1} x^{it+1} > 0 \quad \text{where} \quad \frac{\partial g^{it+1}}{\partial x^{it}} = -\delta \left(\frac{g^{it}}{x^{it}}\right)^{1-\delta} < 0. \tag{15}$$

Given our estimate for δ, the mc_d^{it+1} term is observed since the only other requirements to construct it are observed prices, extraction volumes, and grades. Ore degradation is an important feature of mining for metals that is distinct from depletion in fossil

fuel extraction (Aguirregabiria and Luengo 2016).

Cost non-linearities

Apart from the dynamic depletion and degradation costs, the mine pays a per-period static extraction cost C^{it} that is a function of observed extraction x^{it} and unobserved idiosyncratic cost shocks ε^{it},

$$C^{it} = F(x^{it}; \kappa) + H(x^{it}, \varepsilon^{it}). \tag{16}$$

$F(x^{it}; \kappa)$ is a flexible, potentially non-linear, function of extraction that is parameterized by κ. The parameters in κ govern the degree of non-linearity of the cost function and are the main object we seek to estimate. $H(x^{it}, \varepsilon^{it})$ is a function of unobserved cost shocks ε^{it} that are allowed to interact with extraction decisions. The average costs implied by 16 are

$$ac^{it} = f(x^{it}; \kappa) + h(x^{it}, \varepsilon^{it}), \tag{17}$$

where $f(x; \kappa) \equiv F(x; \kappa)/x$ and $h(x, \varepsilon) \equiv H(x, \epsilon)/x$. Marginal costs implied by 16 are

$$mc^{it} = \underbrace{f(x^{it}; \kappa) + f'(x^{it}; \kappa)x^{it}}_{\equiv \widetilde{mc}(x^{it}; \kappa)} + \underbrace{h(x^{it}, \varepsilon^{it}) + h'(x^{it}, \varepsilon^{it})x^{it}}_{\equiv \widetilde{h}(x^{it}, \varepsilon^{it})}. \tag{18}$$

The $\widetilde{mc}(x^{it}; \kappa)$ term collects the parametrized components of marginal costs, while $\widetilde{h}(x^{it}, \varepsilon^{it})$ does the same for the unobserved idiosyncratic components.

Optimal extraction path

The Euler equation that results from the mine's optimal extraction decision is,

$$mr^{it} - mc^{it} - \beta \mathbb{E}_{it}\left[mc_d^{it+1}\right] = \beta \mathbb{E}_{it}\left[mr^{it+1} - mc^{it+1} - \beta mc_d^{it+2}\right]. \tag{19}$$

The left hand side is the payoff from extracting at t and the right hand side is the same for $t+1$. First, depletion dynamics are clearly isolated when shutting down degradation by setting $\delta = 0 \implies mc_d^{it} = 0 \; \forall t$. This delivers the standard Hotelling (1931) condition: the payoff from extraction increases at a rate of $1/\beta$. Second, degradation dynamics show up when $\delta > 0$. On the left hand side, extracting at t

reduces grade at $t+1$, which shows up as an expected degradation cost at time t, $\mathbb{E}_{it}\left[mc_d^{it+1}\right]$. On the right hand side, extracting at $t+1$ reduces grade at $t+2$, which also shows up as an expected degradation cost $\mathbb{E}_{it}\left[mc_d^{it+2}\right]$, but one period ahead.

5.2 Estimation

As a first step to obtaining an estimating equation we decompose the expectational term of the Euler equation into its realization and a forecast error η^{it+1}.[9] Rearranging terms delivers

$$\underbrace{\left[\beta mr^{it+1} - mr^{it}\right]}_{\Delta \text{ PV of marginal revenue}} - \underbrace{\beta\left[\beta mc_d^{it+2} - mc_d^{it+1}\right]}_{\Delta \text{ PV of degradation costs}} = \underbrace{\left[\beta mc^{it+1} - mc^{it}\right]}_{\Delta \text{ PV of static marginal costs}} + \eta^{it+1}.$$

The left hand side consists of observables: marginal revenues are observed from 12 using prices and grade, and degradation costs are estimated offline from 14-15. The right hand side consists of unobserved (static) marginal costs and shocks. To make notation concise let $\Delta y^{it} = \beta y^{it} - y^{it-1}$ denote the change in present value of variable y between $t-1$ and t, thus streamlining the previous Euler equation,

$$\Delta mr^{it} - \beta \Delta mc_d^{it+1} = \Delta mc^{it} + \eta^{it}. \tag{20}$$

5.2.1 Endogeneity

To see the endogeneity problem explicitly we replace the marginal cost definition from 18 in Euler equation 20,

$$\Delta mr^{it} - \beta \Delta mc_d^{it+1} = \Delta \widetilde{mc}^{i}\left(x^{it};\kappa\right) + \Delta \widetilde{h}(x^{it},\varepsilon^{it}) + \eta^{it}. \tag{21}$$

Estimates of κ will be biased because the extraction choice x^{it} inside $\Delta \widetilde{mc}^{i}\left(x^{it};\kappa\right)$ and the idiosyncratic shock ε^{it} inside $\Delta \widetilde{h}(x^{it},\varepsilon^{it})$ are negatively correlated.[10]

Given we are estimating supply, the standard solution to this type of endogeneity

[9] To do so, rearrange 19 so that all $t+1$ terms are on the right hand side and define $X^{it+1} \equiv mr^{it+1} - mc^{it+1} - \beta(mc_d^{it+2} - mc_d^{it+1})$. It follows that $X^{it+1} = \mathbb{E}[X^{it+1}|\mathcal{I}_t] + \tilde{\eta}^{it+1}$ where $\mathbb{E}[\tilde{\eta}^{it+1}|\mathcal{I}_t] = 0$. Finally, define $\eta^{it+1} = \beta\tilde{\eta}^{it+1}$.

[10] If $\Delta\varepsilon^{it}$ is positive, then marginal costs have risen for idiosyncratic reasons, so we should have lower extraction growth Δx^{it}, which implies lower growth in marginal costs $\Delta \widetilde{mc}^{i}\left(x^{it};\kappa\right)$.

problem is to use a demand shifter as an instrument. We take an alternative approach by leveraging our cost data and noting that observed cost realizations contain information on unobserved cost shocks. Concretely, we can invert the shocks as a function of observables using the average cost equation 17,

$$\varepsilon^{it} = h^{-1}\left(ac^{it} - f(x^{it};\kappa), x^{it}\right). \tag{22}$$

The key requirement is that $h(x^{it}, \varepsilon^{it})$ is invertible. After replacing ε^{it} in 21 with the inversion from 22, the right hand side of the Euler equation is now purged of the cost shocks. The only endogeneity concern that remains is due to the forecast error η^{it}, which can be shown to be negatively correlated with the right hand side variables, biasing estimates downward. This endogeneity problem is solved with lagged variables z^{it-1} that belong to $\mathcal{I}_{t-1}$, and are thus orthogonal to η^{it} but relevant for x^{it}.

5.2.2 Implementation

Our strategy for addressing endogeneity is general in the sense it does not depend on the functional form of the parametric component of costs, $F(x^{it};\kappa)$. Moreover, the only requirement for the idiosyncratic component $H(x^{it}, \varepsilon^{it})$ is an invertibility condition so that equation 22 is well defined.[11]

However, to implement the procedure we do need to settle on a functional form for $F(x^{it};\kappa)$ and $H(x^{it}, \varepsilon^{it})$. We assume $F(x^{it};\kappa)$ is convex in extraction x^{it}.[12] As a result, the implied marginal costs are linear in extraction

$$\widetilde{mc}^{i}(x^{it};\kappa) = \kappa_0^{mk} + \left(\frac{\kappa_1^{mk}}{\overline{x}^{i}}\right) x^{it}. \tag{23}$$

The κ_0^{mk} and κ_1^{mk} parameters are mineral-m, country-k specific intercepts and slopes of the marginal cost function. The $\overline{x}^{i}$ term is the mine's capacity, which we observe. The interpretation of 23 is that as the mine increases extraction, the extent to which its marginal costs rise beyond κ_0^{mk} depends on the κ_1^{mk} slope parameter and its capacity $\overline{x}^{i}$. Therefore, κ_1^{mk} governs the degree to which marginal costs are driven by the

[11] An auxiliary condition is required to avoid a degenerate case where the parameters κ are simply canceled out of the Euler equation, in which case κ is not identified. Given it is a degenerate case, we discuss it in Appendix B.2.2.

[12] Concretely, $F(x^{it};\kappa) = \kappa_0^{mk} x^{it} + \frac{1}{2}\left(\frac{\kappa_1^{mk}}{\overline{x}^{i}}\right)(x^{it})^2$.

convex component of costs. Capacity $\overline{x}^i$ adds mine-level heterogeneity to the impact of κ_1^{mk}. Intuitively, mines with higher capacity are less subject to decreasing returns to scale, so their marginal costs rise slower with extraction. Another way to interpret 23 is in terms of the mine's utilization rate $u^{it} \equiv \left(\frac{x^{it}}{\overline{x}^i}\right)$ rather than extraction volume x^{it}. As mines increase their utilization rate, marginal costs rise at a rate of κ_1^{mk}.

For the idiosyncratic component of costs we assume $H(x^{it}, \varepsilon^{it}) = x^{it}\varepsilon^{it}$. This implies the cost shock can be inverted as $\varepsilon^{it} = ac^{it} - f(x^{it}; \kappa)$. After imposing our functional forms and inverting for ε^{it} the Euler equation becomes,

$$\Delta mr^{it} - \Delta ac^{it} - \beta \Delta mc_d^{it+1} = \frac{\kappa_1^{mk}}{2} \Delta u^{it} + \eta^{it}. \tag{24}$$

The observed correlation between changes in marginal revenue on the left hand side (net of average and degradation costs) and changes in utilization on the right hand side pins down κ_1^{mk}. Namely, if we observe utilization rising while marginal revenues stay flat, we would infer utilization does not affect marginal costs ($\kappa_1^{mk} \approx 0$). In other words, we would infer the degree of cost convexity to be small, i.e., nearly linear costs.

To estimate 24 we address the remaining endogeneity bias from the forecast error by instrumenting changes in utilization rates Δu^{it} with past utilization u^{it-1}, which is orthogonal to η^{it} by construction. Given estimates $\widehat{\kappa}_1^{mk}$ we can recover the intercepts κ_0^{mk} from the definition of average costs,[13]

$$ac^{it} - \frac{\widehat{\kappa}_1^{mk}}{2} u^{it} = \kappa_0^{mk} + \varepsilon^{it}. \tag{25}$$

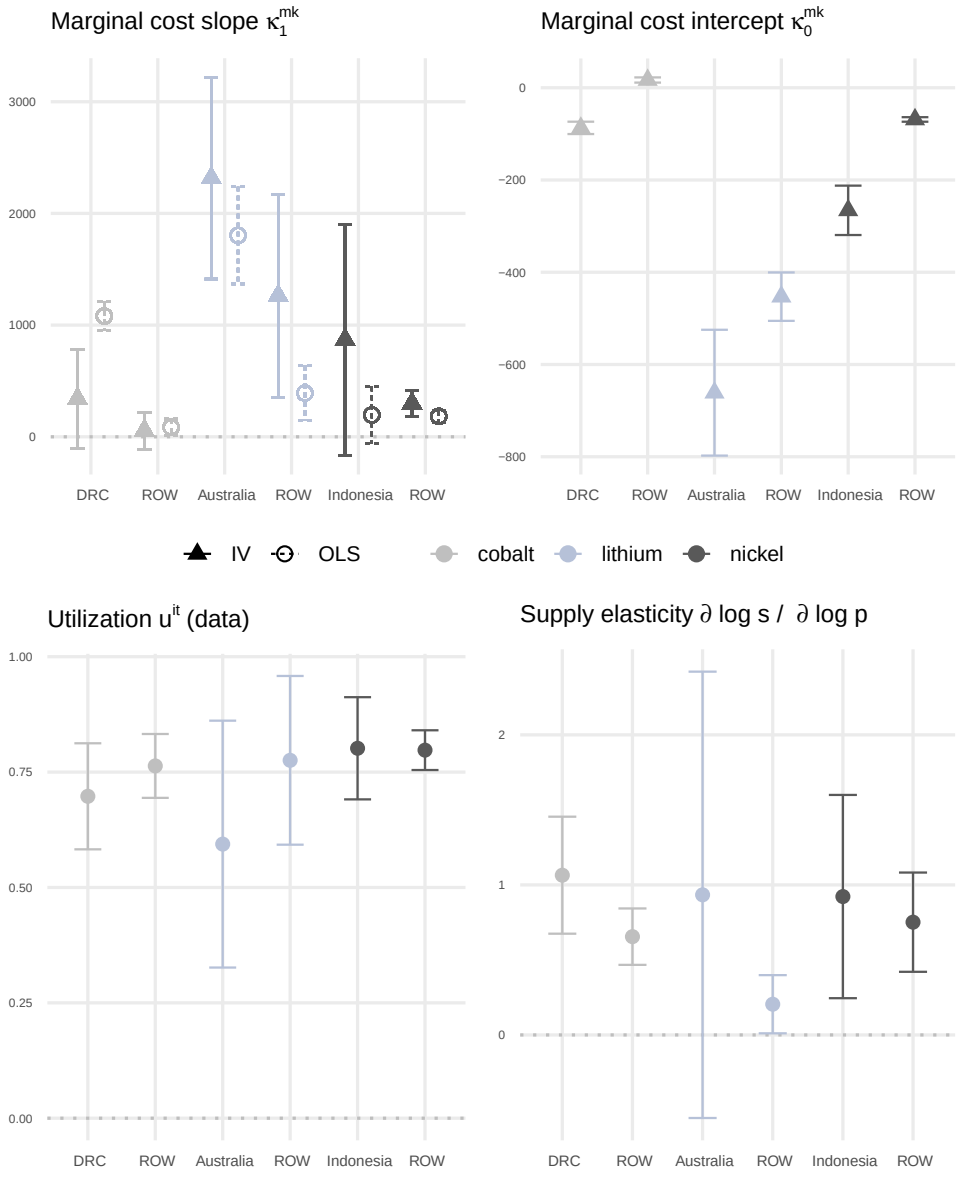
Note the κ_0^{mk} estimate will largely track the realized average costs on the left hand side, but with a correction due to the slope estimate $\widehat{\kappa}_1^{mk}$. This is the sense in which our approach is anchored in the empirical step function from Figure 6, but also "corrects" it because cost non-linearities and dynamics are embedded in the $\widehat{\kappa}_1^{mk}$ estimate.

5.3 Results

Figure 7 presents our results. The top producers in each mineral market have lower intercepts κ_0^{mk} but higher slopes κ_1^{mk}. Thus, intercepts largely track observed

[13] Our assumptions on $F(x^{it}; \kappa)$ and $H(x^{it}, \varepsilon^{it})$ imply average costs are $ac^{it} = \kappa_0^{mk} + \frac{\kappa_1^{mk}}{2} u^{it} + \varepsilon^{it}$.

Figure 7: Supply estimation results



average costs. This qualitative configuration of parameters implies the top producers operate at lower utilization rates. Since they have more room to respond to price increases, their supply elasticities are larger. In terms of external validation, our estimates are broadly in line with metal supply elasticities from the literature. The meta-analysis in Fally and Sayre (2018) reports cobalt elasticities ranging between 0.2-1, nickel between 0.133-2.03, but no reference values for lithium though.

5.4 Equilibrium

An equilibrium is defined by a vector of mineral prices $\boldsymbol{p}^t = \{p^{mt}\}^{m \in \mathcal{M}}$ that clears global mineral markets period-by-period.

$$d^{mt}(\boldsymbol{p}^t) = s^{mt}(p^{mt}) \quad \forall\ m, t, \tag{26}$$

Note demand depends on the prices of all minerals because they are used jointly in battery technologies and battery consumers can switch across technologies. By equation 8, mineral prices $\boldsymbol{p}^t$ pin down technology prices $\boldsymbol{p}_t = \{p_{jt}\}_{j \in \mathcal{J}}$ in equilibrium.

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

Table 2 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

Table 2: 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 are reported as percentage point changes. Percentage changes in battery quantities are computed using changes in battery capacity (MWh).

higher-cost mines. Such mines have higher costs because of an extensive margin (they have lower ore grades) and an intensive margin (they need to 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 4-fold. This is because ore grades of cobalt mines in the DRC are dramatically higher than in the rest of the world, resulting in substantially lower costs (Figure 2).

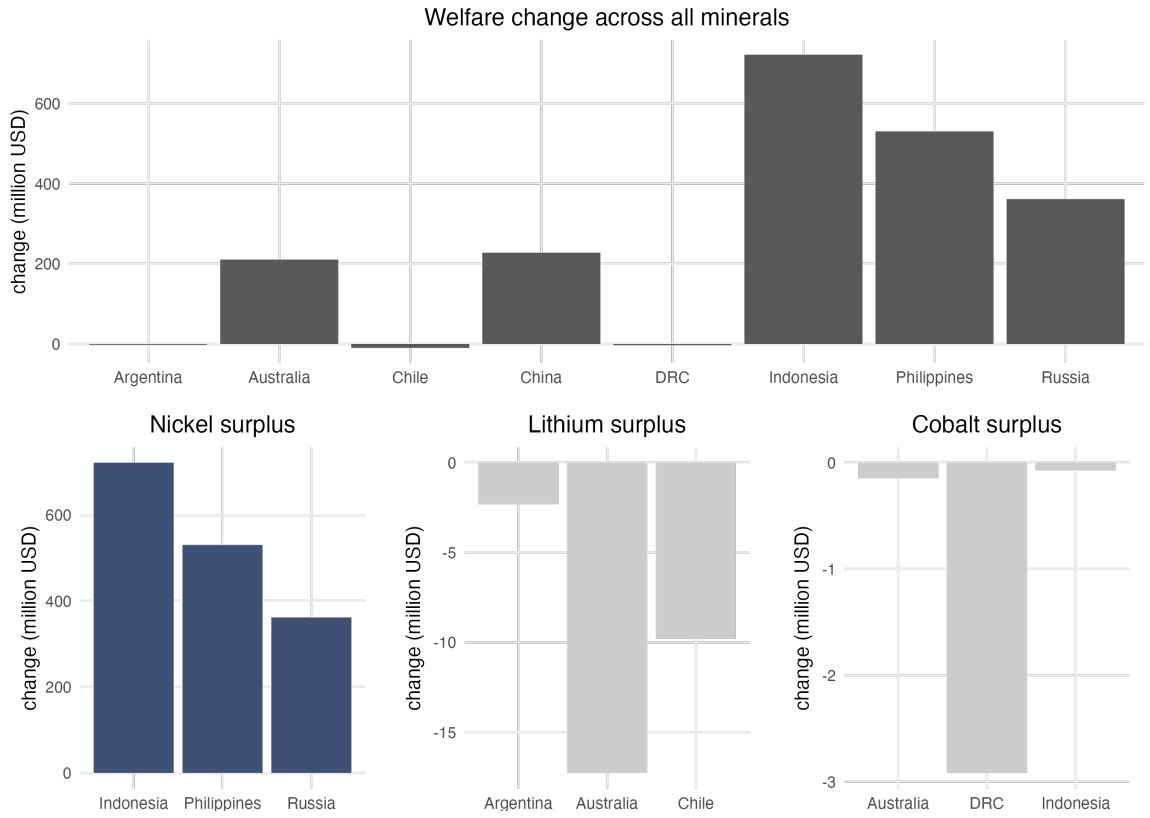
Battery prices increase for technologies that use the affected mineral most intensively. As for technologies that are less exposed to the affected mineral, their battery prices may rise or fall. On the one hand, their prices rise because they face a surge in demand that is shifting away from the exposed 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.[14] This exercise is motivated by recent export restrictions imposed by Indonesia and DRC

Figure 8: 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.

[14] 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.

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 8 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 8. Notice Australia produces all three minerals, so even though it loses cobalt and lithium surplus, it is more than compensated by gains from nickel.

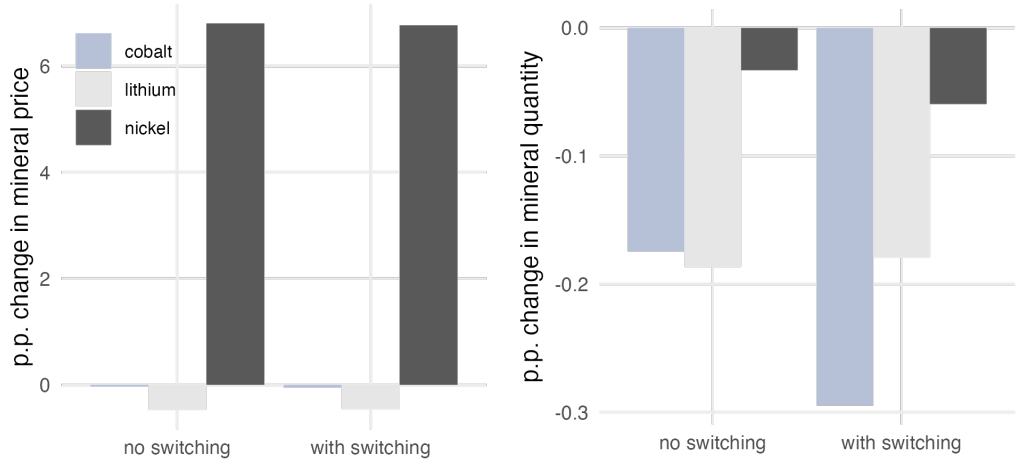
6.2.2 Green adoption

Figure 9a 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.

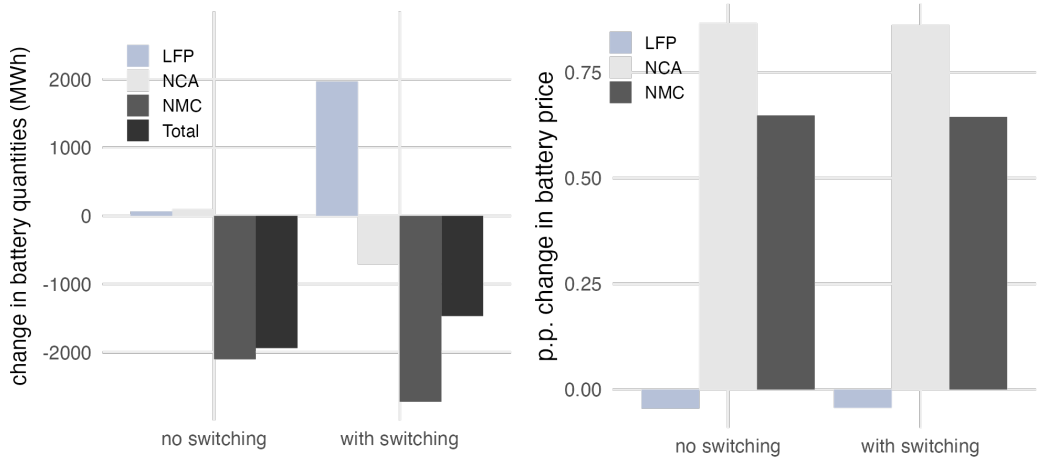
Figure 9b shows impacts on battery market outcomes. Higher nickel prices lead to higher battery prices for the nickel-intensive battery technologies (NMC, NCA). Quantities of these technologies fall while demand for LFP rises. The increase in LFP is significantly larger when we allow for demand switching. However, in all cases total battery adoption falls because the decline in nickel-intensive battery technologies is 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 9: Market impacts of an Indonesian nickel supply cut

(a) Impacts on mineral market outcomes



(b) Impacts on battery market outcomes



6.3 Mineral cartels

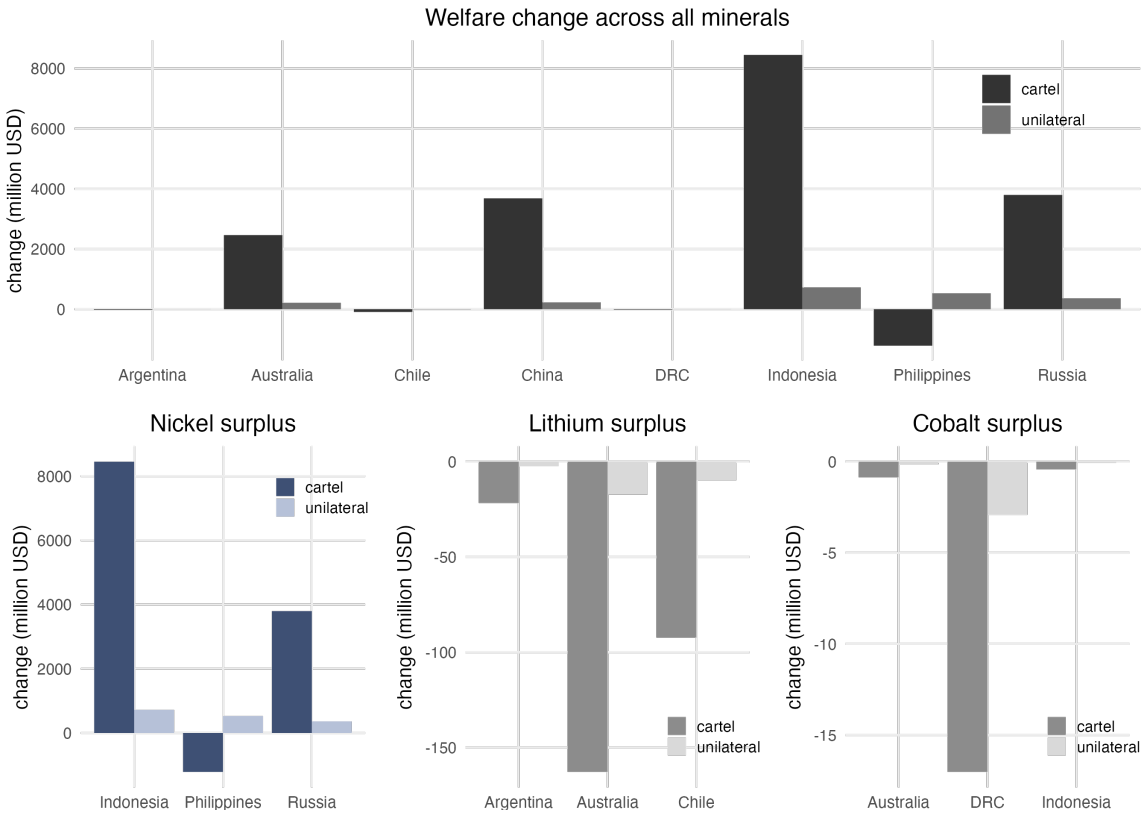
We next turn to policies set by coalitions of countries forming a cartel. Some energy commodities with concentrated production are organized through producer cartels, such as crude oil under OPEC. Studies on market power in natural resource markets often implement a single-commodity analysis where the only margin of product differentiation is the origin of production, resulting in high substitutability across producers (e.g., Russian oil versus Saudi oil). Our setting differs because it involves multiple commodities, thus allowing for standard substitution forces while also intro-

ducing a novel complementarity mechanism. In such a setting, what impact could a mineral cartel have on the full set of minerals relevant for renewable energy adoption?

6.3.1 Single-mineral cartels

We consider coalitions of all subsets of the top three producers within each mineral market. Cartel members restrain supply with the objective of maximizing cartel surplus.[15] Our full set of results 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.

Figure 10: 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).

[15] 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.

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 10). Third, coalitions can exacerbate the cross-country and cross-mineral spillover effects that were the focus of section 6.2.1. Coalitions of countries producing the same mineral—i.e., single-mineral mergers—implement larger supply cuts than if they were to act independently because they are substitutes with each other. As a result, single-mineral cartels lead to larger spillovers on producers of other minerals and less green adoption.

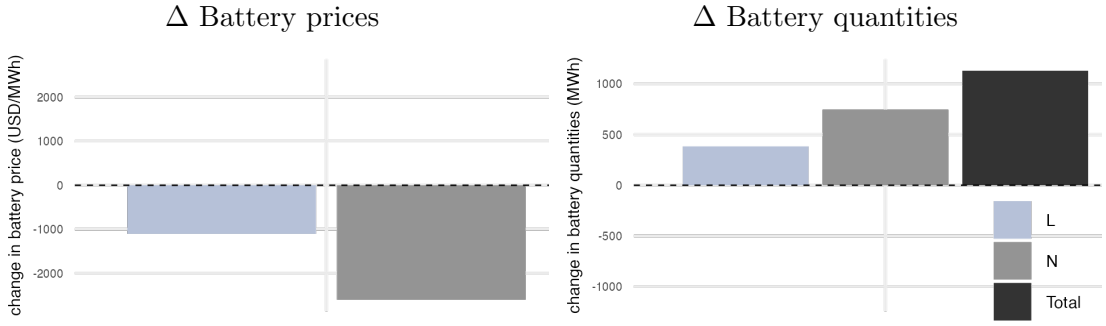
6.3.2 Multi-mineral cartels

The key conceptual difference between a single-mineral cartel and a multi-mineral cartel is that the former consists of members producing goods that are substitutes with each other, while in the latter they are complements.

Consider a case where several countries are separately exercising their market power in a single mineral market. For example Indonesia, Philippines, and Russia in the nickel market. If they form a nickel cartel they implement a larger joint supply cut and a larger price increase, as shown in the previous section. Now suppose there is also a lithium cartel acting in parallel. It is also implementing a larger joint supply cut than if its members were to act independently. We have a baseline situation with a lithium and a nickel cartel acting separately, and the question is: what happens if the two cartels merge into a lithium-nickel cartel?

The baseline situation is that of a duopoly that produces complementary goods. The nickel cartel does not internalize that when it marks up nickel prices it destroys lithium demand due to complementarity in the battery bundle. The lithium cartel also fails to internalize that when it marks up lithium prices it destroys nickel demand for the same reason. A merger of the two cartels internalizes the negative spillovers being inflicted on each other, leading to *lower* mineral prices, *lower* battery prices and *higher* battery quantities (Figure 11). The logic is the same as double marginalization: the two separate cartels independently choose excessive mark-ups, resulting in bundle

Figure 11: Pro-competitive and pro-adoption impacts of a multi-mineral merger



The figure is constructed by simulating a baseline equilibrium where a lithium and a cobalt cartel independently decide the optimal production levels for their members. The counterfactual equilibrium is simulated as a merger of the two cartels. Hence, the optimal production levels are jointly decided for members across both minerals, internalizing and removing the double marginalization effects that were present at baseline.

(battery) prices that are too high and quantities that are too low.

To conclude, multi-mineral mergers are pro-competitive and pro-adoption for the same reason vertical mergers are: elimination of double marginalization. Analogously, single-mineral mergers are anti-competitive and anti-adoption for the same reason horizontal mergers are: substitutability of the goods sold by the merging parties.

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 policies 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.

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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

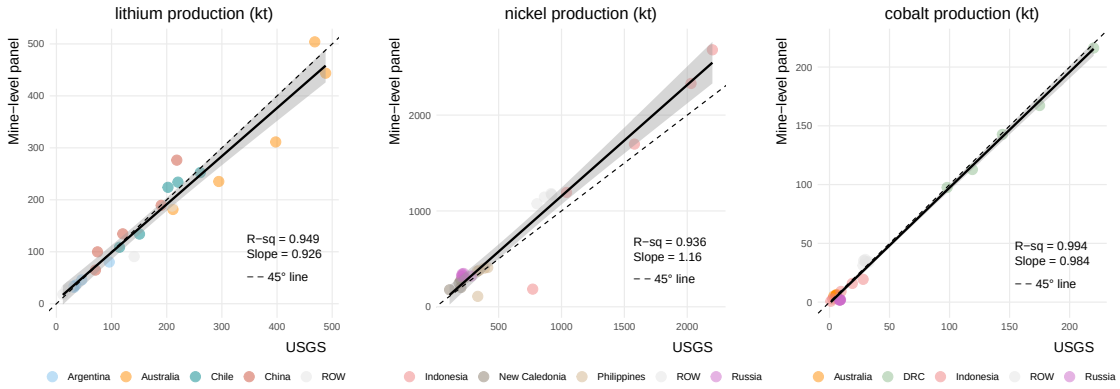
Mineral intensities are obtained from the battery technology data described in section 2.2.

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

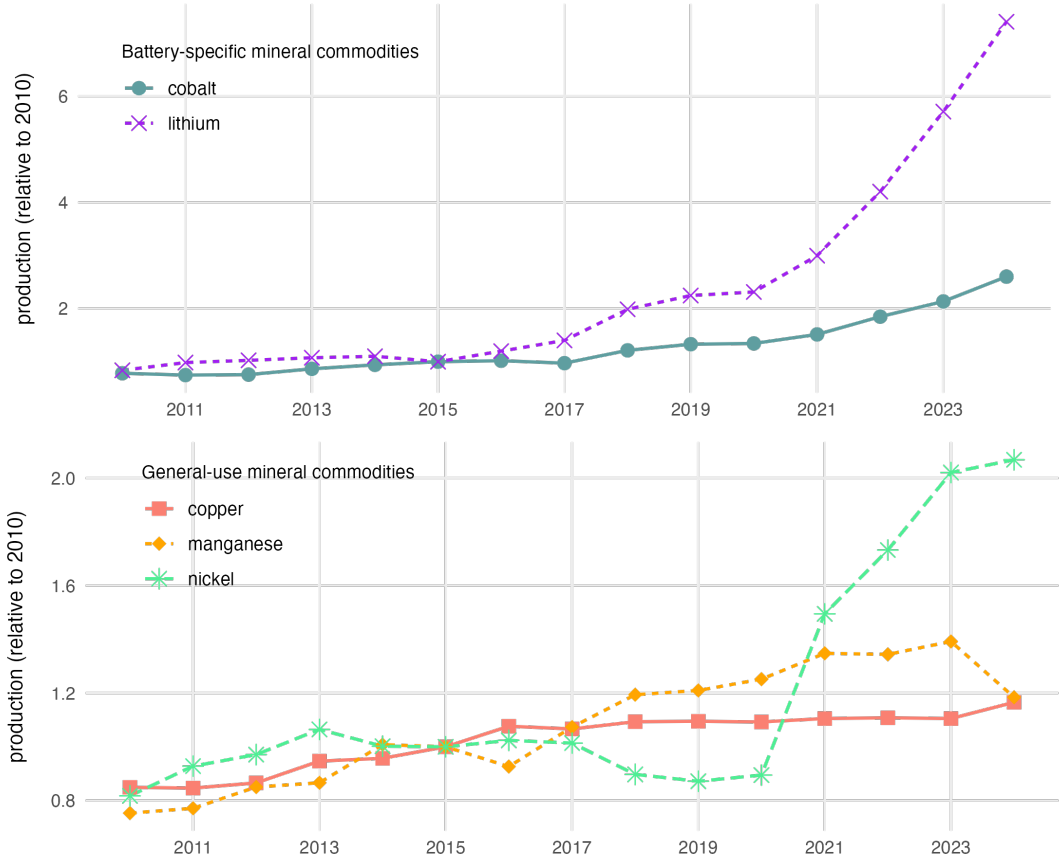


The vertical axes display country-level production values aggregated from our mine-level data. The horizontal axes show country-level production values reported by USGS for 2020 to 2024.

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)



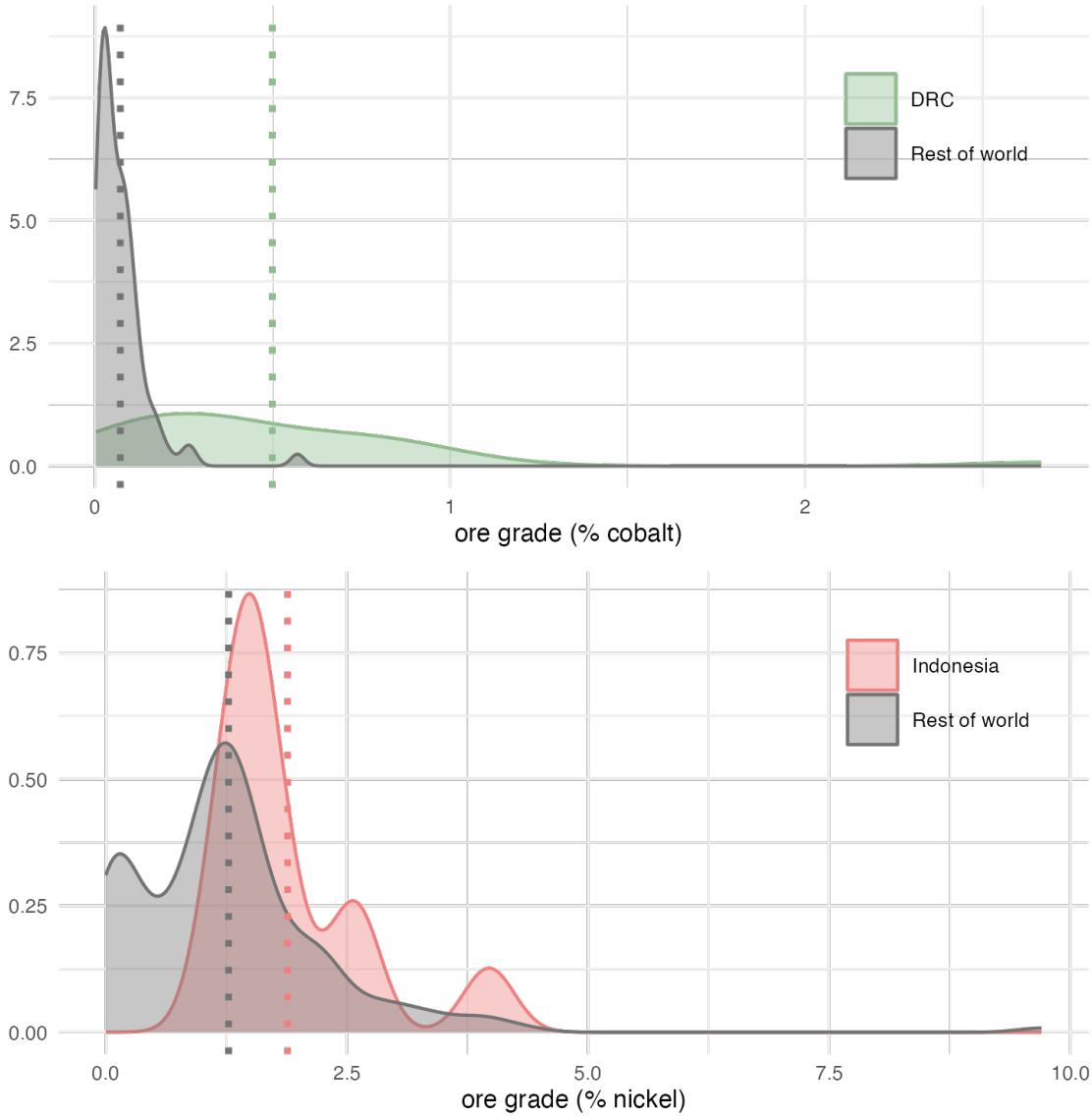
Values are constructed from mine-level production data described in section 2.2. Categorization of mineral commodities into battery-specific versus general-use minerals is based on demand composition values from Table 1.

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

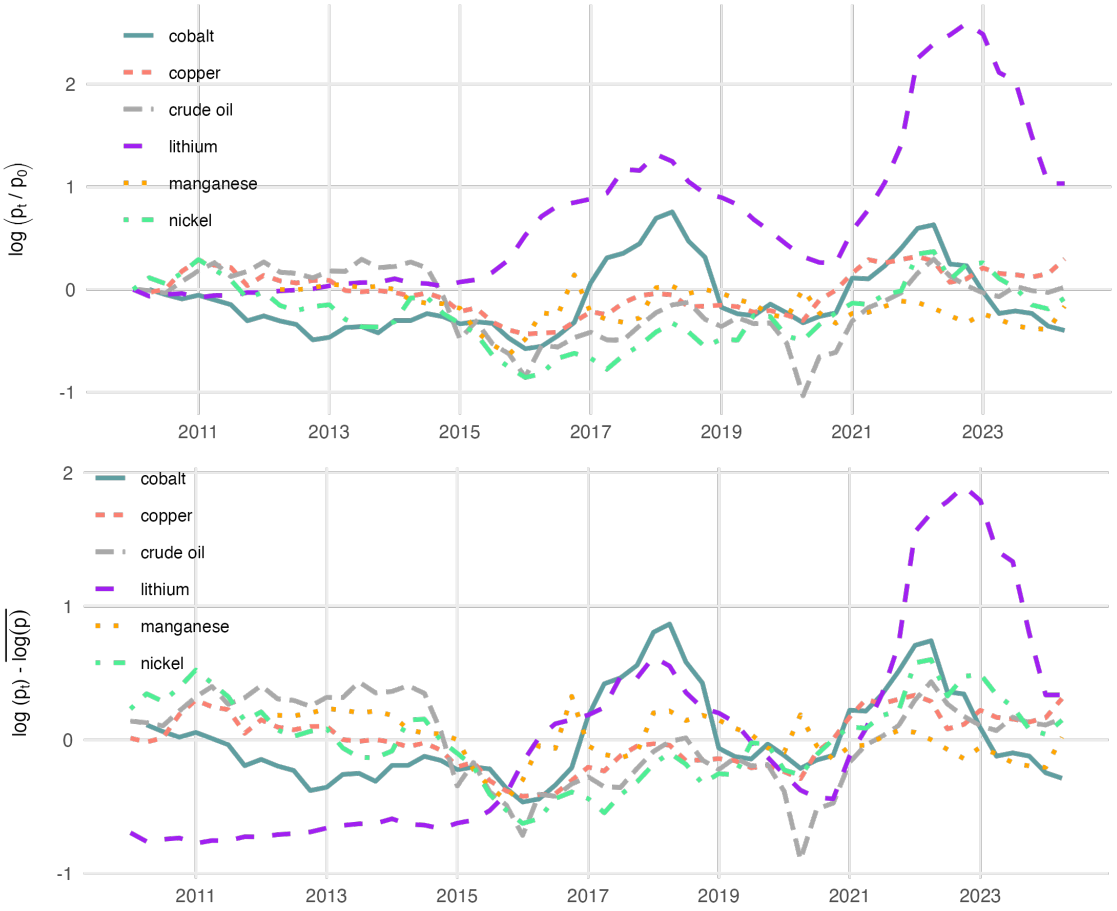
A.5.1 Mineral markets

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)

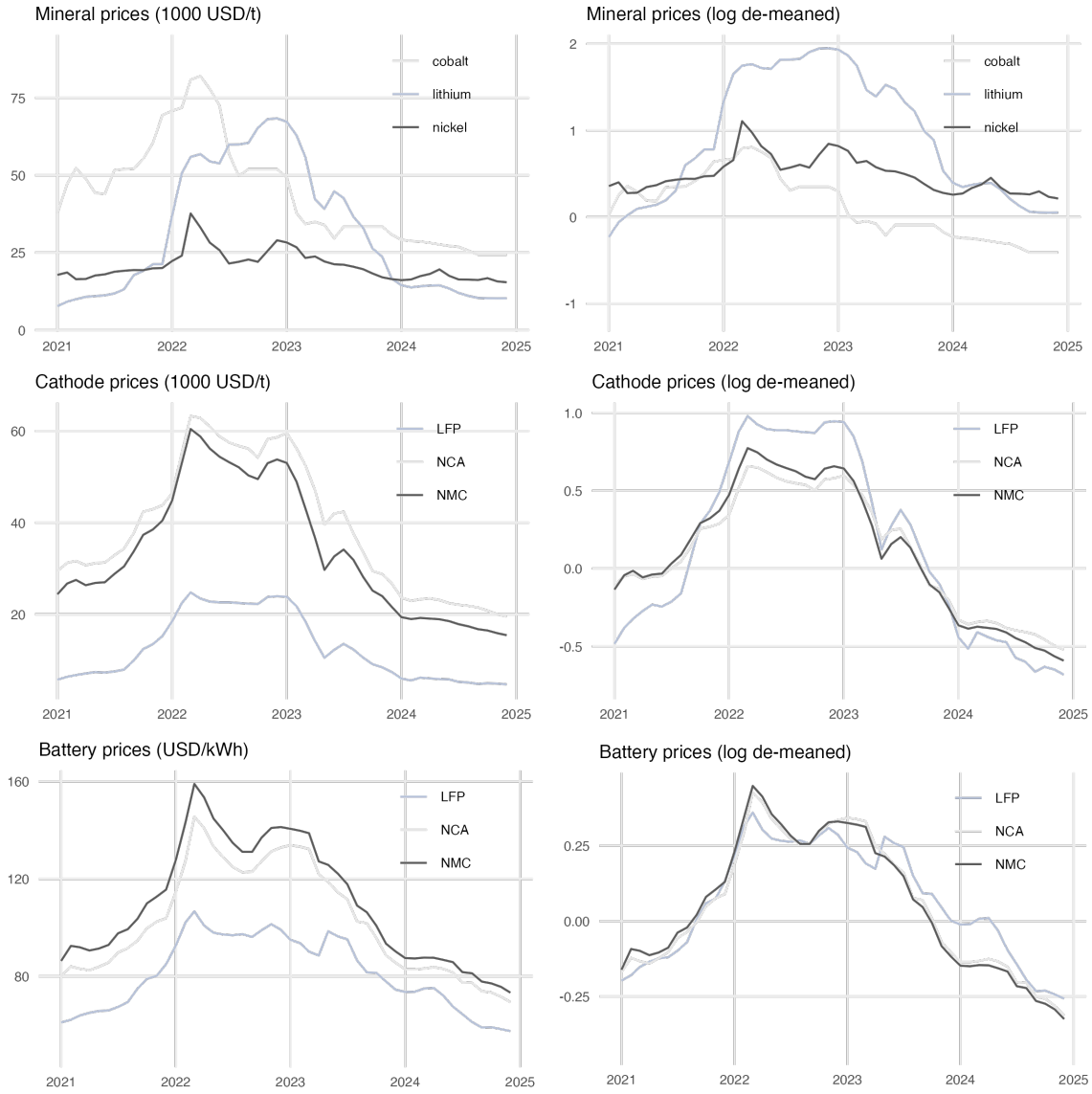


The two panels show the price of each commodity normalized by (i) its price at the start of the sample, and (ii) its average value across the sample period. Nominal values from which this figure is constructed are quarterly-averaged prices from SP Global. Cobalt, nickel, and copper prices are based on 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,

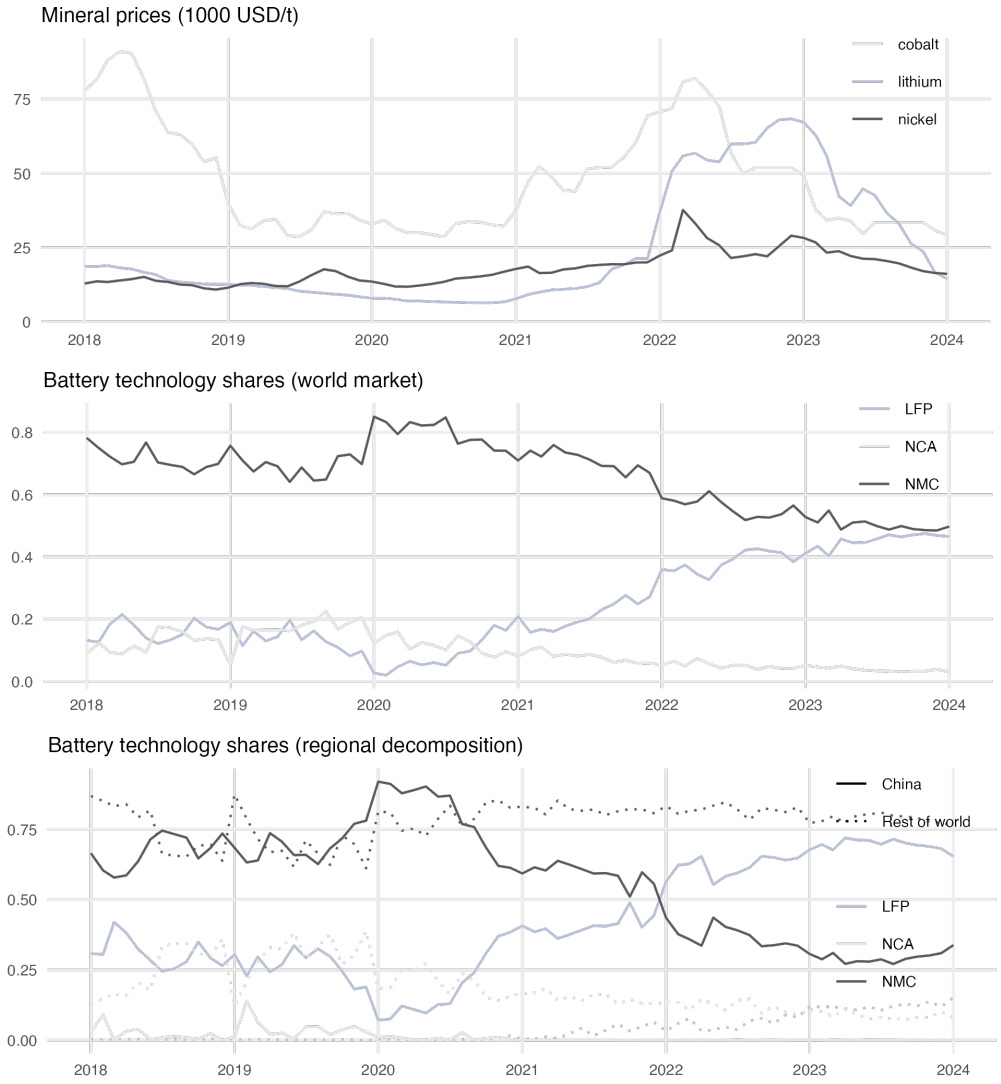
returning to their 2021 levels. Since then, increased lithium production has led to a supply glut. Additionally, many automakers shifted to LFP chemistries, which require less lithium (IEA 2024a).

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



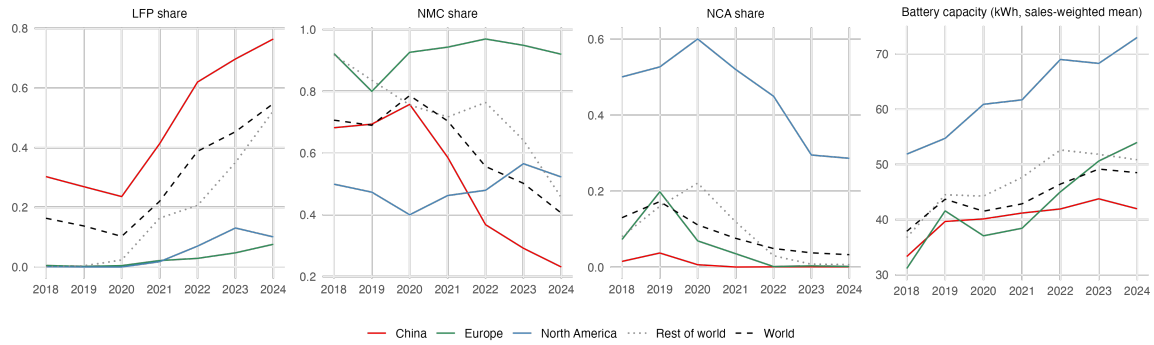
Mineral prices are monthly-averaged prices from SP Global. Battery technology market shares constructed from units sold, using monthly EV sales data from Benchmark Mineral Intelligence.

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

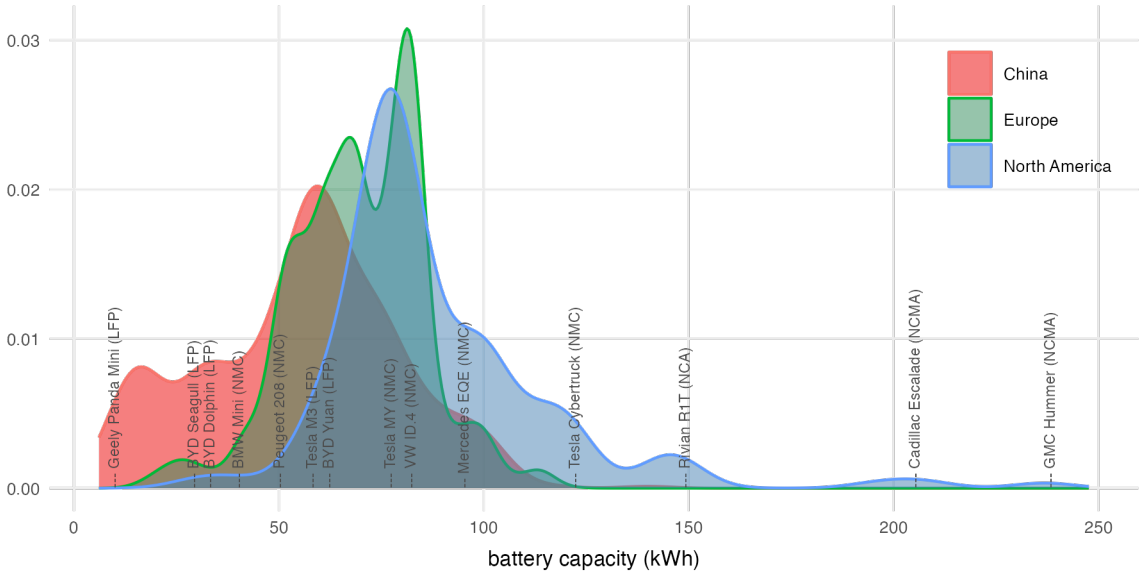


Market shares constructed from units sold, using EV sales data from Benchmark Mineral Intelligence.

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 EV 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

To estimate the almost ideal demand system we impose the standard adding-up, homogeneity, and symmetry restrictions. The adding-up restriction, $\sum_j w_{jkt} = 1 \; \forall k, t$, implies $\sum_j \alpha_{jt} = 1$, $\sum_j \beta_j = 0$, and $\sum_j \gamma_{jj'} = 0 \; \forall j'$. Homogeneity is obtained by imposing $\sum_{j'} \gamma_{jj'} = 0 \; \forall j$. Symmetry is obtained by imposing $\gamma_{jj'} = \gamma_{j'j} \; \forall j, j'$. The adding-up restriction results in collinearity among the J expenditure share equations, so one of these equations has to be dropped in estimation. The technology that corresponds to the dropped equation is defined as the base technology, which we choose to be technology N. Therefore, the estimating equation for technology L is,

$$w_{Lkt} = \alpha_{Lt} + \gamma_{LN} \log\left(\frac{p_{Lt}}{p_{Nt}}\right) + \beta_L \log\left(\frac{X_{kt}}{P_t}\right) + \epsilon_{Lkt}$$

where the relative price shows up on the right hand side because of the homogeneity restriction. As a result, the first stage is defined in terms of the relative price,

$$\log\left(\frac{p_{Lt}}{p_{Nt}}\right) = \beta_0 + \beta_L \log\left(z_{Lt}\right) + \beta_N \log\left(z_{Nt}\right) + \beta_X \log\left(\frac{X_t}{P_t}\right) + \delta_t + \varepsilon_t,$$

where the instruments z_{jt} are defined as in equation 10 of the main text. For our main IV the first stage F-statistic is 7301.6.

Figure B1: Ore grade over time (nickel)

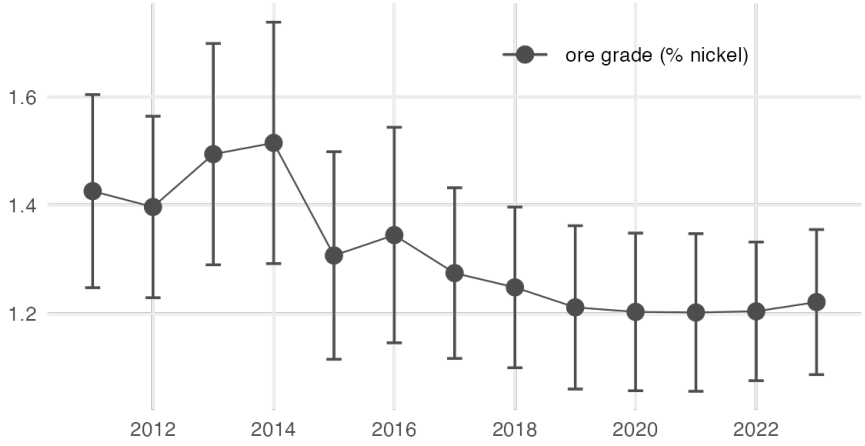


Figure shows world average nickel grades (weighted by mine output) with 95% confidence intervals.

B.2 Supply

B.2.1 Ore grade dynamics

Figure B1 shows how world average ore grade has decayed over time in the case of nickel. We use the mine-level data from which this figure is constructed to estimate degradation elasticities δ as follows

$$\log\left(\text{grade}_{it+1}\right) = \log\left(\text{grade}_{it}\right) - \delta \log\left(\text{production}_{it}\right) + \alpha_i + \lambda_t + \varepsilon_{it} \tag{27}$$

where α_i and λ_t are mine and year fixed effects (Aguirregabiria and Luengo 2016). We estimate 27 separately for each mineral, finding $\hat{\delta}^{Li} = 0.02$, $\hat{\delta}^{Co} = 0.09$, $\hat{\delta}^{Ni} = 0.06$. These elasticities are then used to construct the degradation cost terms in our Euler equation estimation from section 5.

B.2.2 Degenerate case of supply estimation

Recall the Euler equation from the main text and the cost shock inversion

$$\Delta mr^{it} - \beta \Delta mc_d^{it+1} = \Delta mc^{it+1} + \eta^{it} \tag{28}$$

$$\Delta mr^{it} - \beta \Delta mc_d^{it+1} = \Delta \widetilde{mc}^i \left(x^{it}; \kappa\right) + \Delta \widetilde{h}(x^{it}, \varepsilon^{it}) + \eta^{it} \tag{29}$$

$$\text{where } \varepsilon^{it} = h^{-1}\left(ac^{it} - f(x^{it}; \kappa), x^{it}\right) \tag{30}$$

After plugging in the inversion of ε^{it} in 29 we need to make sure to avoid the degenerate case where κ is canceled out from the Euler equation. To see how this might happen, recall the average and marginal cost functions from the main text,

$$ac^{it} = f(x^{it}; \kappa) + h(x^{it}, \varepsilon^{it}) \tag{31}$$

$$mc^{it} = f(x^{it}; \kappa) + f'(x^{it}; \kappa)x^{it} + h(x^{it}, \varepsilon^{it}) + h'(x^{it}, \varepsilon^{it})x^{it} \tag{32}$$

Assume we can decompose $f(x; \kappa) = a(\kappa)w(x)$ and $h(x, \varepsilon) = b(\varepsilon)v(x)$. Then,

$$b(\varepsilon) = \frac{ac - f(x; \kappa)}{v(x)}$$

$$h'(x, \varepsilon) = b(\varepsilon)v'(x) = \frac{v'(x)}{v(x)}\left[ac - f(x; \kappa)\right]$$

Substitute the expression for $h'(x, \varepsilon)$ above into the marginal cost equation 32, as well as the $f(x^{it}; \kappa)$ term from the average cost equation 31,

$$mc^{it} = ac^{it} + f'(x^{it}; \kappa)x^{it} + \frac{v'(x^{it})}{v(x^{it})}\left[ac^{it} - f(x^{it}; \kappa)\right]x^{it} \tag{33}$$

$$= ac^{it} + \frac{v'(x^{it})}{v(x^{it})}ac^{it}x^{it} + \left[f'(x^{it}; \kappa) - f(x^{it}; \kappa)\frac{v'(x^{it})}{v(x^{it})}\right]x^{it} \tag{34}$$

$$= ac^{it} + \frac{v'(x^{it})}{v(x^{it})}ac^{it}x^{it} + a(\kappa)\left[w'(x^{it}) - w(x^{it})\frac{v'(x^{it})}{v(x^{it})}\right]x^{it} \tag{35}$$

In the degenerate case in which $w(x) = v(x)$ we obtain that mc^{it} is no longer a function of κ, and therefore κ does not appear on the right hand side of Euler equation 28. Intuitively, notice that in such a case we obtain $ac^{it} = \left[a(\kappa) + b(\varepsilon^{it})\right]v(x^{it})$. Variation in x^{it} doesn't separately identify κ and ε^{it}.

To summarize, our inversion approach requires the following conditions

1. Separability of κ and ε^{it} in the cost function,

$$C^{it} = F(x^{it}; \kappa) + H(x^{it}, \varepsilon^{it}).$$

2. $h(x, \varepsilon)$ needs to be invertible so that the inversion in equation 30 is well-defined.

3. $f(x; \kappa)$ and $h(x, \varepsilon)$ cannot be of the same polynomial degree in x. If they are, then we are in a degenerate case where κ is not identified.

C Counterfactuals

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

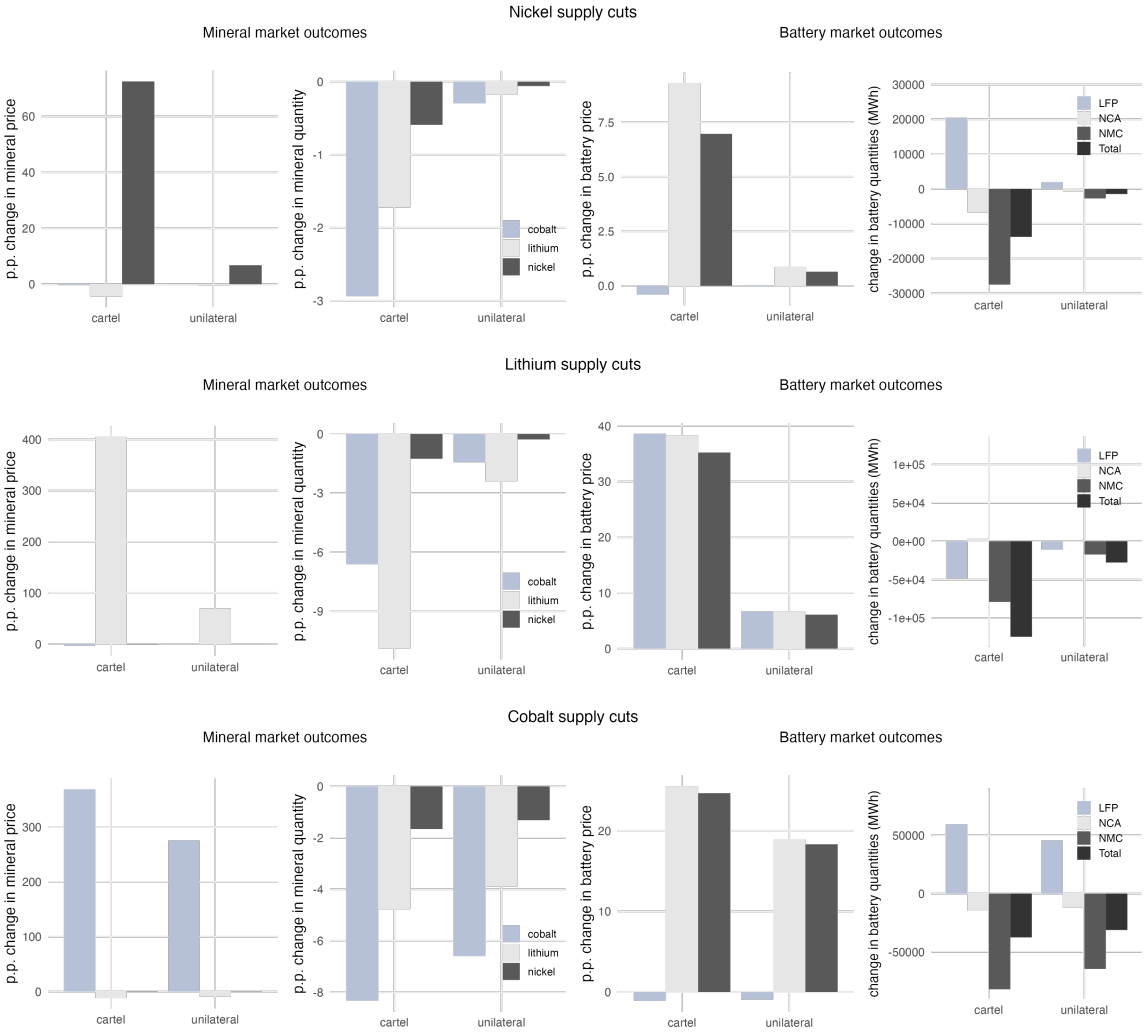
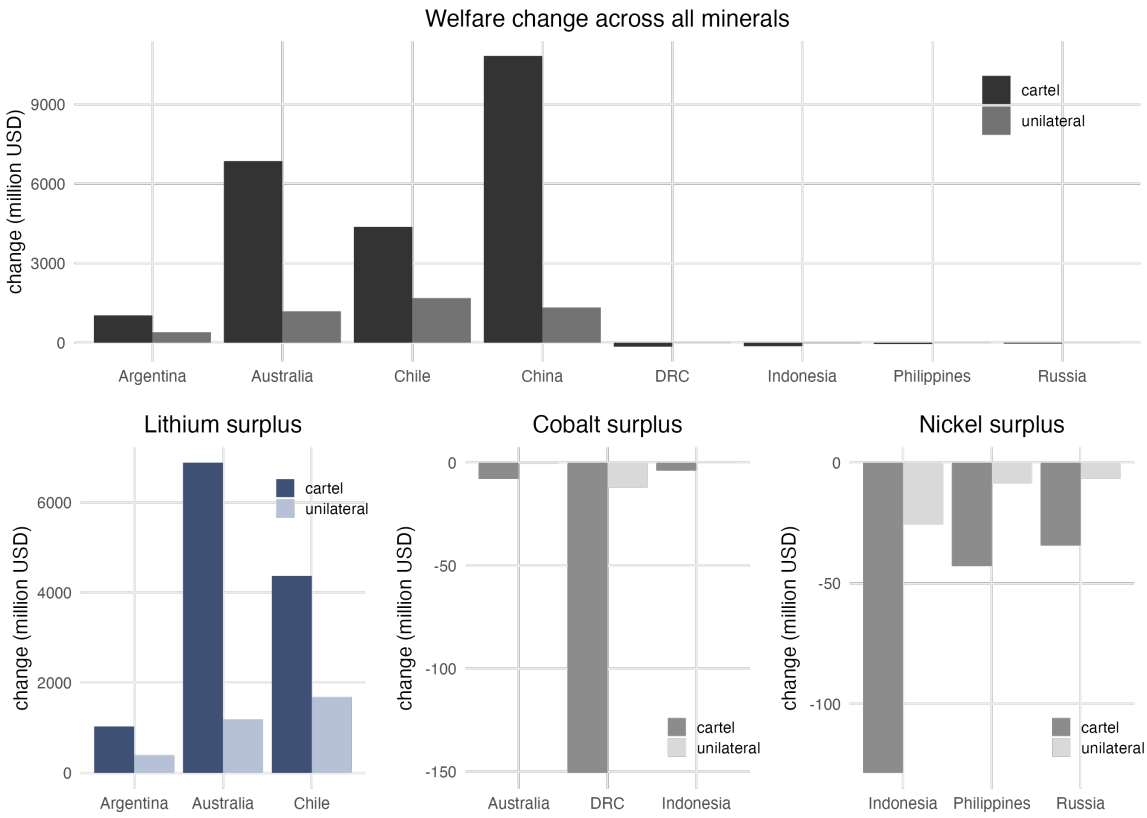
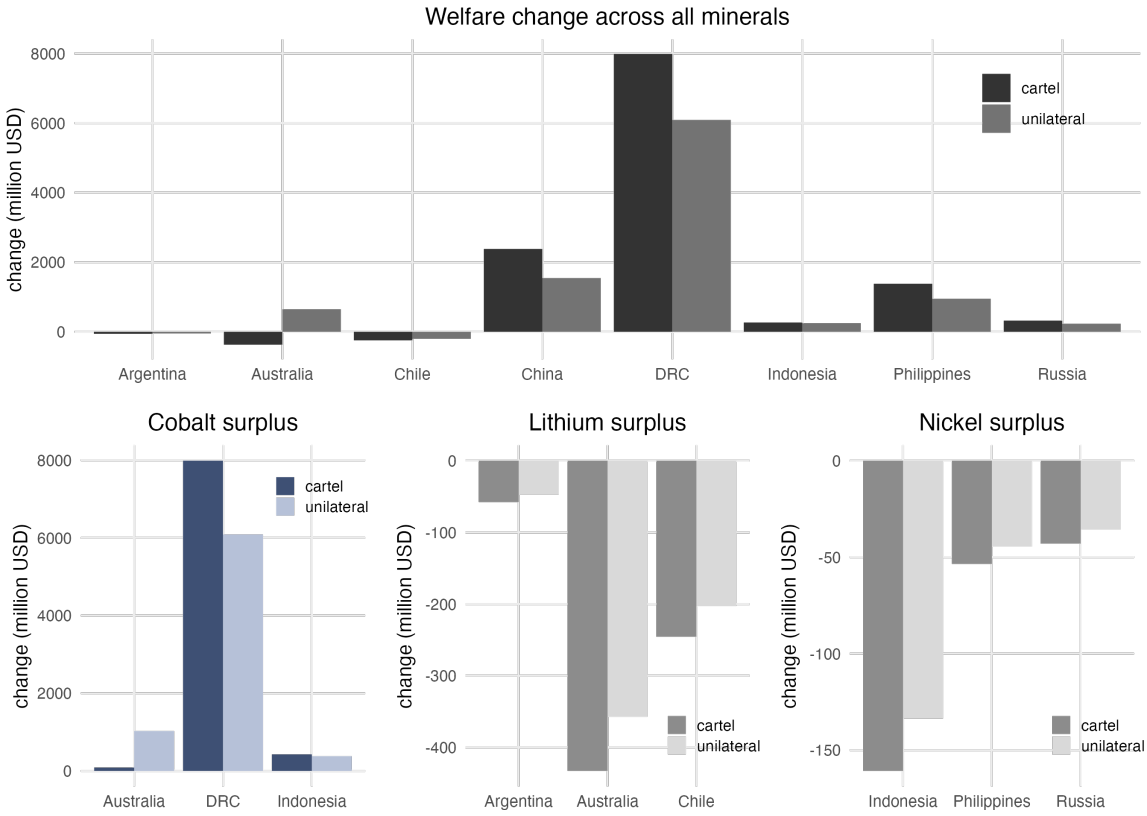


Figure C2: Welfare impacts of a lithium cartel (Australia-Chile-Argentina)



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.	55,867	33,083,691,167.23	0.00	228,039,852.68	238,897,448,480.95	122,371,725.85	0.00	315,536,993,525.94	0.00	0.00
Chl.	-0	33,083,623,019.12	0.00	228,021,211.51	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Arg.	3,238	33,083,623,808.85	0.00	228,021,247.35	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Aus. & Chl.	55,867	33,083,691,167.23	0.00	228,039,852.68	238,897,448,480.95	122,371,725.85	0.00	315,536,993,525.94	0.00	0.00
Aus. & Arg.	78,531	33,083,726,939.94	0.00	228,025,145.79	238,897,447,918.11	122,371,673.72	0.00	315,536,992,044.33	0.00	0.00
Chl. & Arg.	3,238	33,083,623,808.86	0.00	228,021,247.35	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Aus., Chl. & Arg.	78,531	33,083,726,939.94	0.00	228,025,145.79	238,897,447,918.11	122,371,673.72	0.00	315,536,992,044.33	0.00	0.00
Nickel policies										
Ind.	10,350	33,083,621,920.26	0.00	228,021,107.16	238,897,459,291.70	122,373,957.72	11.12	315,536,995,590.16	0.00	0.00
Phl.	1,052	33,083,622,981.45	0.00	228,021,207.88	238,897,449,924.11	122,371,836.88	0.00	315,536,996,219.29	0.00	0.00
Rus.	-0	33,083,623,019.12	0.00	228,021,211.51	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Ind. & Phl.	12,783	33,083,621,286.14	0.00	228,021,046.51	238,897,466,108.69	122,372,130.35	49.01	315,536,995,229.41	0.00	0.00
Ind. & Rus.	10,457	33,083,621,902.14	0.00	228,021,105.41	238,897,459,391.49	122,374,001.54	0.00	315,536,995,579.36	0.00	0.00
Phl. & Rus.	1,052	33,083,622,981.45	0.00	228,021,207.88	238,897,449,924.12	122,371,836.88	0.00	315,536,996,219.29	0.00	0.00
Ind., Phl. & Rus.	13,013	33,083,621,238.38	0.00	228,021,041.91	238,897,466,430.20	122,372,141.77	0.00	315,536,995,200.60	0.00	0.00
Cobalt policies										
DRC	631,143	33,083,593,313.36	0.00	228,018,410.03	238,897,443,496.88	122,371,274.48	0.00	315,537,509,658.75	0.00	66,259.69
Aus.	-0	33,083,623,019.12	0.00	228,021,211.51	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Ind.	-0	33,083,623,019.12	0.00	228,021,211.51	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
DRC & Aus.	589,880	33,083,594,677.83	0.00	228,018,538.19	238,897,443,788.70	122,371,300.03	0.00	315,537,509,939.22	0.00	57,233.29
DRC & Ind.	862,208	33,083,586,201.88	0.00	228,017,744.65	238,897,441,944.60	122,371,142.07	0.00	315,537,672,657.30	717.99	0.00
Aus. & Ind.	-0	33,083,623,019.12	0.00	228,021,211.51	238,897,449,365.27	122,371,807.27	0.00	315,536,996,240.40	0.00	0.00
Aus., DRC & Ind.	789,360	33,083,588,154.74	0.00	228,017,927.54	238,897,442,372.47	122,371,178.53	0.00	315,537,698,034.17	0.00	0.00
Li & Ni policies										
Li: Aus.; Ni: Ind.	$\begin{bmatrix}54,325\\14,982\end{bmatrix}$	33,083,688,621.00	0.00	228,038,955.37	238,897,468,184.73	122,376,521.26	53.03	315,536,992,626.34	0.00	0.00
Li & Co policies										
Li: Aus.; Co: DRC	$\begin{bmatrix}60,911\\626,193\end{bmatrix}$	33,083,696,931.45	0.00	228,042,916.48	238,897,443,247.10	122,371,255.33	0.00	315,537,504,060.69	0.00	65,011.73
Ni & Co policies										
Ni: Ind.; Co: DRC	$\begin{bmatrix}734,119\\860,161\end{bmatrix}$	33,083,584,794.36	0.00	228,017,612.49	238,897,321,717.32	122,382,449.64	352.47	315,537,667,833.03	696.59	0.00
Li, Ni & Co policies										
Li: Aus.; Ni: Ind.; Co: DRC	$\begin{bmatrix}106,093\\160,197\\306,602\end{bmatrix}$	33,083,707,154.10	0.00	228,072,649.99	238,897,321,717.32	122,397,086.76	2,362.08	315,537,420,706.53	0.00	0.00

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.