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Input uncertainty and firm performance: evidence from critical minerals

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Abstract
We study the effect of input uncertainty about critical minerals on firm performance, separating the second-moment risk channel from first-moment mineral sentiment and from general firm-level uncertainty. Using earnings-call transcripts matched to financial data for more than 14,000 publicly listed firms in 92 countries (2010-2022), we construct text-based measures of perceived critical-mineral risk. Higher perceived risk is robustly associated with lower revenue growth among downstream non-mining firms, consistent with risk-averse firms contracting output under input uncertainty. A one-standard-deviation increase in mineral risk is associated with 0.71 percentage points lower revenue growth for the average non-mining firm, rising to roughly 1.9 percentage points for smaller firms, and is concentrated in thinly traded minerals (lithium, cobalt, rare earths) rather than deeply traded ones (copper, nickel). Firms discuss hedging an stockpiling in response to price volatility rather than price levels, revealing the risk aversion that underlies the output contraction. These findings highlight a new uncertainty channel in the green transition relevant to strategic stockpiling and price transparency.

Keywords: critical minerals; green transition; risk; exposure; sentiment; stockpiling; hedging
JEL codes: D81, L60, Q31, Q42, G32

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1 Introduction

The green transition depends on the mass deployment of low-carbon technologies such as electric vehicles, solar and wind power, and energy storage systems, requiring vast and growing quantities of minerals classified as critical resources (Ali et al., 2017; World Bank, 2017). Recurring disruptions, including the weaponisation of rare-earth exports, the cobalt price spike driven by exuberant demand, and the broad commodity rally following the pandemic and recent wars-have raised persistent concerns about whether mineral reserves are sufficient for the transition at scale, whether annual production can be scaled up quickly enough to meet climate commitments, and whether supply chains can deliver these inputs reliably (Graedel et al., 2015; Boer et al., 2024; Vertier et al., 2025).[1] For firms that depend on these minerals as inputs, including those along clean-energy supply chains, these disruptions have created a new source of input uncertainty.[2]

This paper empirically studies the firm-level consequences of this input uncertainty related to five critical minerals - copper, nickel, cobalt, lithium, and rare-earth elements - in a global setting.[3] Two prior contributions are particularly close to ours. Concordel et al. (2026) formalise a model in which mineral price shocks propagate through the economy via channels distinct from those associated with oil, reflecting the fact that critical minerals are inputs embedded in long-lived capital goods rather than consumed as intermediate energy inputs. Panon et al. (2026), using firm-level customs and balance-sheet data for five EU economies, simulate a counterfactual supply disruption and estimate substantial losses in manufacturing value added. These contributions quantify the consequences of first-moment

[1]Rare-earth elements comprise 17 metallic elements: cerium, lanthanum, praseodymium, neodymium, promethium, samarium, europium, gadolinium, terbium, dysprosium, holmium, erbium, thulium, ytterbium, lutetium, yttrium, and scandium.

[2]Following Bloom (2014), we use ‘uncertainty’ and its lexical synonyms throughout to encompass both quantifiable risk and the deeper unpredictability that arises when the distribution of future outcomes is itself unknown (Knight, 1921).

[3]The first four are projected to see production values rise more than fourfold by 2040 under net-zero scenarios, rivalling the total value of crude oil production (Boer et al., 2024). Rare-earth elements, while smaller in market value, are indispensable for permanent magnets in EV motors and wind turbines and face acute supply concentration (Graedel et al., 2015). These minerals also face growing demand from AI-driven digitalisation and renewed defence investment, though the sample period (2010-2022) predominantly captures the clean-energy phase of this demand expansion. Section 2.1 provides further background.

shocks, namely directional price changes and discrete supply shortfalls.

Yet each disruption also makes the future availability, cost, and the reliability of these inputs harder to predict. This unpredictability operates through a distinct channel: risk-averse firms perceive higher risk-adjusted marginal costs and contract planned output (Sandmo, 1971; Hartman, 1972; Batra and Ullah, 1974; Holthausen, 1976), even when no disruption materialises, calling for a different set of policy interventions.

We provide the first global, firm-level evidence on how critical-mineral input uncertainty affects firm performance. Doing so requires overcoming three empirical challenges. First, firms' exposure to critical minerals varies substantially within industries and evolves as the green transition progresses (Section 2.1). Among firms that depend on these minerals, the opacity and immaturity of many mineral markets mean that the degree of input uncertainty differs across firms depending on their contractual arrangements and capacity to manage price risk. Conventional industrial classifications and aggregate commodity prices cannot capture this variation (IEA, 2024a), requiring a firm-level measurement approach.[4] Second, input uncertainty must be separated from correlated first-moment shocks, since price levels and volatility move together in commodity markets (Pindyck, 2004; Kilian, 2009). Third, mineral-specific uncertainty must be distinguished from broader macroeconomic disturbances, including economic policy uncertainty (Baker et al., 2016), pandemic-driven demand swings (Hassan et al., 2021), and geopolitical risk (Caldara and Iacoviello, 2022), all of which would conflate the mineral-specific input channel with a broader firm distress effect if left uncontrolled (Bloom, 2009).

We address these challenges by combining firm-level financial data from Compustat North America and Compustat Global with textual data from earnings-call transcripts for more than 14,000 publicly listed firms across 92 countries, covering 2010 to 2022.[5] Earnings-

[4]For example, even within the automotive sector, the mineral exposure of electric vehicle producers differs fundamentally from that of firms focused on internal combustion engine vehicles, yet standard SIC classifications assign both to the same industry code. These persistent and time-varying differences account for 70 to 90 percent of the variation in our text-based risk measures (Table 2).

[5]The full transcript corpus covers more than 14,000 firms; the estimation sample comprises approximately 11,729 firms (76,910 firm-year observations) after matching to Compustat financial data and requiring non-missing revenue growth and controls.

call text has recently become a workhorse source for measuring novel, hard-to-observe uncertainty shocks (Hassan et al., 2019, 2021; Sautner et al., 2023; Hassan et al., 2025). Earnings calls, held quarterly by publicly listed firms, combine prepared management remarks with a live analyst Q&A session, providing both the firm's own assessment and external scrutiny from sophisticated participants who probe issues management may prefer to downplay (Matsumoto et al., 2011; Hollander et al., 2010).[6] From these transcripts, we construct text-based measures aligned with the identification challenges above.

First, we construct binary measures of time-varying firm-level exposure to critical minerals using a keyword-dictionary approach (Bloom et al., 2021). Validation exercises confirm that the measures vary intuitively across firms and industries, co-move with the relevant clean-energy technologies, and track commodity price signals.[7]

From there, we construct measures of the direction of mineral shocks by analysing the neighbouring text of mineral mentions for risk and uncertainty language (Baker et al., 2016) and for positive and negative tone words (Loughran and Mcdonald, 2011). As demonstrated in the literature on the impact of uncertainty on firm performance (Bloom, 2009; Hassan et al., 2019, 2020, 2021; Berger et al., 2020), this method allows us to distinguish second-moment risk shocks from first-moment sentiment shocks and, by conditioning on proximity to mineral mentions, to isolate *mineral-specific signals* from broader sources of uncertainty such as the pandemic or geopolitical conflicts. Variance-decomposition exercises highlight the importance of the firm-level approach, with 70 to 90 percent of variation arising at the firm level rather than from common industry shocks. We also construct a measure of unconditional risk, capturing the overall intensity of risk-related language in the transcript without the mineral anchor, to control for confounding sources of general firm anxiety.

[6] A natural concern with text-based measures is that managerial communication may constitute cheap talk. Several institutional features of earnings calls mitigate this concern: securities law imposes penalties for materially misleading statements, analyst scrutiny generates reputational costs for evasive responses, and market participants routinely verify managerial claims against subsequent firm behaviour (Hassan et al., 2025).

[7] Exposure is highest in mining, metal processing, and the manufacture of transportation equipment, electronics, and machinery, but varies substantially within sectors and over time as clean technologies diffuse. For example, lithium, cobalt, and nickel are frequently co-mentioned with energy-storage batteries and electric vehicles.

Our main result documents a robust negative association between perceived input uncertainty about critical minerals and revenue growth among downstream non-mining firms. The empirical analysis is guided by a theoretical framework that derives predictions on the heterogeneous impact across firms and mineral markets (Section 2.2; Appendix C). In our preferred specification, which includes all controls and conditions on firm, country-by-year, and industry-by-year fixed effects, a one-standard-deviation increase in mineral risk is associated with lower revenue growth of 0.52 percentage points for the average firm and 0.71 percentage points for non-mining firms. The effect is absent when the sample is restricted to mining firms, consistent with the result being driven by downstream firms exposed to minerals as inputs.

The contraction effect is heterogeneous in two dimensions (and their interaction) consistent with our theoretical framework. It is concentrated among smaller firms (approximately 1.9 percentage points for below-median firms versus statistically indistinguishable from zero for above-median firms), consistent with large firms having greater capacity to manage input risk. It is also concentrated in minerals transacted in thin, opaque bilateral markets (lithium, cobalt, and rare-earth elements). Non-traded mineral risk carries a coefficient roughly double that on traded minerals (copper, nickel) and significant at the 5% level, whereas traded mineral risk is not. The firm-size gradient is steeper for non-traded minerals, indicating that the two sources of heterogeneity compound each other. Transcript-level discussion of hedging and stockpiling responds to price volatility rather than price levels, consistent with the risk-aversion mechanism underlying the output contraction.

Related literature. This study contributes to three strands of literature. First, a growing literature documents how various forms of risk impede the green energy revolution. Ryan (2026) shows that counterparty risk in the output market deters investment in new solar capacity where contract enforcement is weak. We provide evidence on a complementary risk on the input side, showing that uncertainty about critical-mineral inputs constrains the production of downstream firms, including those that produce clean-energy capital goods. This source of uncertainty is more acute for smaller firms, complementing prior evidence that uncertainty shocks affect firms unevenly (Ghosal and Loungani, 2000; Lakdawala and Moreland, 2026).

Second, our study extends a rapidly growing body of work on the economic consequences of critical-mineral constraints, including macroeconomic evidence on how mineral price shocks propagate through channels distinct from oil (Concordel et al., 2026) and firm-level simulations of supply disruptions for some European economies (Panon et al., 2026). A related literature on natural resource scarcity and innovation (Hassler et al., 2021; Acemoglu et al., 2023) has motivated recent patent-based evidence on induced innovation in rare-earth-saving (Alfaro et al., 2025) and critical-mineral-saving (Bastianin et al., 2026) technologies. These contributions focus on first-moment realised shocks and related innovation outcomes. We provide firm-level evidence on the second-moment uncertainty channel at a global scale and show that firm-level discussion of hedging and stockpiling responds to this second-moment variation, capturing a distinct, short-run margin of adjustment that complements the innovation channel documented in patent data.

Third, an emerging body of work applies text-as-data methods in economics (Gentzkow et al., 2019; Dugoua et al., 2022; Hassan et al., 2025). Our measurement approach builds on a tradition of text-based uncertainty indices, including newspaper-based measures of economic policy uncertainty (Baker et al., 2016) and geopolitical risk (Caldara and Iacoviello, 2022), and their extension to firm-level measures using earnings-call transcripts for political risk (Hassan et al., 2019), the pandemic (Hassan et al., 2021), and climate risk (Sautner et al., 2023). We extend this strand by developing text-based indices that capture firm-level exposure to critical-mineral input uncertainty globally and linking them to firm performance. Our work also relates to the broader literature on supply-chain shocks, which documents that disruptions to specific inputs can have aggregate consequences disproportionate to the input's cost share (Acemoglu, Daron et al., 2012; Boehm et al., 2019; Carvalho et al., 2021). Our finding that critical minerals, despite their small share of total input costs, are significantly associated with lower downstream firm growth is consistent with this insight.

The remainder of the paper is organised as follows. Section 2 provides background on critical minerals and their role in the energy transition. Section 3 outlines the data and measurement approach. Section 4 presents the empirical strategy. Section 5 examines the link between perceived input uncertainty and firm performance. Section 6 concludes.

2 Background and Conceptual Framework

2.1 Critical Minerals and the Green Transition

The green transition is shifting the material foundations of the global economy from fossil fuels, consumed as intermediate energy inputs, toward critical minerals embedded in the long-lived capital goods that generate, transmit, and store low-carbon energy (Concordel et al., 2026). Historical energy transitions have typically required close to a century to complete (Fouquet, 2010, 2016), but the current shift to renewables is proceeding at a markedly faster pace (Appendix Figure A1). Since 2019, clean energy capacity additions have grown at roughly twice the rate of fossil fuels (IEA, 2024b), with record installations in 2023: 117 GW in wind, 420 GW in solar PV, and 13.7 million EV sales, representing 2.5-, 14-, and 137-fold increases relative to 2012. This speed matters for economic analysis as the composition of industrial activity is shifting faster than conventional data systems, including standard industrial classifications, can track (IEA, 2024a), and firms' exposure to new input markets is evolving within sectors and over time in ways that aggregate statistics do not capture.

This rapid deployment is intensifying demand for a narrow set of critical minerals. An electric vehicle requires three to four times more copper than a conventional internal combustion engine vehicle (Jones et al., 2020). Solar, onshore wind, and offshore wind plants require two to seven times more copper to match the capacity of coal- or gas-fired power plants (IEA, 2022). Lithium, cobalt, and nickel are critical inputs for EV batteries and energy storage systems, while rare-earth elements are indispensable for manufacturing EV motors and wind turbines (IRENA, 2023). Demand for these minerals is increasingly compounded by sources beyond the energy transition, including AI-driven digitalisation and renewed defence investment, though these pressures intensified largely after our 2010–2022 sample period and reinforce the forward-looking relevance of the input-uncertainty channel we study.

These minerals are geographically concentrated in both extraction and processing, creating acute trade dependencies and exposure to supply disruptions. Figure 1 shows that concentration levels, measured as the combined share of the top three producers, exceed those observed for oil and gas across both upstream and midstream stages. This concentration introduces structural vulnerabilities. Nickel supply was disrupted by Russia's invasion of Ukraine, a major producer. Rare earths are highly sensitive to export restrictions from China. Cobalt faces persistent risks due to political instability in the Democratic Republic of Congo (Graedel et al., 2015), which accounts for approximately two-thirds of global output. Labour strikes in Chile and Peru have significantly affected copper supply. Global shocks such as the COVID-19 pandemic have simultaneously disrupted multiple critical-mineral supply chains.

[Figure 1 about here.]

Market structures vary substantially across minerals, a distinction that is important for the empirical results that follow. Copper and nickel are mature commodities with deep, liquid markets.[8] By contrast, cobalt, lithium, and rare-earth elements operate in nascent or thin markets.[9] Market sizes in unprocessed form differ by orders of magnitude: copper reached approximately USD 91 billion in 2021, followed by nickel at USD 4.2 billion, lithium at USD 1.5 billion, cobalt at USD 0.59 billion, and rare earths collectively at USD 0.12 billion (IRENA, 2023). Panel B of Figure 1 shows that monthly prices for the nascent-

[8]Copper has been traded on the London Metal Exchange since the nineteenth century, with average daily volumes exceeding 170,000 lots in recent years, and its official price serves as the global benchmark for physical transactions. Nickel occupies a similar position, although the 2022 short squeeze temporarily disrupted trading.

[9]Cobalt futures were introduced on the LME in 2010, but trading remains so thin that the exchange has periodically suspended lending rules to prevent a single party from dominating available inventories. Lithium hydroxide futures launched on the CME in 2021 and have grown rapidly, but open interest remains roughly eighty times smaller than copper futures in notional terms. Rare earths remain predominantly traded through bilateral agreements with no standardised exchange contract.

market minerals exhibit frequent outliers, some exceeding the volatility range observed in energy markets, particularly for rare earths and lithium.

Throughout this paper, we classify copper and nickel as "traded" minerals and lithium, cobalt, and rare-earth elements as "non-traded," reflecting effective market depth and price transparency rather than the formal existence of an exchange contract. The depth and transparency of traded mineral markets provide downstream firms with observable price signals, standardised hedging instruments, and credible cost benchmarks for pass-through negotiations, while the thinness and opacity of non-traded markets limit firms' access to these tools (Bulow and Pfleiderer, 1983; Weyl and Fabinger, 2013). In thin bilateral markets, information advantages and bargaining power tend to accrue to larger firms (Inderst and Wey, 2007) with established supplier relationships and the capacity to commit to long-term offtake agreements, amplifying the exposure of smaller firms to input-cost uncertainty.

2.2 Conceptual Framework

The theoretical framework, developed formally in Appendix C, builds on canonical models of production under uncertainty (Sandmo, 1971; Hartman, 1972; Batra and Ullah, 1974; Holthausen, 1976) and adapts them to the critical-mineral context. The model has three inputs that differ in adjustment speed: capital is sunk, labour is committed at the start of each period before uncertainty is resolved, and the critical mineral input is the only factor that adjusts within the period under uncertainty. The mineral is "critical" in the model in two senses: it is non-substitutable in the short run, modelled via a Leontief structure that bounds output by mineral procurement, and it is risky, subject to both first-moment shocks that shift the expected cost of the input and second-moment shocks that make future costs harder to predict.

All sources of input uncertainty, whether commodity-price fluctuations, quantity constraints, delivery delays, or sourcing difficulties, are captured through the *effective input price* facing the firm: $w_{it} = \bar{w} + \mu_{it} + \epsilon_{it}$, where $\bar{w}$ is a common baseline, μ_{it} is a firm-specific mean deviation (first-moment shock), and $\epsilon_{it} \sim N(0, \sigma_{it}^2)$ captures second-moment uncertainty. This effective price is firm-specific: two firms exposed to the same mineral face different μ_{it} and σ_{it}^2 depending on their contractual arrangements, procurement channels, and capacity to manage input risk. The first-moment component μ_{it} shifts the expected cost of the mineral and therefore has a direct effect on profitability; the second-moment component σ_{it}^2 operates through a distinct channel that depends on the firm's attitude toward risk.

The firm inherits an operating scale, then chooses mineral procurement under uncertainty. For simplicity and tractability, we assume constant absolute risk aversion (CARA), so that the firm maximises expected profit net of a variance penalty. A risk-averse firm then sets mineral input M_{it}^* to satisfy:

$$\underbrace{\alpha}_{\text{marginal product (Leontief)}} = \underbrace{\bar{w} + \mu_{it}}_{\text{expected price}} + \underbrace{A_i \, \sigma_{it}^2 \, M_{it}}_{\text{risk premium}} \tag{1}$$

where α is the marginal product of the mineral input, constant under the Leontief structure, and $A_i > 0$ is firm i's coefficient of risk aversion.[10] The first-moment term μ_{it} raises the expected input cost, reducing procurement and output through the standard price channel. The risk premium $A_i \sigma_{it}^2 M_{it}$ represents an additional, distinct channel: it raises the perceived marginal cost beyond the expected price even when no disruption materialises. The firm responds by procuring less, producing below capacity, and realising lower revenue growth relative to its planned scale. Higher σ_{it}^2 widens this gap.[11]

This framework generates three testable predictions.

H1 (Input dependency). Perceived input uncertainty about critical minerals is negatively associated with revenue growth among firms that depend on these minerals as production inputs.

[10] Appendix **??** shows that the first-order condition takes the same form under CES production, with a diminishing marginal product replacing α; all qualitative predictions are unchanged.

[11] This has direct implications for the pace of the green transition: meeting climate commitments requires rapid scaling of clean-energy supply chains, and uncertainty-induced contractions in planned output slow the capacity build-out on which those commitments depend.

H2 (Firm heterogeneity). The negative association is larger for smaller firms, which face higher effective A_i due to more limited risk-management capacity (Rajan and Zingales, 1998; Hennessy and Whited, 2007).

H3 (Market structure and firm heterogeneity). The large-firm advantage is sharper in thinly traded minerals (lithium, cobalt, rare earths), where bargaining power (Inderst and Wey, 2007), established supplier relationships, and long-term offtake agreements are most valuable and standardised hedging instruments are less available. The firm-size gradient (H2) is therefore steeper for non-traded than for traded minerals.

3 Data and Measurement

We compile data from several sources. Textual data are obtained from S&P Machine Readable Transcripts, which provide earnings-call transcripts for publicly listed firms worldwide between 2006 and 2022, with substantial coverage beginning in 2008. Each transcript contains a prepared management presentation followed by a live analyst Q&A session. Firm-level financial data, including revenue, total assets, capital expenditure, and employment, are drawn from Compustat North America and Compustat Global, with monetary variables converted to US dollars using historical exchange rates from the International Financial Statistics. Monthly commodity prices are sourced from the IMF Primary Commodity Price Index, supplemented with US Geological Survey data for lithium and rare-earth elements in 2010–2011, when IMF coverage begins only in 2012.

After consolidating these sources, we restrict the sample to 2010–2022, a period that provides strong coverage of listed firms and captures a key phase in the development of clean-energy technologies after financial crisis. The final dataset contains 280,867 transcripts matched to quarterly financial data, which we collapse to the firm-year level, yielding 80,466 observations across 92 countries. Table 1 reports summary statistics. Full details on the data construction pipeline, including deduplication rules, exchange-rate conversions, and sample restrictions, are provided in Online Appendix.

[Table 1 about here.]

From these transcripts, we construct three families of text-based measures, moving progressively from undirected exposure to directional shocks to firm-level responses. Formal definitions and equations are provided in Appendix D.

Mineral exposure. We first identify which firms are exposed to critical minerals at a given point in time. Using a keyword-dictionary approach similar to how Bloom et al. (2021) track firms' exposure to disruptive technologies, we search each transcript for mineral-specific unigrams, namely technical terms that are easily distinguishable from general business vocabulary (e.g., "lithium," "cobalt," "spodumene," "ferronickel," "neodymium"). A transcript is classified as exposed to mineral μ if any match is found. This binary indicator captures whether the mineral is salient for the firm's operations, reflecting both the firm's position in the supply chain and the occurrence of a mineral-related shock at that point in time. We similarly detect exposure to clean-energy technologies (electric vehicles, lithium-ion batteries, solar, and wind) using bigram sets from Bloom et al. (2021), extended for wind power through human-validated candidates. By combining transcript timing with firm identifiers, we obtain time-varying, firm-level exposure measures that exploit within-industry and within-firm variation over time. The full keyword dictionaries are listed in Appendix F.

These exposure measures are undirected: they indicate that a mineral is being discussed but not whether the discussion reflects risk, opportunity, or routine operational commentary. They however provide a first layer of validation for the textual approach. If the measures are capturing economically meaningful variation, we would expect mineral exposure to co-occur systematically with exposure to the clean-energy technologies that use these minerals (e.g., lithium with batteries and electric vehicles, rare earths with wind turbines), and to track observable commodity-price movements over time. We verify both properties in Section 4 and in Appendix E, confirming that the textual signals are informative before constructing the directional measures that enter the main regressions.

Mineral risk and sentiment. The conceptual framework identifies two channels through which input conditions affect firm performance: a second-moment channel, in which the risk premium $A_i\sigma^2_{it}$ raises the perceived marginal cost and contracts output, and a first-moment channel, in which the expected cost deviation μ_{it} shifts profitability directly. The paper's object of interest is the second-moment channel. We construct empirical proxies for each following the approach of Hassan et al. (2019, 2025).

MineralRisk, the focal measure, counts mineral-keyword occurrences within a 10-word window of risk or uncertainty synonyms derived from the Oxford Dictionary (e.g., "uncertainty," "possibility," "exposed," "variability," "fluctuating"), normalised by transcript length (Baker et al., 2016). This measure captures the perceived second-moment variation in the firm's input conditions. *MineralSentiment* is the net count of mineral-keyword occurrences near positive tone words (e.g., "strong," "good," "able," "opportunity") minus those near negative tone words (e.g., "decline," "difficult," "volatility," "loss"), using the financial-text dictionary of Loughran and Mcdonald (2011). This measure captures the first-moment variation in the firm's mineral-market conditions and is included as a control to absorb directional shocks that could otherwise confound the uncertainty estimate, mirroring the separability of the two channels in Equation (1). Word clouds illustrating the risk and sentiment vocabularies, with word size proportionate to frequency in mineral-related text, are shown in Figure A2. Illustrative transcript excerpts demonstrating how these measures capture risk and sentiment discussions in practice are provided in Tables A6 and A7.

Composite measures are constructed by summing across the five minerals. All transcript-level measures are averaged to the firm-year level, giving each transcript equal weight regardless of length.[12] All measures are standardised by their cross-sectional standard deviation so that regression coefficients are interpretable as the effect of a one-standard-deviation increase.

To separate mineral-specific uncertainty from general firm anxiety, we also construct *UnconditionalRisk*, which applies the same risk-word dictionary to the full transcript with-

[12]This mean-of-ratios aggregation avoids the Jensen's inequality bias that would arise from dividing the mean of numerator counts by the mean of token counts (ratio-of-means).

out conditioning on proximity to mineral mentions. This measure captures the overall level of risk-related discussion in the earnings call and serves as a control for confounding sources of uncertainty, such as macroeconomic conditions or firm-specific distress, that may jointly influence both mineral-risk discussion and revenue outcomes. Including $UnconditionalRisk$ alongside $MineralRisk$ in the regression ensures that the estimated effect of mineral-specific uncertainty is not driven by general firm-level exposure to aggregate uncertainty shocks.

Response indicators. We also construct indicators of firm-level responses to mineral-price shocks. Among these, we focus on hedging and stockpiling, identified by locating mineral terminology within a 10-word window of financial-instrument and inventory-related synonyms following approach of Hassan et al. (2021). These represent costly actions that firms undertake specifically to manage input uncertainty and their responsiveness to price volatility rather than price levels provides a direct test of the risk-aversion mechanism (Section 5.5). Full detection patterns and additional response channels are detailed in Appendix D.7 and Table A5.

4 Empirical Strategy

Before turning to the regressions, we summarise the validation properties of the text-based measures (full results in Appendix E). Mineral exposure co-occurs systematically with the clean-energy technologies that use these minerals as inputs, with a cotton falsification test confirming specificity (Table A1). Aggregated across firms, exposure tracks observable commodity-price signals (Figure 2), and the directional measures co-move with the corresponding price moments: sentiment tracks price levels, risk tracks price volatility (Figure A3). These co-movements confirm the measures are anchored in real economic signals.

[Figure 2 about here.]

Crucially, however, commodity prices are common to all firms, whereas the object of interest is firm-specific. Available indices for non-traded minerals are composites from thin markets that poorly reflect individual procurement costs, and even for traded minerals the same price signal maps into different perceived uncertainty depending on a firm's capacity to hedge. Variance decomposition confirms this, with 70 to 90 percent of the variation in perceived mineral risk arising idiosyncratically at the firm level (Table 2), motivating the firm-level text-based approach and the fixed-effect strategy below.

[Table 2 about here.]

We investigate the relationship between perceived mineral-input uncertainty and firm performance using a global firm-by-year panel, indexing firms, headquarter countries, industries, and years by i, c, s, and t. Consistent with the short-run output-planning margin in the theoretical framework, the outcome is year-on-year revenue growth:[13]

$$
\begin{aligned}
SaleGrowth_{ict} = \delta_i + \delta_{tc} + \delta_{ts} + \beta_1 MineralRisk_{it} \\
+ \beta_2 MineralSentiment_{it} + \beta_3 UnconditionalRisk_{it} \\
+ \gamma X_{it} + \varepsilon_{ict}
\end{aligned}
\tag{2}
$$

$MineralRisk_{it}$ and $MineralSentiment_{it}$ denote the composite risk and net sentiment measures for the five minerals, averaged over firm i's transcripts in year t (typically four). $UnconditionalRisk_{it}$ applies the same risk-word dictionary to the full transcript without conditioning on proximity to mineral mentions. All specifications control for firm size (X_{it}, log total assets). We predict $\beta_1 < 0$ (H1) and $\beta_2 > 0$.

The fixed effects and the text controls together isolate the mineral-specific second-moment signal. Firm fixed effects (δ_i) absorb time-invariant heterogeneity, including a manager's baseline propensity to use risk language and persistent strategic orientations such as battery-electric versus internal-combustion-engine production. Country-by-year (δ_{tc}) and industry-by-year (δ_{ts}) fixed effects absorb annual macroeconomic and sectoral shocks, including monetary-policy changes, demand cycles, and commodity-price movements common to all

[13] Results are qualitatively identical using log revenue levels rather than growth (Table 5, columns 3–4), confirming the finding is not an artefact of the growth-rate transformation.

firms in a country or sector.

$UnconditionalRisk_{it}$ absorbs the firm's time-varying general risk-language intensity, whatever its source. In any given call, a manager's risk discourse reflects not only mineral-specific concerns but also broad macroeconomic and geopolitical conditions, including economic policy uncertainty (Baker et al., 2016), geopolitical risk (Caldara and Iacoviello, 2022), and pandemic-driven disruption (Hassan et al., 2021), as well as a firm's idiosyncratic, possibly inflated, tendency invoke risk language. Each of these would load onto $MineralRisk_{it}$ through correlated risk vocabulary if left uncontrolled. Conditioning on $UnconditionalRisk_{it}$, together with firm fixed effects that net out time-invariant verbosity, ensures that $MineralRisk_{it}$ reflects risk language tied specifically to critical minerals rather than a firm's general level of expressed uncertainty. $MineralSentiment_{it}$ controls for the correlated first-moment channel, so that β_1 isolates the second-moment, mineral-specific effect. Standard errors are clustered at the firm level.[14]

Identification rests on an assumption that after conditioning on the fixed effects and controls, the residual variation in $MineralRisk$ reflects firm-specific uncertainty shocks orthogonal to short-run revenue growth. We probe its plausibility in three ways. First, we compare mining and non-mining firms: if $MineralRisk$ captures input uncertainty, its effect should appear among downstream non-mining firms, for whom minerals are inputs, and not among upstream mining firms, for whom they are outputs (H1). Second, we examine alternative outcomes. The framework predicts that mineral-specific uncertainty constrains planned output through the production under uncertainty channel, whereas general uncertainty dampens investment through the real-options channel in which higher uncertainty raises the option value of waiting (Bloom, 2009). This yields a testable double dissociation: $MineralRisk$ should predict revenue but not investment, while $UnconditionalRisk$ should predict investment but not revenue (Table 5). Third, lead $MineralRisk_{t+1}$ should not predict current revenue growth, ruling out anticipatory reverse causality (Table A4).

[14]Industry is defined at the 2-digit SIC level to avoid near-singularity when estimating industry-by-year and country-by-year fixed effects simultaneously in a global panel where many narrow sectors contain few firms per country-year cell. Results are robust to 4-digit SIC-by-year fixed effects and to clustering at the SIC2-by-year level (Table A3).

We test H2 and H3 through interactions with firm size. For H2, we add $Largefirm_{it}$ and $Largefirm_{it} \times MineralRisk_{it}$ to Equation (2); because $Largefirm$ is defined relative to the year-specific median, it varies within firms over time and is identified alongside the firm fixed effects (Table 6). H3 has two components, tested in Table 7. First, we decompose $MineralRisk$ into traded (copper, nickel) and non-traded (lithium, cobalt, rare earths) components to locate the effect by market structure (columns 3–4). Second, we interact each component with firm size in the fully saturated specification:

$$\begin{aligned} SaleGrowth_{ict} = \delta_i + \delta_{tc} + \delta_{ts} &+ \beta_1 MineralRisk_{it}^{traded} + \beta_2 MineralRisk_{it}^{nontraded} \\ &+ \beta_3 Largefirm_{it} + \beta_4 Largefirm_{it} \times MineralRisk_{it}^{traded} \\ &+ \beta_5 Largefirm_{it} \times MineralRisk_{it}^{nontraded} \\ &+ \boldsymbol{\beta}' \mathbf{Z}_{it} + \gamma X_{it} + \varepsilon_{ict} \end{aligned} \tag{3}$$

where $\mathbf{Z}_{it}$ collects the sentiment and unconditional-risk controls from Equation (2). H3 predicts $\beta_5 > \beta_4$: the risk-management advantage of larger firms, and hence the firm-size gradient, is steeper for non-traded minerals, where bargaining power and hedging access are most valuable.

5 Results

5.1 Baseline Results

Table 3 presents estimates across three panels: the full global sample (Panel A), upstream mining firms with two-digit SIC codes 10–14 (Panel B), and downstream non-mining firms (Panel C). Across all specifications, and regardless of whether the dependent variable is trimmed or winsorised, the coefficients exhibit the signs predicted in Equation 2: perceived risk is negatively associated with revenue growth, and net mineral sentiment enters with a positive coefficient.

[Table 3 about here.]

MineralRisk is statistically significant across all full-sample specifications, and its estimated negative association is stable as *MineralSentiment* and *UnconditionalRisk* are progressively added as controls. The coefficient therefore reflects neither confounding first-moment shocks (captured by the sentiment measure) nor general risk-laden language unrelated to minerals (captured by *UnconditionalRisk* and firm fixed effects). Results are robust to both treatments of outliers in the dependent variable, though winsorisation, which retains a slightly larger sample, yields marginally larger coefficients.

The cross-panel heterogeneity sharpens the interpretation. Panel C provides a direct test of H1: *MineralRisk* is negatively and significantly associated with revenue growth among downstream non-mining firms, for whom minerals are inputs, consistent with the input-uncertainty channel. Panel B provides evidence against the alternative that the result reflects output-revenue uncertainty: *MineralRisk* is insignificant for upstream mining firms, for whom mineral-price variation operates through the revenue channel rather than the input-cost channel.[15] Based on the preferred winsorised specification with all controls, a one-standard-deviation increase in perceived mineral risk is associated with lower revenue growth of 0.52 percentage points for the average firm and 0.71 percentage points for non-mining firms.

Because *MineralRisk* takes non-zero values for a subset of firms with active mineral exposure, we verify in Table 4 that the baseline estimate is robust to restricting the sample to firms that discuss any critical mineral in at least one earnings call during the sample period, and to firm-year observations in which the firm mentions a critical mineral in that year.[16] The coefficient is stable and more precisely estimated under both restrictions. We report the full non-mining sample as the preferred specification to avoid selection on an endogenous indicator of mineral exposure and to better absorb nation-wide and industry-wide common

[15] Mineral-price uncertainty also affects mining firms, but through the output-revenue channel rather than the input-cost channel. Mining firms' extensive use of forward-sale agreements and financial hedging instruments likely attenuates this effect.

[16] These restrictions reduce the sample from approximately 72,000 to 22,000 and 5,200 firm-years respectively.

shocks through the fixed-effect structure.

[Table 4 about here.]

The ever-mention sample provides a natural reference population for interpreting economic magnitude. Moving from the 25th to the 75th percentile of mineral-risk intensity among exposed firm-years, an interquartile range of 3.27 standard deviations, is associated with approximately 2.2 percentage points lower revenue growth (0.67×3.27), or roughly 17% of the sample mean. We view this as a lower-bound estimate of the population effect. The sample consists of publicly listed firms, which are larger and better capitalised than the private and domestic producers that dominate clean-energy supply chains, while our heterogeneity results (Section 5.3) show that the contraction is concentrated among smaller firms. A sample skewed toward large firms therefore likely presents a conservative estimate of the effect for the broader population of exposed firms.

5.2 Channel Specificity

Table 5 estimates the preferred specification with alternative dependent variables. The results confirm the differential effects predicted in Section 4: *MineralRisk* is significant only for revenue (both growth and levels), while *UnconditionalRisk* is significant only for investment. This pattern suggests that mineral-specific input uncertainty operates through the production channel, constraining planned output as the risk-adjusted marginal cost of inputs rises, rather than through the investment channel associated with general uncertainty raising the option value of waiting and dampening capital expenditure (Bloom, 2009).

The pattern also reinforces the identification: since *UnconditionalRisk* absorbs general sources of firm-level anxiety, including economic policy uncertainty (Baker et al., 2016) and geopolitical risk (Caldara and Iacoviello, 2022) that may simultaneously drive mineral-market volatility, the significance of *MineralRisk* for revenue growth but not investment confirms that it captures a mineral-specific input channel rather than a broader uncertainty effect. Neither form of uncertainty affects contemporaneous employment, consistent with the predetermined labour assumption in the theoretical framework.

[Table 5 about here.]

5.3 Firm-Size Heterogeneity

Table 6 tests H2 by splitting the sample at the year-specific median of log total assets and by estimating a pooled interaction specification. The effect of *MineralRisk* on revenue growth is approximately 1.3 to 1.9 percentage points for below-median firms depending on specification, and statistically indistinguishable from zero for above-median firms.

[Table 6 about here.]

The interaction specification confirms this pattern: the coefficient on $Largefirm \times MineralRisk$ is positive and significant (1.49 to 1.90), indicating that above-median firms experience a significantly smaller revenue contraction for a given level of perceived mineral risk. This size gradient is consistent with larger firms having a greater capacity to manage input risk, lowering their effective risk aversion.

5.4 Market Structure

Table 7 tests H3, which has two components. We first decompose the composite *MineralRisk* into risk from traded minerals (copper, nickel) and non-traded minerals (lithium, cobalt, rare-earth elements). The coefficient on non-traded mineral risk is roughly double that on traded mineral risk and significant at the 5 percent level (−0.61 to −0.64), while the coefficient on traded mineral risk is negative (−0.21 to −0.35) but does not reach significance at the 5 percent level in either specification. The point estimates are thus ordered as the model predicts, though we cannot statistically distinguish the two coefficients.

[Table 7 about here.]

This pattern is consistent with the market-structure differences documented in Section 2.1: firms exposed to minerals with transparent benchmark pricing face lower perceived input uncertainty and have access to standardised hedging instruments, while firms exposed to minerals with opaque bilateral pricing bear greater uncertainty about future input costs.[17]

The second component of H3 concerns firm size. Columns 5–6 of Table 7 interact each risk component with firm size. The interaction of firm size with non-traded mineral risk is positive and significant (1.27 to 1.61), while the interaction with traded mineral risk is smaller and insignificant, indicating that the firm-size gradient documented in Section 5.3 is concentrated among non-traded minerals. We interpret this as consistent with the prediction that the size gradient is steeper for non-traded minerals. The capacity to manage input risk, for which firm size is a proxy, appears most valuable precisely where market opacity is greatest, and standardised hedging instruments are unavailable.

5.5 Revealed Risk Aversion

The preceding firm-level results establish that perceived mineral-input uncertainty is associated with lower revenue growth, consistent with risk-averse firms contracting planned output. If this interpretation is correct, firms should also actively seek to reduce their exposure to mineral-input uncertainty. Table 8 tests this using the transcript-quarter panel for non-mining firms, regressing binary indicators of mineral exposure and hedging or stockpiling discussion on the logged price level and logged 12-month rolling price volatility of each mineral simultaneously, controlling for firm size, firm fixed effects, and quarter-of-year fixed effects, with standard errors clustered by quarter.

[Table 8 about here.]

Panel A confirms the aggregate pattern in Figure 2 at the firm level: firms are more likely to mention critical minerals when commodity prices signal adverse market conditions.

[17] The traded/non-traded distinction correlates with other mineral characteristics, including supply concentration, market maturity, and near-term substitutability. We interpret the decomposition as capturing a bundle of market-structure features rather than tradability alone.

Because price levels and price volatility are positively correlated in commodity markets, we include both *LogPrice* and *LogPriceVol* simultaneously to separate first-moment from second-moment effects.[18] Both coefficients are significant across all four minerals, confirming that firms' mineral-related discussion reflects both first-moment and second-moment variation and strengthening the case for including both risk and sentiment controls in the baseline specification.

Panel B focuses on hedging and stockpiling, the primary short-run operational responses to input uncertainty among a broader set of firm responses that also includes cost pass-through, material substitution, and circular-economy strategies (Appendix Figure A4; Table A5).[19] The coefficients on *LogPriceVol* are consistently positive and significant across all four minerals, while the coefficients on *LogPrice* are generally insignificant. The prevalence of hedging and stockpiling discussion is substantial, ranging from 3 to 7 percent of transcripts for non-traded minerals to 14 to 23 percent for traded minerals (Appendix Figure A4), with the gradient itself reflecting the availability of standardised hedging instruments across market structures. The responsiveness of these discussions to price volatility rather than price levels reveals a preference for uncertainty reduction, supporting the $A > 0$ assumption underlying the theoretical framework and suggesting that the revenue contraction documented above reflects risk aversion toward input uncertainty.

5.6 Robustness

The baseline results are robust to a range of sensitivity checks. Table 4, discussed in Section 5.1, confirms that the coefficient is stable and more precisely estimated when restricting the sample to firms with demonstrated mineral exposure, whether defined as firms that discuss any critical mineral in at least one earnings call (ever-mention firms) or as firm-year

[18]Rare-earth elements are excluded from this analysis due to sparse mineral-specific discussions in transcripts and interpolated quarterly price data before 2012, which would introduce measurement error in *LogPriceVol*.

[19]We focus on hedging and stockpiling because these represent costly actions undertaken specifically to manage input uncertainty. The remaining channels, which include both operational and longer-run innovation responses, are examined in Appendix Table A5.

observations in which the firm actively discusses a critical mineral in that year. Table A2 shows that the coefficient is robust to alternative trimming and winsorisation thresholds for the dependent variable. The point estimate attenuates as the threshold tightens from 1% to 5%, consistent with the more aggressive trimming removing real variation in the tails rather than outlier-driven noise, but remains statistically significant across all specifications. Table A3 verifies that the results are not sensitive to the choice of clustering level or fixed-effect granularity. The coefficient is stable under clustering at the SIC2-by-year level rather than the firm level, under 4-digit SIC-by-year fixed effects rather than 2-digit, and under the stricter SIC2-by-country-by-year fixed effects that absorb all common shocks within each sector-country-year cell.

Table A4 addresses temporal stability and reverse causality. The baseline coefficient is stable when restricting the sample to the pre-COVID period (2010–2019) or excluding the US-China trade-war escalation (2010–2018), confirming that the results are not driven by large common shocks concentrated in the later years of the sample.

Reverse causality could operate through two channels. A contemporaneous channel arises if managers experiencing poor performance invoke mineral constraints as a post-hoc rationalisation, inflating $MineralRisk$ precisely when revenue growth is low. Including $UnconditionalRisk$ partially addresses this by absorbing general risk-laden language correlated with firm-level distress, but it cannot rule out the case where managers direct rationalisation toward minerals specifically. The stronger discipline comes from the pattern of results across specifications: rationalisation-driven language should not be sector-specific (Table 3, Panel B vs Panel C), should not predict revenue growth but not investment (Table 5), and should not concentrate among small firms exposed to non-traded minerals (Tables 6 and 7). Several institutional features of earnings calls further raise the cost of mineral-specific cheap talk. Securities law imposes penalties for materially misleading statements, analyst scrutiny during the Q&A segment enables real-time verification of supply-chain claims against observable market conditions, and repeated misattribution erodes managerial credibility with the analyst community (Hassan et al., 2025). These costs make systematic mineral-specific rationalisation less plausible than vague references to "challenging conditions," which is the variation absorbed by $UnconditionalRisk$.

An anticipatory channel arises if firms expecting future revenue declines begin discussing mineral risk in advance. The lead specification in column 4, where $MineralRisk_{t+1}$ is insignificant alongside a significant contemporaneous coefficient (column 5), provides direct evidence against this interpretation.

6 Conclusion

Meeting climate commitments requires an unprecedented scaling of clean-energy supply chains (Ryan, 2026). This paper documents a channel that may impede that scaling: uncertainty about critical-mineral inputs is associated with lower revenue growth among downstream firms, with a pattern of heterogeneity consistent with the mechanism predicted by production-under-uncertainty theory. The burden falls disproportionately on smaller firms and on firms reliant on minerals traded in thin, opaque markets. The responsiveness of hedging and stockpiling to price volatility rather than price levels supports a risk-aversion mechanism rather than a mechanical correlation.

Our estimates are likely conservative with respect to the broader population of firms in clean-energy supply chains. Panon et al. (2026) document substantial value-added losses from simulated mineral supply disruptions using customs and balance-sheet data for five EU economies, capturing smaller and private firms that our sample excludes. The text-based approach sacrifices this intensive coverage for global scale across 92 countries and timeliness at a low marginal cost if compared to large-scale surveys. The sample comprises publicly listed firms with English-language earnings calls, which are typically larger, better capitalised, and more internationally diversified than the private firms and domestic producers that constitute the bulk of these supply chains. Non-English-language firms, which may face greater information asymmetries in mineral procurement, represent a further dimension along which our estimates may understate the prevalence of the input-uncertainty channel.

The heterogeneity across mineral markets implies that the economic cost of input uncertainty depends not only on underlying supply risk but also on the transparency, depth, and structure of the markets in which minerals are traded. The traded/non-traded decomposition captures a bundle of market features, including price opacity, supply concentration, and the availability of hedging instruments, that are difficult to disentangle empirically. Policy interventions targeting any dimension of this bundle, for example the development of exchange-traded benchmarks, strategic stockpiling arrangements, or more accessible risk-management tools for smaller firms, may be as important to the pace of the transition as securing physical supply itself (Leruth et al., 2022; Concordel et al., 2026).

Our text-based measures capture perceived input risk at the firm level, which is the decision-relevant object in the production-under-uncertainty framework: firms contract output in response to their own assessment of input uncertainty, not to aggregate commodity-price volatility that is common to all firms. The sample period ends in 2022, before major market corrections and recent policy interventions such as the EU Critical Raw Materials Act. As the transition matures, the firm-level text-based framework developed here offers a scalable tool for tracking whether the relationship between critical-mineral uncertainty and firm performance intensifies or attenuates as mineral markets deepen.

Bibliography

Acemoglu, D., Aghion, P., Barrage, L., Hémous, D., 2023. Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution. Working Paper 31657. National Bureau of Economic Research. URL: http://www.nber.org/papers/w31657, doi:10.3386/w31657.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, Alireza Tahbaz-salehi, 2012. The Network Origins of Aggregate Fluctuations. Econometrica 80, 1977–2016. URL: http://doi.wiley.com/10.3982/ECTA9623, doi:10.3982/ECTA9623.

Alfaro, L., Fadinger, H., Schymik, J.S., Virananda, G., 2025. Trade and Industrial Policy in Supply Chains: Directed Technological Change in Rare Earths. NBER Working Paper 33877.

Ali, S.H., Giurco, D., Arndt, N., Nickless, E., Brown, G., Demetriades, A., Durrheim, R., Enriquez, M.A., Kinnaird, J., Littleboy, A., Meinert, L.D., Oberhänsli, R., Salem, J., Schodde, R., Schneider, G., Vidal, O., Yakovleva, N., 2017. Mineral supply for sustainable development requires resource governance. Nature 543, 367–372. URL: https://www.nature.com/articles/nature21359, doi:10.1038/nature21359. publisher: Nature Publishing Group.

Arrow, K.J., Chenery, H.B., Minhas, B.S., Solow, R.M., 1961. Capital-labor substitution and economic efficiency. The Review of Economics and Statistics 43, 225–250. doi:10.2307/1927286.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring Economic Policy Uncertainty*. The Quarterly Journal of Economics 131, 1593–1636. URL: https://doi.org/10.1093/qje/qjw024, doi:10.1093/qje/qjw024.

Bastianin, A., Castelnovo, P., Frattini, F.F., Vona, F., 2026. Induced Innovation in Critical Mineral Saving Technologies. FEEM Working Papers 391378. Fondazione Eni Enrico Mattei (FEEM). URL: https://ideas.repec.org/p/ags/feemwp/391378.html, doi:10.22004/ag.econ.391378.

Batra, R., Ullah, A., 1974. Production and pricing under uncertainty: A survey. Journal of Economic Literature 12, 985–1020.

Berger, D., Dew-Becker, I., Giglio, S., 2020. Uncertainty Shocks as Second-Moment News Shocks. The Review of Economic Studies 87, 40–76. URL: https://doi.org/10.1093/restud/rdz010, doi:10.1093/restud/rdz010.

Blazquez, J., Fuentes, R., Manzano, B., 2020. On some economic principles of the energy transition. Energy Policy 147, 111807. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421520305267, doi:10.1016/j.enpol.2020.111807.

Bloom, N., 2009. The Impact of Uncertainty Shocks. Econometrica 77, 623–685. URL: http://doi.wiley.com/10.3982/ECTA6248, doi:10.3982/ECTA6248.

Bloom, N., 2014. Fluctuations in Uncertainty. Journal of Economic Perspectives 28, 153–176. URL: https://pubs.aeaweb.org/doi/10.1257/jep.28.2.153, doi:10.1257/jep.28.2.153.

Bloom, N., Hassan, T.A., Kalyani, A., Lerner, J., Tahoun, A., 2021. The Diffusion of Disruptive Technologies. Working Paper 28999. National Bureau of Economic Research. URL: http://www.nber.org/papers/w28999, doi:10.3386/w28999. series: Working Paper Series.

Boehm, C.E., Flaaen, A., Pandalai-Nayar, N., 2019. Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake. The Review of Economics and Statistics 101, 60–75. URL: https://direct.mit.edu/rest/article/101/1/60/58658/Input-Linkages-and-the-Transmission-of-Shocks-Firm, doi:10.1162/rest_a_00750.

Boer, L., Pescatori, A., Stuermer, M., 2024. Energy transition metals: Bottleneck for net-zero emissions? Journal of the European Economic Association 22, 200–229. URL: https://doi.org/10.1093/jeea/jvad039, doi:10.1093/jeea/jvad039, arXiv:https://academic.oup.com/jeea/article-pdf/22/1/200/56636974/jvad039.pdf.

Bulow, J.I., Pfleiderer, P., 1983. A note on the effect of cost changes on prices. Journal of Political Economy 91, 182–185. URL: http://www.jstor.org/stable/1840437.

Caldara, D., Iacoviello, M., 2022. Measuring Geopolitical Risk. American Economic Review 112, 1194–1225. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20191823, doi:10.1257/aer.20191823.

Carvalho, V.M., Nirei, M., Saito, Y.U., Tahbaz-Salehi, A., 2021. Supply Chain Disruptions: Evidence from the Great East Japan Earthquake*. The Quarterly Journal of Economics 136, 1255–1321. URL: https://academic.oup.com/qje/article/136/2/1255/6030033, doi:10.1093/qje/qjaa044.

Concordel, A., Ho, P., Knittel, C.R., 2026. The Differential Impacts of Critical Mineral Prices and Oil Prices on the Economy. Working Paper 34847. National Bureau of Economic Research. URL: http://www.nber.org/papers/w34847, doi:10.3386/w34847.

Dugoua, E., Dumas, M., Noailly, J., 2022. Text as data in environmental economics and policy. Review of Environmental Economics and Policy 16, 346–356. URL: https://doi.org/10.1086/721079, doi:10.1086/721079, arXiv:https://doi.org/10.1086/721079.

Ersahin, N., Giannetti, M., Huang, R., 2022. Supply Chain Risk: Changes in Supplier Composition and Vertical Integration. SSRN Electronic Journal URL: https://www.ssrn.com/abstract=4036798, doi:10.2139/ssrn.4036798.

Fouquet, R., 2010. The slow search for solutions: Lessons from historical energy transitions by sector and service. Energy Policy 38, 6586–6596. URL: https://www.sciencedirect.com/science/article/pii/S0301421510004921, doi:10.1016/j.enpol.2010.06.029.

Fouquet, R., 2016. Historical energy transitions: Speed, prices and system transformation. Energy Research Social Science 22, 7–12. URL: https://www.sciencedirect.com/science/article/pii/S2214629616301979, doi:https://doi.org/10.1016/j.erss.2016.08.014.

Gentzkow, M., Kelly, B., Taddy, M., 2019. Text as Data. Journal of Economic Literature 57, 535–574. URL: https://pubs.aeaweb.org/doi/10.1257/jel.20181020, doi:10.1257/jel.20181020.

Ghosal, V., Loungani, P., 2000. The Differential Impact of Uncertainty on Investment in Small and Large Businesses. Review of Economics and Statistics 82, 338–343. URL: https://direct.mit.edu/rest/article/82/2/338-343/57178, doi:10.1162/003465300558722.

Graedel, T.E., Harper, E.M., Nassar, N.T., Nuss, P., Reck, B.K., 2015. Criticality of metals and metalloids. Proceedings of the National Academy of Sciences 112, 4257–4262. URL: https://www.pnas.org/doi/10.1073/pnas.1500415112, doi:10.1073/pnas.1500415112. publisher: Proceedings of the National Academy of Sciences.

Hartman, R., 1972. The effects of price and cost uncertainty on investment. Journal of Economic Theory 5, 258–266.

Hassan, T.A., Hollander, S., Kalyani, A., Van Lent, L., Schwedeler, M., Tahoun, A., 2025. Text as Data in Economic Analysis. Journal of Economic Perspectives 39, 193–220. URL: https://pubs.aeaweb.org/doi/10.1257/jep.20231365, doi:10.1257/jep.20231365.

Hassan, T.A., Hollander, S., van Lent, L., Schwedeler, M., Tahoun, A., 2021. Firm-Level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1 , 73.

Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2019. Firm-Level Political Risk: Measurement and Effects*. The Quarterly Journal of Economics 134, 2135–2202. URL: https://academic.oup.com/qje/article/134/4/2135/5531768, doi:10.1093/qje/qjz021.

Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2020. The Global Impact of Brexit Uncertainty. Working Paper 26609. National Bureau of Economic Research. URL: http://www.nber.org/papers/w26609, doi:10.3386/w26609. series: Working Paper Series.

Hassler, J., Krusell, P., Olovsson, C., 2021. Directed Technical Change as a Response to Natural Resource Scarcity. Journal of Political Economy 129, 3039–3072. URL: https://www.journals.uchicago.edu/doi/10.1086/715849, doi:10.1086/715849.

Hennessy, C.A., Whited, T.M., 2007. How costly is external financing? Evidence from a structural estimation. The Journal of Finance 62, 1705–1745.

Hollander, S., Pronk, M., Roelofsen, E., 2010. Does Silence Speak? An Empirical Analysis of Disclosure Choices During Conference Calls. Journal of Accounting Research 48, 531–563. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1475-679X.2010.00365.x, doi:10.1111/j.1475-679X.2010.00365.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1475-679X.2010.00365.x.

Holthausen, R.W., 1976. Uncertainty, risk aversion, and the effects of changes in the price level. Journal of Finance 31, 195–210.

IEA, 2022. The Role of Critical Minerals in Clean Energy Transitions. Technical Report.

IEA, 2024a. Advancing Clean Technology Manufacturing. Technical Report. URL: https://iea.blob.core.windows.net/assets/7e7f4b17-1bb2-48e4-8a92-fb9355b1d1bd/CleanTechnologyManufacturingRoadmap.pdf.

IEA, 2024b. Clean Energy Market Monitor .

IMF, 2023. IMF Primary Commodity Prices. URL: https://www.imf.org/en/Research/commodity-prices.

Inderst, R., Wey, C., 2007. Buyer power and supplier incentives. European Economic Review 51, 647–667.

IRENA, 2023. Geopolitics of the energy transition: Critical materials .

Jones, B., Elliott, R.J.R., Nguyen-Tien, V., 2020. The EV revolution: The road ahead for critical raw materials demand. Applied Energy 280, 115072. URL: https://www.sciencedirect.com/science/article/pii/S0306261920305845, doi:10.1016/j.apenergy.2020.115072.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review 99, 1053–69. URL: https://www.aeaweb.org/articles?id=10.1257/aer.99.3.1053, doi:10.1257/aer.99.3.1053.

Knight, F.H., 1921. Risk, uncertainty and profit. Dover Publications, Mineola, NY.

Lakdawala, A., Moreland, T., 2026. Firm-Level Uncertainty and the Transmission of Monetary Policy. Review of Economics and Statistics 108, 807–816. URL: https://direct.mit.edu/rest/article/108/3/807/120181/Firm-Level-Uncertainty-and-the-Transmission-of, doi:10.1162/rest_a_01440.

Leruth, L., Mazarei, A., Régibeau, P., Renneboog, L., 2022. Working Paper 22-12: Green Energy Depends on Critical Minerals. Who Controls the Supply Chains? Pterson Institution For International Economics Working paper .

Loughran, T., Mcdonald, B., 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. The Journal of Finance 66, 35–65. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2010.01625.x, doi:10.1111/j.1540-6261.2010.01625.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2010.01625.x.

Matsumoto, D., Pronk, M., Roelofsen, E., 2011. What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. The Accounting Review 86, 1383–1414. URL: https://www.jstor.org/stable/23045606. publisher: American Accounting Association.

Morseletto, P., 2020. Targets for a circular economy. Resources, Conservation and Recycling 153, 104553. URL: https://www.sciencedirect.com/science/article/pii/S0921344919304598, doi:10.1016/j.resconrec.2019.104553.

Panon, L., Lebastard, L., Mancini, M., Borin, A., Tofani, P.C., Cariola, G., Essers, D., Gentili, E., Linarello, A., Padellini, T., Requena, F., Timini, J., 2026. Inputs in distress: Geoeconomic fragmentation and firms' sourcing. European Economic Review 187, 105355. URL: https://linkinghub.elsevier.com/retrieve/pii/S0014292126000991, doi:10.1016/j.euroecorev.2026.105355.

Pindyck, R.S., 2004. Volatility and commodity price dynamics. Journal of Futures Markets 24, 1029–1047. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/fut.20120, doi:10.1002/fut.20120. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/fut.20120.

Rajan, R.G., Zingales, L., 1998. Financial dependence and growth. American Economic Review 88, 559–586.

Ryan, N., 2026. Holding up green energy: Counterparty risk in the indian solar power market. Econometrica 94, 767–810. doi:10.3982/ECTA21084.

Sandmo, A., 1971. On the theory of the competitive firm under price uncertainty. American Economic Review 61, 65–73.

Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2023. Firm-level Climate Change Exposure. URL: https://papers.ssrn.com/abstract=3642508, doi:10.2139/ssrn.3642508.

Vertier, P., Jacolin, L., Mien, É., Léon, F., 2025. Critical Minerals: Estimating Price Elasticity of Supply Using Mine-Level Data. Working Paper 356. FERDI.

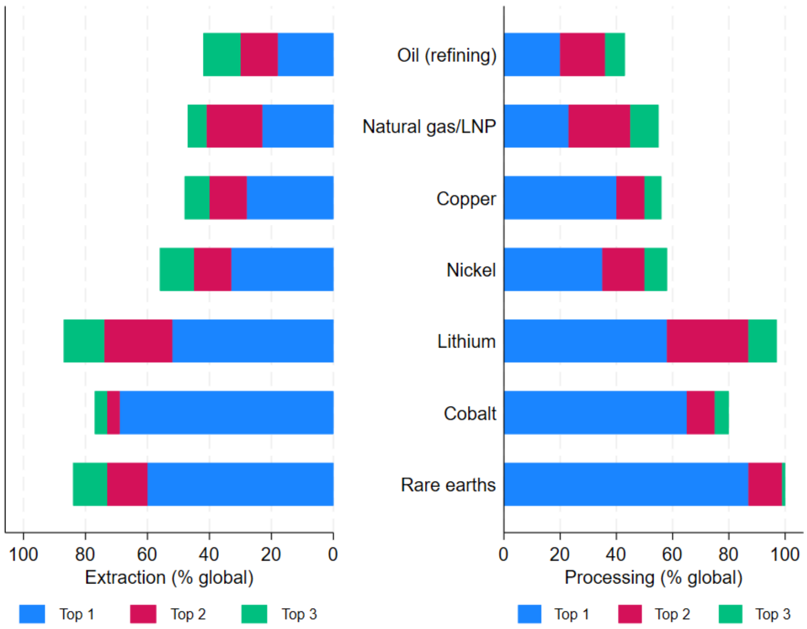
Weyl, E.G., Fabinger, M., 2013. Pass-through as an economic tool: Principles of incidence under imperfect competition. Journal of Political Economy 121, 528–583. URL: http://www.jstor.org/stable/10.1086/670401.

World Bank, 2017. The Growing Role of Minerals and Metals for a Low Carbon Future. World Bank, Washington, DC. URL: http://hdl.handle.net/10986/28312, doi:10.1596/28312.

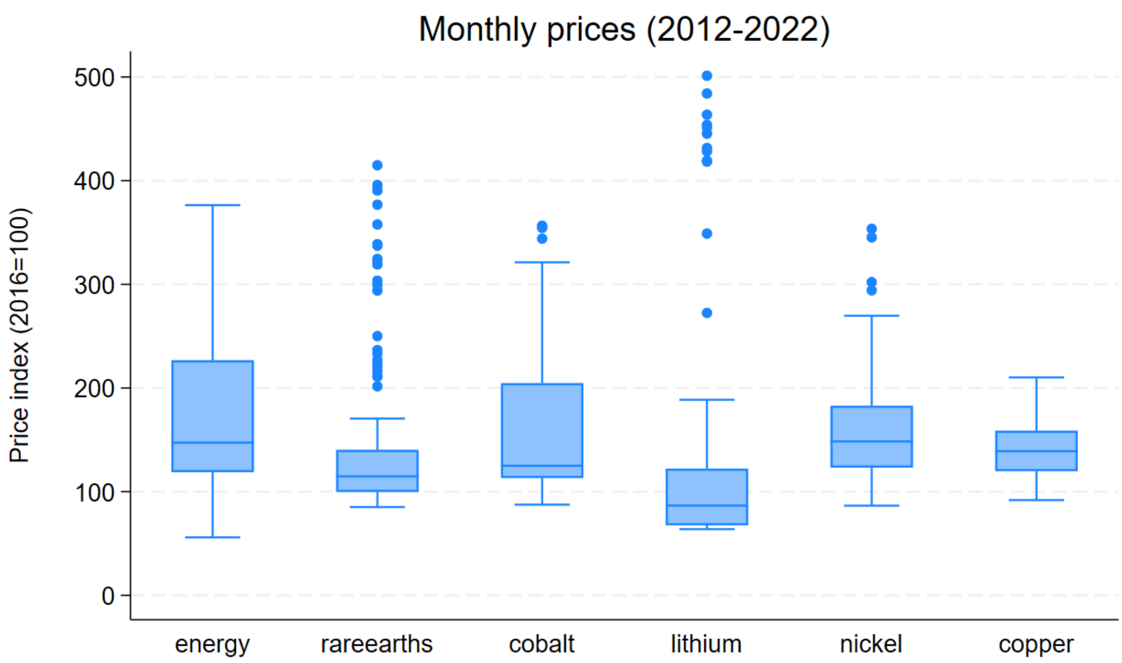
Figures

Figure 1: Concentration and Price Variability of Critical Minerals

Panel A: Top 3 countries producing Fossil Fuels vs Critical Minerals (2019)

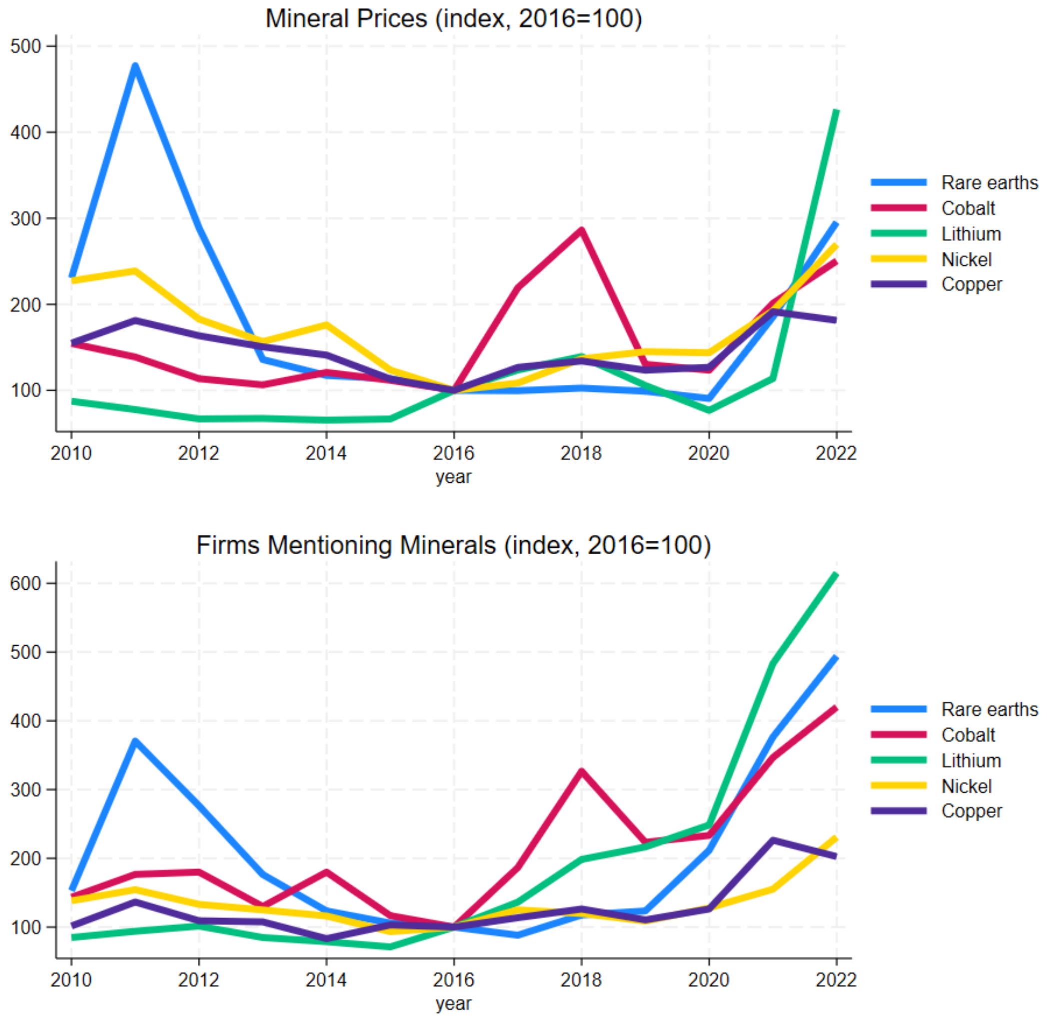


Panel B: Monthly price variability



Notes: Panel A compares the geographical concentration in the extraction and processing of fossil fuels and critical minerals as the total global share of the top 1, 2, or 3 producers. Panel B shows the monthly price variability of these commodities between 2012 and 2022. Data for the years 2010 and 2011 are excluded due to the unavailability of monthly data for lithium and rare-earth elements. The lower line, midline, and upper line of boxes represent the 25th, 50th (median), and 75th percentiles of the monthly prices. The whiskers extend the box to no more than 1.5 times the box length (interquartile ranges) on both sides. The dots represent outliers that fall beyond the whiskers range, defined by the upper and lower adjacent values. *Sources:* IEA (2022) and IMF (2023).

Figure 2: Mineral Mentions and Mineral Prices



Notes: This figure presents a comparison of critical mineral price series (Panel A) and the count of listed firms mentioning these minerals in their earnings conference calls (Panel B). *Sources:* Price data sourced from IMF (2023), with linear imputation for lithium and rare earths using USGS data for the years 2010–2011, and computation based on earnings conference call transcript data.

Tables

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
MineralRisk	0.08	1.01	0.00	64.54	80466
MineralRisk: exchange-traded (Cu, Ni)	0.07	1.00	0.00	76.75	80466
MineralRisk: non-exchange-traded (Li, Co, REE)	0.04	1.00	0.00	105.88	80466
MineralSentiment	0.08	0.99	-40.17	51.59	80466
UnconditionalRisk	0.90	1.01	0.00	217.50	80466
Log total assets	7.56	2.20	-1.19	15.61	80384
Revenue growth (trim 1%)	11.08	32.27	-78.22	264.46	77594
Revenue growth (wins 1%)	12.72	41.70	-78.22	264.46	79176
Investment/capital (trim 1%)	26.13	28.37	0.15	250.54	67661
Investment/capital (wins 1%)	28.11	36.00	0.15	250.58	69042
Employment growth (trim 1%)	4.33	16.96	-70.97	80.18	70953
Employment growth (wins 1%)	4.34	19.90	-70.97	80.22	72400

Notes: Summary statistics for the firm-year panel (2010–2022). The sample comprises publicly listed firms across 92 countries with earnings-call transcripts matched to Compustat financial data. Risk and sentiment measures are standardised to have unit standard deviation. *MineralRisk_traded* aggregates risk from exchange-traded minerals (copper, nickel). *MineralRisk_nontrad* aggregates risk from non-exchange-traded minerals (lithium, cobalt, rare earths). Revenue growth, investment-to-capital ratio, and employment growth are expressed in percentage points and trimmed or winsorised at the 1% level in both tails.

Table 2: Variance Decomposition of Text-Based Risk and Sentiment Measures

Sector granularity	2-digit SIC (1)	4-digit SIC (2)
Panel A: MineralRisk		
Time FE	0.04%	0.04%
Sector FE	6.22%	12.49%
Sector × Time FE	8.10%	18.14%
Firm-level	91.90%	81.86%
Permanent differences (Firm FE)	44.47%	37.68%
Residual	47.43%	44.18%
Number of sectors	71	439
Panel B: MineralSentiment		
Time FE	0.08%	0.08%
Sector FE	7.71%	14.62%
Sector × Time FE	10.28%	19.92%
Firm-level	89.72%	80.08%
Permanent differences (Firm FE)	53.73%	47.05%
Residual	36.00%	33.03%
Number of sectors	71	439

Notes: This table reports the share of variation (in percentage terms) in the text-based *MineralRisk* (Panel A) and net *MineralSentiment* (Panel B) measures attributable to different sets of fixed effects, reported separately for 2-digit and 4-digit SIC sector granularity. *Firm-level* is 100% minus the Sector×Time FE R^2; it combines *Permanent differences* (the additional increment from firm fixed effects) and *Residual* (time-varying, firm-specific variation not explained by firm or sector-time effects). The predominance of firm-level variation (70–90%) indicates that the text-based measures capture firm-specific uncertainty beyond common industry or country shocks, motivating the firm-level fixed-effect identification strategy in Section 5. Sample: firm-year panel, 2010–2022.

Table 3: Annual Revenue Growth (Percentage Points, 2010–2022) in Response to Critical Mineral Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Trimmed			Winsorised		
Panel A: Full sample						
MineralRisk	-0.41**	-0.43**	-0.42**	-0.51**	-0.53***	-0.52***
	(0.20)	(0.19)	(0.19)	(0.21)	(0.20)	(0.20)
MineralSentiment		0.81***	0.81***		0.67***	0.67***
		(0.17)	(0.17)		(0.22)	(0.22)
UnconditionalRisk			-0.37			-0.55
			(0.28)			(0.41)
Observations	75,314	75,314	75,314	76,910	76,910	76,910
R^2	0.39	0.39	0.39	0.36	0.36	0.36
Firms	11,529	11,529	11,529	11,729	11,729	11,729
Panel B: Mining firms						
MineralRisk	-0.20	-0.23	-0.23	-0.30	-0.34	-0.33
	(0.29)	(0.28)	(0.28)	(0.30)	(0.30)	(0.30)
MineralSentiment		1.25***	1.26***		1.29***	1.29***
		(0.25)	(0.25)		(0.28)	(0.28)
UnconditionalRisk			0.45			-0.67
			(1.94)			(2.41)
Observations	4,332	4,332	4,332	4,456	4,456	4,456
R^2	0.50	0.50	0.50	0.49	0.49	0.49
Firms	640	640	640	659	659	659
Panel C: Non-mining firms						
MineralRisk	-0.57**	-0.59**	-0.58**	-0.70**	-0.72**	-0.71**
	(0.27)	(0.27)	(0.27)	(0.28)	(0.28)	(0.28)
MineralSentiment		0.49**	0.48**		0.25	0.25
		(0.20)	(0.20)		(0.30)	(0.30)
UnconditionalRisk			-0.39			-0.56
			(0.29)			(0.42)
Observations	70,811	70,811	70,811	72,274	72,274	72,274
R^2	0.38	0.38	0.38	0.34	0.34	0.34
Firms	10,872	10,872	10,872	11,051	11,051	11,051

Notes: This table reports regression estimates of the relationship between annual revenue growth and standardised text-based measures of *MineralRisk*. Panel A uses the full global sample of listed firms. Panel B restricts the sample to mining firms (2-digit SIC codes 10–14). Panel C includes non-mining firms (i.e., Panel A excluding Panel B). The dependent variable is trimmed (Columns 1–3) or winsorised (Columns 4–6) at the 1% level in both tails. All specifications control for firm size (log of total assets). Fixed effects: firm, country×year, SIC2×year. Risk and sentiment measures are standardised and averaged at the firm-year level. Standard errors clustered at the firm level in parentheses. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Robustness: Restricted to Mineral-Exposed Firms

	(1) Baseline	(2) Ever-mention	(3) Mentioners
MineralRisk	-0.71**	-0.67***	-0.62**
	(0.28)	(0.26)	(0.29)
UnconditionalRisk	-0.56	-3.54***	-5.43***
	(0.42)	(0.74)	(2.01)
Observations	72,274	22,283	5,184
R^2	0.34	0.35	0.50
Firms	11,051	2,604	1,221

Notes: Annual revenue growth (winsorised at 1%, percentage points) for non-mining firms, 2010–2022. Column 1: baseline (all non-mining firms). Column 2 restricts to firms that discuss any critical mineral in at least one earnings call during the sample period ("ever-mention" firms). Column 3 restricts to firm-year observations in which the firm mentions a critical mineral in that year, isolating the intensive margin of mineral-risk variation. All columns use the preferred specification with $MineralSentiment$ (not shown) and log total assets. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Alternative Outcome Variables

	Rev. growth		Log revenue		Investment		Emp. growth	
	(tr.)	(w.)	(tr.)	(w.)	(tr.)	(w.)	(tr.)	(w.)
MineralRisk	-0.584**	-0.709**	-0.004**	-0.005***	0.210	0.078	0.001	0.186
	(0.268)	(0.280)	(0.002)	(0.002)	(0.268)	(0.271)	(0.121)	(0.146)
UnconditionalRisk	-0.390	-0.560	-0.002	-0.003	-0.526***	-0.525***	-0.202	-0.208
	(0.294)	(0.425)	(0.003)	(0.003)	(0.179)	(0.175)	(0.131)	(0.138)
Observations	70,811	72,274	70,964	72,497	60,907	62,221	64,687	66,014
R^2	0.38	0.34	0.98	0.98	0.54	0.52	0.35	0.33
Firms	10,872	11,051	10,969	11,138	9,448	9,628	9,976	10,098

Notes: Non-mining firms, 2010–2022. Columns 1–2: annual revenue growth (trimmed and winsorised, percentage points). Columns 3–4: log revenue level (trimmed and winsorised). Columns 5–6: investment-to-capital ratio (trimmed and winsorised, percentage points). Columns 7–8: annual employment growth (trimmed and winsorised, percentage points). All trimming and winsorisation at the 1% level in both tails. Additional controls (not shown): $MineralSentiment$, *UnconditionalRisk*, and log total assets. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level in parentheses. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Firm Size Heterogeneity in the Effect of Mineral Risk on Revenue Growth

	Small		Large		Interaction	
	(tr.)	(w.)	(tr.)	(w.)	(tr.)	(w.)
MineralRisk	-1.32*	-1.87**	-0.07	-0.12	-1.58***	-1.96***
	(0.71)	(0.74)	(0.24)	(0.25)	(0.48)	(0.51)
Largefirm					-0.67	-0.89
					(0.63)	(0.80)
Largefirm × MineralRisk					1.49***	1.90***
					(0.56)	(0.59)
Observations	33,787	34,895	36,259	36,607	70,811	72,274
R^2	0.40	0.36	0.41	0.37	0.38	0.34
Firms	6,524	6,689	5,240	5,267	10,872	11,051

Notes: Annual revenue growth (percentage points) for non-mining firms, 2010–2022. Columns 1–2 restrict to small firms (below year-specific median of log total assets); Columns 3–4 to large firms (above median). Odd columns are trimmed, even columns winsorised, both at the 1% level. Columns 5–6 report the pooled interaction specification; $MineralRisk$ is the small-firm effect and $Largefirm \times MineralRisk$ is the differential for above-median firms. The $Largefirm$ indicator varies within firms over time (year-specific median), permitting identification alongside firm fixed effects. All columns include $MineralSentiment$, $UnconditionalRisk$, and log total assets. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level in parentheses. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Revenue Growth and Mineral Risk: Exchange-Traded vs Non-Exchange-Traded Minerals

	Composite		Decomposed		Interaction	
	(tr.)	(w.)	(tr.)	(w.)	(tr.)	(w.)
MineralRisk	-0.58**	-0.71**				
	(0.27)	(0.28)				
MineralRisk (traded)			-0.21	-0.35*	-0.52	-0.85
			(0.19)	(0.20)	(0.57)	(0.58)
MineralRisk (non-traded)			-0.61**	-0.64**	-1.22***	-1.40***
			(0.26)	(0.29)	(0.33)	(0.40)
Largefirm					-0.68	-0.90
					(0.63)	(0.80)
Largefirm × Traded					0.37	0.63
					(0.60)	(0.61)
Largefirm × Non-traded					1.27**	1.61***
					(0.54)	(0.58)
Observations	70,811	72,274	70,811	72,274	70,811	72,274
R^2	0.38	0.34	0.38	0.34	0.38	0.34
Firms	10,872	11,051	10,872	11,051	10,872	11,051

Notes: Annual revenue growth (percentage points) for non-mining firms, 2010–2022. $MineralRisk$ is the composite measure across all five minerals. $MineralRisk\_traded$ aggregates risk from exchange-traded minerals with transparent benchmark pricing (copper, nickel). $MineralRisk\_nontrad$ aggregates risk from non-exchange-traded minerals characterised by opaque bilateral pricing, concentrated supply, and thin markets (lithium, cobalt, rare earths). All measures are standardised to have unit standard deviation. Columns 5–6 interact traded and non-traded risk with $Largefirm$ (above year-specific median of log total assets). The dependent variable is trimmed (odd columns) or winsorised (even columns) at the 1% level in both tails. All columns include $MineralSentiment$, $UnconditionalRisk$, and log total assets. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level in parentheses. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Revealed Risk Aversion: Price Volatility and Input Risk Management

	(1) Cobalt	(2) Lithium	(3) Nickel	(4) Copper
Panel A: Mineral Exposure				
LogPrice	0.2173***	0.2175***	0.3773***	0.9005***
	(0.0453)	(0.0747)	(0.0924)	(0.2587)
LogPriceVol	0.0310*	0.1543***	0.1943**	0.8264***
	(0.0162)	(0.0320)	(0.0841)	(0.0819)
Observations	246,594	246,594	246,594	246,594
Mean	0.3463	0.9599	1.1083	2.7957
Panel B: Input Risk Management				
LogPrice	0.0068	-0.0186	0.0221	0.1372*
	(0.0115)	(0.0180)	(0.0340)	(0.0733)
LogPriceVol	0.0160***	0.0257***	0.0690***	0.1354***
	(0.0053)	(0.0080)	(0.0230)	(0.0359)
Observations	246,594	246,594	246,594	246,594
Mean	0.0260	0.0669	0.1375	0.2778

Notes: Non-mining firms, transcript-quarter panel, 2010–2022. Panel A: dependent variable is whether the transcript mentions the mineral (0 or 100). Panel B: dependent variable is whether the transcript discusses input risk management (hedging or stockpiling) for the mineral (0 or 100). Both panels include *LogPrice* (logged quarterly price level) and *LogPriceVol* (logged 12-month rolling volatility of monthly prices) simultaneously. All regressions include firm size (log of total assets), firm fixed effects, and quarter-of-year fixed effects. Standard errors clustered by quarter. *,**,*** denote significance at the 10%, 5%, and 1% levels.

Appendix

A Supplemental Tables

Table A1: Validating Co-occurrence between Critical Mineral Exposure and Technology Exposure at the Transcript Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technology	rareearth	cobalt	lithium	nickel	copper	cotton	energy
(Hybrid) Electric Vehicles	.0016	.0086***	.0447***	.0088***	.0107***	.0009	.0892***
	(0.0020)	(0.0020)	(0.0050)	(0.0030)	(0.0040)	(0.0010)	(0.0070)
Lithium-ion batteries	.0039	.0267***	.8932***	.0388***	.0102	.0024	.1128***
	(0.0060)	(0.0090)	(0.0160)	(0.0110)	(0.0080)	(0.0040)	(0.0170)
Solar power	.004***	.0008	.0191***	.0049**	.0157***	.0012	.1772***
	(0.0010)	(0.0010)	(0.0030)	(0.0020)	(0.0040)	(0.0010)	(0.0070)
Wind power	.0039***	.0031*	.0119***	.0047*	.0122***	.0018	.147***
	(0.0010)	(0.0020)	(0.0030)	(0.0030)	(0.0040)	(0.0010)	(0.0080)

Notes: This table reports transcript-level linear probability model coefficients. The dependent variable is an indicator for mentioning mineral μ; the regressor is an indicator for mentioning technology τ in the same call. Cotton and energy serve as falsification and mechanical co-occurrence benchmarks respectively. Specifications include firm fixed effects, time fixed effects, and firm size (log of total assets). Standard errors clustered at the quarter level. *,**,*** denote significance at the 10%, 5%, and 1% levels.

Table A2: Robustness: Alternative Trimming and Winsorisation Thresholds

	1%		2%		5%	
	Trim	Wins	Trim	Wins	Trim	Wins
MineralRisk	-0.58**	-0.71**	-0.48**	-0.64***	-0.29**	-0.39**
	(0.27)	(0.28)	(0.22)	(0.24)	(0.15)	(0.16)
Observations	70,811	72,274	69,358	72,274	65,224	72,274
R^2	0.38	0.34	0.42	0.37	0.44	0.41
Firms	10,872	11,051	10,708	11,051	10,241	11,051

Notes: Annual revenue growth (percentage points) for non-mining firms, 2010–2022. Each pair of columns applies the indicated threshold to both tails. All columns use the preferred specification. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level. *,**,*** denote significance at the 10%, 5%, and 1% levels.

Table A3: Robustness: Alternative Clustering and Fixed-Effect Granularity

	Baseline		Alt. cluster		Alt. sector FE		Stricter FE	
	Trim	Wins	Trim	Wins	Trim	Wins	Trim	Wins
MineralRisk	-0.58**	-0.71**	-0.58**	-0.71**	-0.55*	-0.75**	-0.59**	-0.80**
	(0.27)	(0.28)	(0.26)	(0.29)	(0.28)	(0.30)	(0.28)	(0.34)
UnconditionalRisk	-0.39	-0.56	-0.39*	-0.56	-0.37	-0.54	-0.33	-0.49
	(0.29)	(0.42)	(0.23)	(0.34)	(0.27)	(0.39)	(0.25)	(0.38)
Sector$\times FE$	SIC2	SIC2	SIC2	SIC2	SIC4	SIC4	SIC2 x Country	SIC2 x Country
Cluster level	Firm	Firm	SIC2 x Year	SIC2 x Year	Firm	Firm	Firm	Firm
Observations	70,811	72,274	70,811	72,274	70,265	71,742	66,034	67,467
R^2	0.38	0.34	0.38	0.34	0.42	0.38	0.43	0.39
Clusters	10,872	11,051	828	828	10,824	11,006	10,268	10,442

Notes: Annual revenue growth (percentage points) for non-mining firms, 2010–2022. All specifications estimate the preferred regression from Equation (2); the columns vary only the fixed-effect granularity and the level at which standard errors are clustered. *Baseline*: sector fixed effects at the 2-digit SIC level interacted with year (SIC2×year), together with firm and country×year fixed effects, and standard errors clustered at the firm level . *Alt. cluster*: identical fixed effects, but standard errors clustered at the SIC2×year level, allowing for correlated shocks within a sector-year. *Alt. sector FE*: finer sector fixed effects at the 4-digit SIC level interacted with year (SIC4×year), with firm-level clustering, testing sensitivity to more granular industry controls. *Stricter FE*: SIC2×country×year fixed effects that absorb all common shocks within each sector-country-year cell, with firm-level clustering. Two-way clustering is infeasible when a clustering dimension coincides with an absorbed fixed effect. Each pair of columns reports the dependent variable trimmed (odd columns) or winsorised (even columns) at the 1% level in both tails. All columns additionally control for $MineralSentiment$, (not shown), $UnconditionalRisk$, and log total assets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Sample Stability and Reverse Causality

	(1)	(2)	(3)	(4)	(5)
	Baseline	Pre-COVID	Pre-trade war	Lead (t+1)	t & t+1
MineralRisk (t)	-0.71**	-0.77**	-0.93**		-0.85**
	(0.28)	(0.34)	(0.40)		(0.34)
MineralRisk (t+1)				0.06	-0.02
				(0.38)	(0.39)
UnconditionalRisk	-0.56	-3.38***	-3.69***	-0.47	-0.46
	(0.42)	(0.62)	(0.69)	(0.36)	(0.36)
Sample	Full	2010-19	2010-18	Lead	t + t+1
Observations	72,274	47,476	40,915	58,823	58,823
R^2	0.34	0.34	0.35	0.35	0.35
Firms	11,051	7,776	7,005	9,138	9,138

Notes: Annual revenue growth (winsorised at 1%, percentage points) for non-mining firms. Column 1: baseline (2010–2022). Columns 2–3: restricted samples excluding the COVID period and the US-China trade war escalation. Column 4: lead $MineralRisk_{t+1}$ tests reverse causality; insignificance confirms that mineral risk predicts revenue growth, not the reverse. All columns include sentiment controls, $UnconditionalRisk$, and log total assets. Fixed effects: firm, country×year, SIC2×year. Standard errors clustered at the firm level. *,**,*** denote significance at the 10%, 5%, and 1% levels.

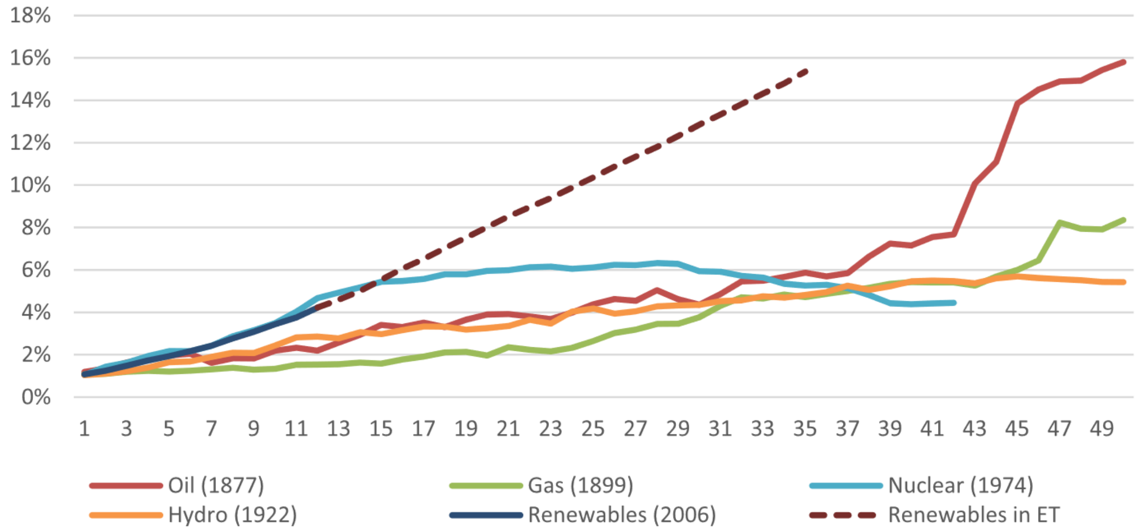
Table A5: Probability of Firms Mentioning Methods to Mitigate Critical Mineral Price Rises

	(1) Cobalt	(2) Lithium	(3) Nickel	(4) Copper
Panel A: Stockpile & Hedge				
LogPrice	0.1431	-0.1072	0.1187	0.2228
	(0.3003)	(0.2201)	(0.1966)	(0.1674)
LogPriceVol	0.6596***	0.3296***	0.3489***	0.3396***
	(0.1398)	(0.0991)	(0.1277)	(0.0821)
Observations	263,386	263,386	263,386	263,386
Base rate (%)	0.0436	0.0776	0.1828	0.5873
Panel B: Pass Through to Customer				
LogPrice	0.5029	2.3676**	1.2514	1.3583***
	(1.7625)	(1.0843)	(0.9024)	(0.5064)
LogPriceVol	-0.1243	-0.1552	0.0967	0.3837*
	(0.8822)	(0.3693)	(0.5600)	(0.2269)
Observations	263,386	263,386	263,386	263,386
Base rate (%)	0.0022	0.0052	0.0122	0.0388
Panel C: Content Reduction & Substitution				
LogPrice	0.4442	0.2017	-0.0908	0.0685
	(0.2753)	(0.1735)	(0.1951)	(0.1013)
LogPriceVol	0.3134**	0.1289	0.1291	0.0466
	(0.1290)	(0.0823)	(0.1315)	(0.0451)
Observations	263,386	263,386	263,386	263,386
Base rate (%)	0.0613	0.0850	0.1577	0.7140
Panel D: Circular Economy Solution				
LogPrice	1.0055***	0.7780**	0.2201	0.8282***
	(0.3753)	(0.3393)	(0.4269)	(0.2988)
LogPriceVol	-0.0615	0.0808	0.9231***	0.1917
	(0.1163)	(0.1107)	(0.2356)	(0.1224)
Observations	263,386	263,386	263,386	263,386
Base rate (%)	0.0240	0.0624	0.0362	0.0820

Notes: The dependent variable indicates whether a transcript mentions a specific method to mitigate critical mineral price rises, normalised by its mineral-specific sample mean so that coefficients represent proportional changes relative to the base discussion rate. Both *LogPrice* (logged quarterly price level) and *LogPriceVol* (logged 12-month rolling volatility of monthly prices) are included simultaneously. All regressions include firm size (log of total assets), firm fixed effects, and quarter-of-year fixed effects. Rare earths are excluded due to sparse mitigation discussions in transcripts. Standard errors are clustered by quarter in parentheses. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

B Supplemental Figures

Figure A1: Speed of Penetration of New Fuels in the Global Energy System



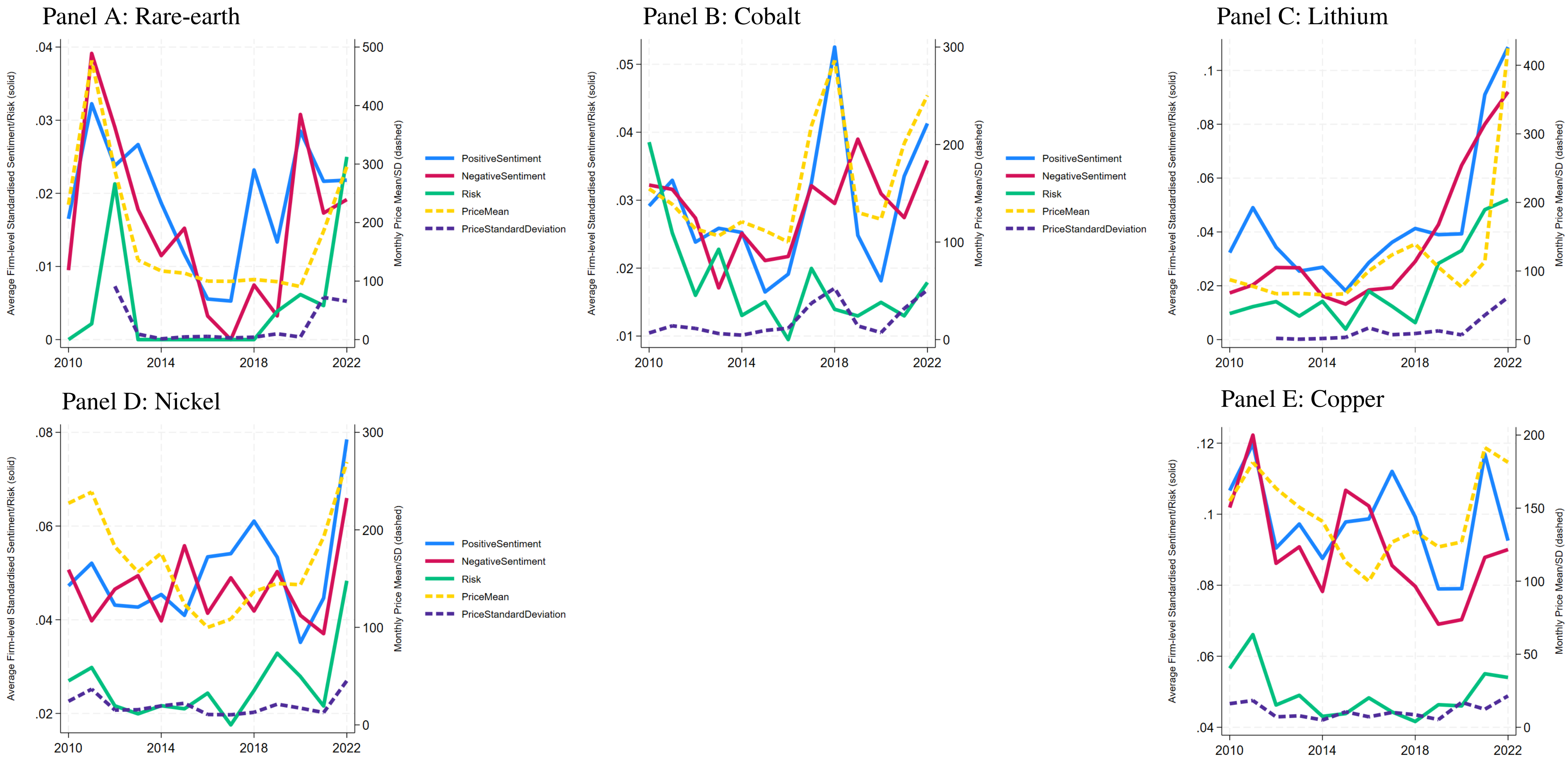
Notes: This figure illustrates the speed of the recent renewable energy transition (ET) compared to previous energy transitions, using the year (x-axis) in which each technology reached a 1% share of the energy mix as the starting point. The expected penetration of renewable energy (y-axis) is based on BP's (2019) Evolving Transition Scenario, which assumes that government policies, technology, and social preferences continue to evolve at a pace similar to recent trends, and is less ambitious than the Paris Agreement. *Sources:* Redirected from Blazquez et al. (2020).

Figure A2: Risk and Sentiment Wordings related to Critical Minerals

Panel A: Risk Panel B: Positive Sentiment Panel C: Negative Sentiment

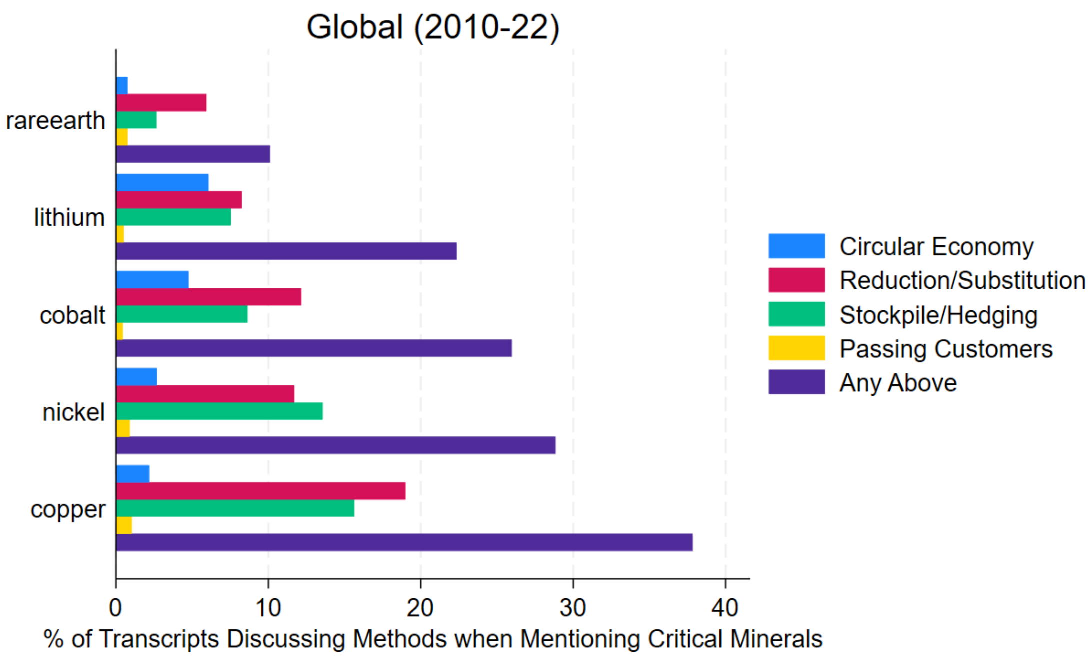
Note: These word clouds illustrate synonyms related to risks (Panel A) and positive and negative tone wordings (Panels B and C), which are used in the construction of *MineralRisk*, *MineralPositiveSentiment*, and *MineralNegativeSentiment*. Word size is proportionate to frequency in texts associated with mineral-related content.

Figure A3: Firm-level Risk, Sentiment and Mineral Prices



Note: Solid lines (left axes) depict the time-average of firm-level risk and sentiments associated with critical minerals, standardised by their standard errors across firms, in each year. Dashed lines (right axes) represent the mean and standard deviation of corresponding monthly commodity prices.

Figure A4: Managing Critical Mineral Prices



Notes: This figure illustrates the share of transcripts mentioning methods for managing critical mineral prices when earnings conference call participants mention critical minerals in our full sample covering 2010–2022. Each transcript can reference multiple methods.

C Theoretical Framework

This appendix develops a model of output planning under input uncertainty to guide the empirical analysis. The model builds on canonical frameworks in which firms choose inputs before prices are realised (Sandmo, 1971; Hartman, 1972; Batra and Ullah, 1974; Holthausen, 1976) and adapts them to the critical-mineral context.

Three features of critical-mineral markets motivate the adaptation. First, disruptions to mineral supply manifest not only as price increases but also as quantity constraints, delivery delays, and quality variability, all of which can be captured through their effect on the effective input price facing the firm. Second, market structures differ across minerals: copper and nickel are exchange-traded on deep, liquid markets with transparent benchmark pricing, whereas lithium, cobalt, and rare-earth elements are procured largely through bilateral negotiation with opaque pricing and thin trading volumes. Third, in bilaterally negotiated markets, larger firms can leverage established offtake agreements and greater bargaining power to secure more favourable terms, so that effective input uncertainty varies not only across minerals but also across firms of different size within the same mineral market. The model incorporates these features through firm-specific effective input-price distributions whose parameters vary across minerals and firms.

C.1 Setup, Timing, and the Revenue-Growth Object

Firm i produces output using three inputs: capital K_i, labour L_{it}, and a critical mineral input M_{it}.[20] The firm is a price taker in the output market. We normalise the output price to unity without loss of generality, so that revenue equals output. In the input market, the firm takes its effective price distribution as given when choosing M_{it}; the parameters μ_{it} and σ^2_{it} are determined by market structure and the firm's contractual arrangements, which are fixed relative to the within-period procurement decision. These three inputs differ in their adjustment speed.

Capital K_i is sunk, determined by prior investment decisions on multi-year horizons. Because capital is irreversible, investment responds to uncertainty about the firm's overall operating environment through the real-options channel (Bloom, 2009), not to mineral-specific price fluctuations within the period. Labour L_{it} is adjusted at the start of each period: having observed output $Y_{i,t-1}$ and prevailing conditions, the firm sets its workforce to support a planned scale of operations for period t, before input uncertainty is resolved.[21] Since L_{it} is committed before mineral prices are known, mineral-specific uncertainty does not affect contemporaneous employment. The mineral input M_{it} is the most flexible factor: it is chosen within the period under uncertainty about the effective input price, making it the only margin through which input uncertainty affects current-period output and therefore revenue.

[20] M_{it} represents any input whose production requires critical minerals, whether the mineral itself, a refined intermediate, or an assembled component such as a battery cell. The defining properties are non-substitutability in the short run and uncertain pricing, which are the criteria used to classify minerals as critical (World Bank, 2017; Graedel et al., 2015).

[21] This ordering reflects the standard hierarchy of factor adjustment speeds: capital adjusts on investment cycles, labour on hiring and contracting cycles, and material procurement within the production cycle (Bloom, 2009).

Together, these timing assumptions yield a testable double dissociation: mineral-specific risk predicts revenue growth but not investment or employment, while unconditional risk predicts investment but not revenue.

This factor timing makes revenue *growth* the natural object of interest. The firm inherits an operating scale $Y_{i,t-1}$ from the previous period and sets capacity $\bar{Y}_{it} = h(K_i, L_{it})$ based on planned expansion from that baseline. Mineral-input uncertainty then constrains how much of this capacity plan is achieved. We define revenue growth as:

$$g_{it} = \frac{Y^*_{it} - Y_{i,t-1}}{Y_{i,t-1}} \tag{4}$$

where Y^*_{it} is the firm's mineral-constrained output, derived below.

We model the non-substitutability of the mineral input using a Leontief structure:

$$Y_{it} = \min\{h(K_i, L_{it}),\ \alpha M_{it}\} \tag{5}$$

where $h(\cdot)$ is a production function in capital and labour and $\alpha > 0$ is a fixed short-run material productivity parameter. When the mineral constraint binds ($\alpha M_{it} \leq \bar{Y}_{it}$), output reduces to $Y_{it} = \alpha M_{it}$, and mineral procurement becomes the binding margin.[22]

C.2 Input Uncertainty

The firm chooses M_{it} before the effective input price w_{it} is realised:

$$w_{it} = \bar{w} + \mu_{it} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma^2_{it}) \tag{6}$$

where $\bar{w}$ is a common baseline price, μ_{it} is the mean deviation of the effective price facing firm i (first-moment component), and σ^2_{it} is its variance (second-moment component). As discussed above, all sources of input uncertainty, including quantity constraints and delivery

[22] We adopt the Leontief case for closed-form transparency. Section **??** confirms that all qualitative results hold under CES production with elasticity of substitution below one.

delays, are captured through the effective price w_{it}.[23]

C.3 Optimal Planned Output and the Effect of Uncertainty on Growth

The firm's planned profit is:

$$\pi_{it} = \alpha M_{it} - (\bar{w} + \mu_{it} + \epsilon_{it})M_{it} \tag{7}$$

where labour costs are suppressed since L_{it} is already committed.

A risk-neutral firm maximises $\mathbb{E}[\pi_{it}] = (\alpha - \bar{w} - \mu_{it})M_{it}$. The objective is linear in M_{it}, so the firm produces at capacity whenever $\alpha > \bar{w} + \mu_{it}$, independently of σ^2_{it}. Under risk neutrality, input uncertainty has no effect on planned output or revenue growth.

A risk-averse firm maximises the certainty equivalent under CARA preferences:

$$\max_{M_{it}} \; (\alpha - \bar{w} - \mu_{it})M_{it} - \frac{A_i}{2}\sigma^2_{it}M^2_{it} \tag{8}$$

where $A_i > 0$ is firm i's coefficient of absolute risk aversion, scaling the variance penalty in units of profit per unit of variance.[24] Firm size proxies for risk-management capacity, so that smaller firms face higher effective A_i (Rajan and Zingales, 1998; Hennessy and Whited, 2007). We maintain the viability assumption $\alpha > \bar{w} + \mu_{it}$, ensuring that production is profitable in expectation; if this condition fails, the firm optimally sets $M^*_{it} = 0$. In the interior, the first-order condition yields:

$$Y^*_{it} = \alpha M^*_{it} = \frac{\alpha(\alpha - \bar{w} - \mu_{it})}{A_i\,\sigma^2_{it}} \tag{9}$$

The denominator $A_i\sigma^2_{it}$ is the risk penalty: it raises the perceived marginal cost of the

[23] The normality assumption on ϵ_{it} ensures that the mean-variance objective below is a sufficient statistic for expected utility under CARA. The qualitative results do not depend on normality.

[24] The objective is strictly concave in M_{it} for $\sigma^2_{it} > 0$ (the second derivative is $-A_i\sigma^2_{it} < 0$), so the first-order condition is necessary and sufficient. If $\sigma^2_{it} = 0$ the objective is linear and the risk-neutral corner solution applies.

mineral input beyond its expected price, inducing the firm to plan below capacity.

Substituting (9) into (4) and differentiating with respect to the second-moment component yields the central comparative static, which applies in the interior where $\alpha > \bar{w} + \mu_{it}$:

$$\frac{\partial g_{it}}{\partial \sigma^2_{it}} = -\frac{\alpha(\alpha - \bar{w} - \mu_{it})}{Y_{i,t-1}\, A_i\, (\sigma^2_{it})^2} < 0 \tag{10}$$

Higher input uncertainty reduces revenue growth. The expression makes explicit that the growth contraction is larger when the firm is more risk-averse (higher A_i) and when the firm faces greater input uncertainty (higher σ^2_{it}). The first-moment component μ_{it} also affects growth, but through the expected-cost channel; the two effects are separable, motivating the inclusion of both risk and sentiment measures as distinct regressors in Equation (2).

C.4 Hypotheses

The model generates three testable predictions, corresponding to the hypotheses stated in Section 2.2.

H1 (Input dependency). Higher input uncertainty reduces revenue growth for firms that depend on critical minerals as production inputs.

H2 (Firm heterogeneity). The growth contraction is larger for firms with higher effective A_i. Smaller firms face higher effective risk aversion, implying a larger revenue-growth contraction for a given level of input uncertainty.

H3 (Market structure and firm heterogeneity). The risk-management advantage of larger firms is sharpest for non-traded minerals. In thin, bilaterally negotiated markets, larger firms can secure more favourable offtake agreements and exercise greater bargaining power, while standardised hedging instruments are unavailable to smaller firms; both forces lower the effective A_i of larger firms relative to smaller ones precisely where markets are opaque. The risk-management advantages of firm size are therefore most valuable in non-traded markets, implying a steeper firm-size gradient for non-traded than for traded minerals.

C.5 Generalisation Beyond the Leontief Case

The Leontief structure above is a limiting case, chosen for closed-form transparency. It is also the empirically relevant one: the short-run substitutability between critical minerals and the capital–labour composite is low, since a mineral embedded in a battery cathode or a permanent magnet cannot be swapped out within the production cycle. We nonetheless verify that the qualitative predictions survive when the firm is allowed to substitute. Replace with a CES aggregator (Arrow et al., 1961):

$$Y_{it} = \Big[\beta\, h(K_i, L_{it})^{\rho} + (1-\beta)\,(\alpha M_{it})^{\rho}\Big]^{1/\rho}, \qquad \rho < 1, \tag{11}$$

so that the elasticity of substitution $\sigma_s = 1/(1-\rho)$ is finite and the mineral input has a diminishing but strictly positive marginal product. The risk-neutral firm equates that marginal product to the expected price:

$$(1-\beta)\,\alpha^{\rho}\, M_{it}^{\rho-1}\, Y_{it}^{1-\rho} = \bar{w} + \mu_{it}. \tag{12}$$

Under CARA preferences the first-order condition gains the familiar risk-premium term:

$$\underbrace{(1-\beta)\,\alpha^{\rho}\, M_{it}^{\rho-1}\, Y_{it}^{1-\rho}}_{\text{marginal product of } M_{it}} = \underbrace{\bar{w} + \mu_{it}}_{\text{expected price}} + \underbrace{A_i\,\sigma_{it}^2\, M_{it}}_{\text{risk premium}}. \tag{13}$$

The risk premium $A_i\,\sigma_{it}^2\, M_{it}$ enters exactly as it does under Leontief, raising the perceived marginal cost of the mineral above its expected price.

Write (13) as $F(M_{it}, \sigma_{it}^2) = 0$, with F the marginal product net of the expected price and the risk premium. Concavity of the CES aggregator in the mineral input holds for any $\rho < 1$, and hence for any finite σ_s; it makes the marginal product strictly decreasing in M_{it}, so that $\partial F/\partial M_{it} < 0$. The variance enters only through the risk premium, giving

$\partial F/\partial\sigma_{it}^2 = -A_i M_{it} < 0$. The implicit function theorem then yields

$$\frac{dM_{it}^*}{d\sigma_{it}^2} = -\frac{\partial F/\partial\sigma_{it}^2}{\partial F/\partial M_{it}} < 0. \tag{14}$$

Higher input uncertainty reduces optimal procurement and output, as under Leontief. The sign is delivered by diminishing marginal product alone; it does not turn on whether the elasticity of substitution lies above or below unity. All three hypotheses carry over: σ_{it}^2 contracts output (H1); the contraction is steeper for firms with higher A_i, since A_i scales the risk premium and $\partial^2 M_{it}^*/\partial\sigma_{it}^2\,\partial A_i < 0$ (H2); and the risk-management advantage of larger firms is sharpest in non-traded markets (H3).

What the elasticity of substitution governs is the *magnitude*. When $\sigma_s > 0$ the firm can lean on the capital–labour composite as the mineral becomes costlier or riskier, and this margin dampens the contraction relative to Leontief, where no such margin exists ($\sigma_s = 0$). Two things follow. First, the Leontief case is an upper bound on the model-implied output effect for a given risk premium, so the substitution model delivers the same predictions a fortiori. Second, and more useful for interpreting the estimates, our regressions impose neither production structure: the coefficient on *MineralRisk* is reduced-form. A contraction of the size we estimate therefore implies input uncertainty large enough to dominate whatever substitution the true technology allows.

The model complements Concordel et al. (2026), who trace the macroeconomic propagation of first-moment mineral price shocks through a neoclassical growth model with CES production. Our margin is different: the second-moment effect of input uncertainty on short-run output planning at the level of the individual firm, where the mineral is the binding factor given sunk capital and committed labour.

D Measurement Methodology

This appendix provides formal definitions of the text-based measures summarised in Section 3 of the main text. The textual data are drawn from earnings-call transcripts. An earnings call typically comprises two distinct segments. In the presentation segment, company managers evaluate the firm's quarterly performance and may provide additional disclosures tailored to market needs. In the subsequent question-and-answer segment, analysts and other participants probe management's interpretation of the disclosed information, seek clarification, and request further details, including on issues where managers may be hesitant or unable to provide information at that moment (Hollander et al., 2010). We combine all textual components of each transcript to integrate information from both segments, thereby capturing both managerial narratives and external scrutiny.

Standard textual preprocessing is applied to all transcripts before construction: text is converted to lowercase, words containing special characters (other than alphanumeric characters, underscores, and whitespace) are removed, and common stop words are filtered using the default English dictionary in Python's `sklearn` package. Compound terms such as "rare earth" and "rare earths" are hyphenated (e.g., "rare-earth") so that they are treated as single tokens.[25]

D.1 Mineral and Technology Exposure

A transcript j is classified as exposed to mineral μ when the set of unigrams obtained from that transcript after preprocessing, denoted U_j, overlaps with the set of unigrams predefined to detect mineral μ, denoted U^{μ}:

$$MineralExposure_j^{\mu} = \mathbf{1}\{U_j \cap U^{\mu} \neq \emptyset\} \tag{15}$$

[25] All transcripts are in English, recorded, processed, edited, and proofread by S&P.

Unigrams are used because mineral-related terminology tends to be technical, often involving specific names of chemical elements, which makes such terms easily distinguishable from general business vocabulary. The full unigram sets for each mineral are listed in Appendix F.1.

Technology exposure is defined analogously using bigrams. A transcript j is classified as exposed to technology τ when its set of bigrams B_j overlaps with the predefined bigram set B^τ:

$$TechExposure_j^\tau = \mathbf{1}\{B_j \cap B^\tau \neq \emptyset\} \tag{16}$$

For lithium-ion batteries, solar power, and hybrid/electric vehicles, we directly use the final bigram sets recommended by Bloom et al. (2021), who selected these through machine-learning methods with human supervision by intersecting business language in earnings-call transcripts with technical language from patent data to identify 29 disruptive technologies. For wind power, we extend their approach by identifying frequent bigrams within transcripts that reliably capture wind-related discussions and validating these candidates through human review. The full bigram sets are listed in Appendix F.3.

By combining the timing of transcripts with firm identifiers, we construct time-varying, firm-level exposure measures. We interpret these as undirected indicators of the realisation of shocks related to minerals or technologies that could affect business operations: the entities are positioned in parts of the supply chain that are sensitive to such shocks, and salient shocks are occurring at that point in time.

D.2 Mineral Shock Framework

From these undirected exposure indicators, we construct directional shock measures. The three families of measures can be summarised as a composite mineral shock indicator:

$$MineralShock_{ijt}^{\mu,d} = \underbrace{MineralExposure_{ijt}^{\mu}}_{\text{Mention } \mu?} \times \underbrace{Directionality_{ijt}^{\mu,d}}_{\text{Risk / Positive / Negative}} \times \underbrace{Magnitude_{ijt}^{\mu,d}}_{\text{Wording intensity (surrounding } \mu)} \tag{17}$$

where the superscript d denotes the direction of the shock (risk, positive, or negative). This formulation highlights that the shock measures combine three elements: whether the mineral is mentioned, the direction of the associated language, and the intensity of that language. The intensity component captures the magnitude of the shock as perceived by management and analysts: a transcript in which multiple risk synonyms cluster around mineral mentions registers a higher *MineralRisk* than one with a single passing reference, reflecting a more intense perception of input uncertainty. The subsections that follow define each component. Illustrative transcript excerpts demonstrating how these measures capture risk and sentiment discussions in practice are provided in Tables A6 and A7.

D.3 Mineral Risk

We construct a *MineralRisk* measure for each transcript j and mineral μ as the frequency of unigrams referring to μ within a 10-word proximity of each occurrence of a risk or uncertainty synonym (derived from the Oxford Dictionary) within the transcript. To account for varying transcript lengths, the frequency is normalised by the total number of unigrams l_j in the transcript:

$$MineralRisk_j^{\mu} = \frac{1}{l_j} \sum_{u \in U_j} [\mathbf{1}\{u \in U^{\mu}\} \times r_{10}(u)] \tag{18}$$

where $r_{10}(u)$ is a binary variable denoting the presence of any risk or uncertainty synonym within a 10-word proximity of the unigram u. Examples of risk-related wordings include "uncertainty," "possibility," "exposed," "variability," and "fluctuating" (see Figure A2, Panel A, for the full word cloud with size proportionate to frequency in mineral-related text).

D.4 Mineral Sentiment

$MineralSentiment$ is calculated as the frequency of words with a positive tone minus the frequency of words with a negative tone within a 10-word proximity of each mineral mention, normalised by the total unigram count:

$$MineralSentiment_j^{\mu} = \frac{1}{l_j} \sum_{u \in U_j} [\mathbf{1}\{u \in U^{\mu}\} \times \{P_{10}(u) - N_{10}(u)\}] \tag{19}$$

where $P_{10}(u)$ and $N_{10}(u)$ respectively count the number of positive and negative words based on the financial-text dictionary of Loughran and Mcdonald (2011) within a 10-word proximity of u.[26] Examples of positive tone words include “strong,” “good,” “able,” and “opportunity”; examples of negative tone words include “decline,” “difficult,” “volatility,” and “loss” (see Figure A2, Panels B and C).

The construct of $MineralSentiment^{\mu}$ implicitly assumes that each positive word may neutralise a negative word. To relax this assumption, we also create two component measures, $MineralPositiveSentiment^{\mu}$ and $MineralNegativeSentiment^{\mu}$, which exclusively take into account the presence of positive or negative tone words near mineral mentions.

D.5 Composite Measures and Aggregation

In addition to the mineral-specific indicators, we construct composite measures $MineralRisk$ and $MineralSentiment$ by summing the corresponding values across the five minerals. These aggregates capture the overall intensity of risk-related and tone-related language associated with the broader set of critical minerals. For the traded/non-traded decomposition (Table 7), we separately sum risk from copper and nickel (traded) and from lithium, cobalt, and rare

[26]The Loughran and Mcdonald (2011) word list is specifically calibrated for financial contexts. In their original study, firms using fewer negative words realise more positive market reactions, confirming that the dictionary captures economically meaningful variation in tone.

earths (non-traded).

All transcript-level measures are averaged across all transcripts belonging to the same firm in the same year (typically four, one per quarter). This mean-of-ratios aggregation ensures that each transcript receives equal weight regardless of length, avoiding the Jensen's inequality bias that would arise from a ratio-of-means approach. All composite measures are then standardised by dividing by their cross-sectional standard deviation (without demeaning), so that regression coefficients are interpretable as the effect of a one-standard-deviation increase.

D.6 Unconditional Risk

To control for general firm-level uncertainty, we construct *UnconditionalRisk* using the same risk-word dictionary but without conditioning on proximity to mineral mentions. This measure captures the overall intensity of risk-related language in the transcript and serves as a control for confounding sources of uncertainty that may jointly drive mineral-risk discussion and revenue outcomes. In the main analysis (Table 5), *UnconditionalRisk* predicts investment but not revenue, while *MineralRisk* predicts revenue but not investment, confirming that the two measures capture distinct channels.

D.7 Response Indicators

We identify four mitigation channels through a systematic reading of five-sentence windows around critical-mineral mentions, combined with expert consultation and domain knowledge. For each channel, we develop a word-pattern-based detection algorithm following Hassan et al. (2021). In the first step, we train a Word2Vec neural network on transcript text within two sentences of critical-mineral mentions, mapping each word into a vector space in which semantically related terms cluster together (Bloom et al., 2021). This procedure generates candidate detector terms for each channel and ensures sufficient sensitivity to minimise false negatives. In the second step, we iteratively refine the detection rules, adjusting proximity windows and introducing prohibited words to reduce false positives. The full set of detection patterns is listed in Appendix F.2.

Each channel indicator is constructed as:

$$MethodExposure^{\mu\kappa}_{ijt} = \underbrace{\mathbf{1}\{Exposed^{\mu}_{ijt}\}}_{\text{Mention } \mu?} \times \underbrace{\mathbf{1}\{MitigationMethod^{\mu\kappa}_{ijt}\}}_{\text{Patterns indicating } \kappa\text{? (surrounding } \mu)} \tag{20}$$

where κ denotes one of the following four channels.

Circular-economy solutions. We search for mineral terminology within a 10-word window of phrases signifying any of seven circularity strategies from the R-framework of Morseletto (2020): reuse (R3), repair (R4), refurbish (R5), remanufacture (R6), repurpose (R7), recycle (R8), and recovery (R9), along with their morphological variants. These strategies represent progressively deeper forms of material circularity, from extending product life (reuse, repair) to recovering raw materials from end-of-life products (recycling, recovery).

Material reduction and substitution. Content reduction is captured by identifying mineral terminology within a 3-word window of reduction-related synonyms (e.g., "reduce," "decrease," "less," "zero"), while excluding proximity to terms such as "cost," "price," or "production" to limit false positives from discussions of cost reduction rather than material reduction. Material substitution is identified separately by searching for mineral terminology within a 3-word window of substitution-related synonyms (e.g., "replace," "substitute," "substitution").

Stockpiling and hedging. Stockpiling is measured by locating mineral terminology within a 10-word window of inventory-related synonyms (e.g., "inventory," "stockpile," "warehouse"). Hedging is measured within a 10-word window of financial-instrument terminology (e.g., "hedge," "derivative," "futures," "collar," "options"). These two indicators are the primary measures used in the main analysis to validate the risk-aversion mechanism (Table 8), as they represent costly actions that firms undertake specifically to manage input uncertainty.

Cost pass-through to customers. This channel is identified by flagging mineral terminology within a 10-word window in which terms related to "pass" (e.g., "pass," "passed," "passing," "transmit") and "customer(s)" occur simultaneously.

An additional channel, supplier diversification and vertical acquisition, is documented in Ersahin et al. (2022) using external transaction data and is not separately modelled here. Illustrative transcript excerpts for each channel are provided in Table A8. As a behavioural validation, Table 8 (Panel B) confirms that discussion of hedging and stockpiling responds significantly to price volatility rather than price levels across all four minerals tested, consistent with these indicators capturing genuine risk-management activity rather than generic commodity commentary. Figure A4 shows the evolution of these four channels from 2010 to 2022, illustrating substantial variation in prevalence across minerals and response types.

E Validation of Text-Based Measures

This appendix reports exercises validating the text-based measures of mineral exposure, risk, and sentiment constructed in Section 3. We establish three properties: (i) mineral exposure co-occurs with energy-transition technology exposure in a pattern consistent with known engineering dependencies; (ii) mineral exposure tracks observable commodity-price movements at the firm level; and (iii) risk and sentiment measures are predominantly idiosyncratic, with 70 to 90 percent of variation arising at the firm level rather than from common industry or country shocks. These properties are summarised in Section 4 of the main text; this appendix provides the underlying regression specifications and detailed interpretation.

E.1 Mineral-Technology Co-occurrence

The primary rationale for analysing the five selected critical minerals is that they are integral inputs into clean-energy technologies. We validate this relationship by estimating a two-way fixed-effects linear probability model at the transcript level:

$$MineralExposure^{\mu}_{ijt} = \delta_i + \delta_t + \beta TechExposure^{\tau}_{ijt} + \gamma X_{it} + \varepsilon_{ijt} \tag{21}$$

where i, j, and t index firms, transcripts, and quarters respectively. The dependent variable is an indicator (0 or 1) for whether transcript j mentions mineral μ. The regressor of interest is an indicator for whether the same transcript mentions energy-transition technology τ. The specification conditions on firm fixed effects (δ_i), time fixed effects (δ_t), and firm size measured by the log of total assets (X_{it}). Standard errors are clustered at the quarter level. A positive β indicates that management and call participants are more likely to mention mineral μ when they also discuss technology τ during the same earnings call.

Table A1 reports the estimated coefficients for each mineral-technology pair. The results reveal a systematic connection between critical minerals and energy-transition technologies in the business context of earnings conference calls, consistent with engineering and materials-science expectations. Transcripts that discuss Lithium-ion Batteries (LiBs) and Electric Vehicles (EVs) are statistically significantly more likely to mention lithium, nickel, and cobalt-materials essential for EV battery cathodes and energy-storage systems. This pattern reflects firms' direct or indirect exposure to these inputs as they engage in or comment on relevant technologies. Copper, which is widely used across EV components such as motors, batteries, inverters, wiring, and charging infrastructure, is likewise significantly more likely to be mentioned in EV-related calls, consistent with exposure to electrification supply chains. Mentions of lithium in conjunction with solar and wind likely reflect these technologies' reliance on energy storage, where lithium-ion batteries remain the dominant solution.

The mean of the dependent variable ranges from 0.3 percentage points (rare-earth exposure) to 3.7 percentage points (copper exposure), highlighting substantial heterogeneity in the prevalence of mineral mentions across minerals and applications. Estimates are noisier for rare earths, which are the least frequently mentioned in the transcript corpus: we observe a false positive with solar and a false negative with EVs.[27] Nonetheless, the model robustly detects a strong and statistically significant association between rare-earth mentions and wind technology, consistent with the role of rare-earth-based permanent magnets in many turbine generators. In magnitude terms, firms associated with wind discussions exhibit a 4.8 percentage point increase in the probability of rare-earth mentions, compared with a sample mean of 0.3 percentage points.

To further validate the specificity of these associations, I conduct a falsification exercise. Mentions of cotton are uncorrelated with any of the considered technologies, confirming that the observed relationships are not driven by generic or spurious word co-occurrences. By contrast, the generic term energy is frequently co-mentioned with all technologies, as expected, supporting the specificity of the mineral–technology co-occurrence captured by the regression framework.

E.2 Mineral Exposure and Commodity Prices

If the text-based exposure measures capture economically meaningful variation, they should respond to observable commodity-price movements. Figure 2 compares aggregate mineral price series with the count of firms mentioning each mineral over time. The number of firms referencing critical minerals in their earnings calls rises sharply during periods of mineral-price surges. Rare-earth mentions nearly quadrupled in 2011 relative to 2016 levels, coinciding with China's export restrictions. Cobalt mentions nearly tripled in 2018, driven by heightened EV-adoption expectations. By 2022, lithium mentions had increased

[27] The observed positive association between solar and rare-earth mentions attenuates when conditioning on wind co-mentions, suggesting the link is driven partially by co-discussion of wind rather than by a direct technological dependence of solar on rare earths. For EVs, although rare-earth magnets play a critical role in many electric-motor designs, the material and economic scale of lithium-ion battery minerals is substantially larger and more central to firms' business strategies, so corporate discussion is dominated by batteries and any average EV–rare-earth signal is muted.

more than sixfold, and rare-earth and cobalt mentions fivefold, relative to 2016. These increases coincide with the broad commodity rally driven by pandemic-related supply disruptions, Russia's invasion of Ukraine, and the acceleration of the global energy transition. Table 8 (Panel A) decomposes this further, showing that firm-level mineral mentions are significantly correlated with both the price level and price volatility of the corresponding commodity.

E.3 Properties of Risk and Sentiment Series

Figure A3 plots the aggregate time series of the mineral-specific risk and sentiment measures alongside commodity-price moments (mean and standard deviation of monthly prices). The positive and negative sentiment measures, designed to capture first-moment shocks, track the mean level of commodity prices closely. The risk measures, intended to capture second-moment shocks, mirror the standard-deviation series. For example, the upswing in rare-earth sentiment corresponds to the sharp price increase in 2011, while the subsequent spike in the risk series aligns with the heightened price volatility in 2012. With the exception of rare earths, all commodities exhibit a pronounced end-of-period peak in both sentiment and risk, consistent with the elevated price levels and increased variability observed toward the end of the sample.

This alignment between the text-based measures and observable price moments provides external validation: the measures capture the intended variation. At the same time, the text-based measures contain cross-sectional and forward-looking information absent from prices. Prices move uniformly for all firms, but exposure varies with a firm's position in the supply chain, its procurement arrangements, and its supplier network. The text therefore provides firm-level information on perceived risks, strategic concerns, and anticipated constraints that is not observable in aggregate price data.

E.4 Cross-Industry Distribution of Exposure

The exposure measures vary intuitively across sectors defined at the 2-digit SIC level. The leading sectors include those directly involved in mining and metal processing (SIC 10, 33), as well as those engaged in the manufacture of transportation equipment (SIC 37), electronics (SIC 36), and machinery (SIC 35). Substantial representation also appears in construction-related sectors and in service-oriented industries such as wholesale trade, utilities, and communications. Within sectors, exposure varies considerably across firms: in SIC 37 (transportation equipment), for example, 24 percent of firms mention lithium and 27 percent mention copper, but only 6 percent mention rare earths, reflecting the heterogeneous mineral dependencies of firms with different product lines within the same industry code. This within-sector heterogeneity motivates the firm-level rather than industry-level approach adopted throughout the paper.

F Dictionaries for Textual Analysis

F.1 Mineral dictionaries

We detect mentions of five critical minerals using predefined sets of unigrams. Keywords include base forms, plurals where commercial usage warrants them, and single-word compounds or ore names that unambiguously identify exposure to the target mineral. Terms indicating absence (e.g. *noncobalt*) are excluded. Company names containing mineral terms (e.g. *Nickelodeon*) are removed during preprocessing. **Cobalt:** *cobalt, cobalts, cobaltite, cobaltate*. **Copper:** *copper, coppers*. **Lithium:** *lithium, lithiums, spodumene*.[28] **Nickel:** *nickel, nickels, ferronickel, ferronickels*. **Rare earths**: *rare-earth, rare-earths, cerium, lanthanum, praseodymium, neodymium, promethium, europium, gadolinium, samarium, dysprosium, yttrium, terbium, holmium, erbium, thulium, ytterbium, lutetium, scandium*.

[28]Spodumene is the dominant hard-rock lithium ore, frequently referenced in mining and battery supply-chain discussions.

Benchmark commodities. Cotton: *cotton* (falsification; Table A1). Energy: *energy* (mechanical co-occurrence benchmark; Table A1).

F.2 Concept dictionaries for mitigation methods

Detection of mitigation strategies follows the word-pattern approach of Hassan et al. (2021), searching within a 10-word window of mineral mentions. The keyword sets, developed through Word2Vec candidate generation and iterative human refinement (Section 6.1), are as follows.

Circular economy (R3–R9 strategies): *repurpose, repurposed, repurposing, repurposes, repurposable, repurposeable, repurposeful, repurposement, repurposings, refurbish, refurbished, refurbishing, refurbishings, refurbishable, refurbisher, refurbishers, refurbishment, refurbishments, refurb, refurbed, refurbing, refurbs, repair, repaired, repairing, repairers, repairable, repairment, repairs, remanufacture, remanufactured, remanufactures, remanufacturing, remanufacturable, remanufacturer, remanufacturers, recycle, recycled, recycler, recyclers, recycling, recyclings, recyclable, recyclables, recyclability, recyclate, recyclates, reuse, reused, reuses, reusing, reusable, reusage, nonrefurbished, unrefurbished*.

Content reduction: *decrease, decreased, decreases, decreasing, free, less, low, lower, reduce, reduced, reduces, reducing, reduction, reductions, zero*.

Material substitution: *replace, replaced, replaces, replacing, replacement, replacements, substitute, substituted, substitutes, substituting, substitution, substitutions, substitutable, substitutability*.

Stockpiling: *inventory, inventories, stockpile, stockpiled, stockpiles, stockpiling, warehouse, warehouses*.

Cost pass-through: *pass, passed, passes, passing, transmit, transmitted, transmits, transmitting, transmission, transmissions* (required to co-occur with *customer(s)* within the same window).

Hedging: *collar, collars, derivative, derivatives, futures, hedge, hedged, hedges, hedging, options, qp, quotational*.

F.3 Technology dictionaries

Technology exposure is detected using bigrams. For lithium-ion batteries, solar power, and hybrid/electric vehicles, we use the sets from Bloom et al. (2021). For wind power, we extend their approach by selecting bigrams that parallel their solar-power terms, validated through human review.

Lithium-ion batteries: *ion battery, ion batteries, lithium ion, lithium battery, lithium batteries, lithium polymer, lithium-ion battery, lithium-ion batteries*.

(Hybrid) Electric vehicles: *electric car, electric vehicle, electric vehicles, electric buses, electric motorcycle, electrical vehicles, hybrid electric, hybrid vehicle, plugin hybrids, vehicle charging*.

Solar power: *crystalline silicon, photovoltaic, rooftop solar, silicon solar, solar applications, solar assets, solar capacity, solar cell, solar cells, solar energy, solar equipment, solar facilities, solar facility, solar farm, solar farms, solar generation, solar grade, solar installation, solar installations, solar materials, solar markets, solar module, solar modules, solar panel, solar panels, solar plant, solar plants, solar power, solar product, solar products, solar pv, solar pwr, solar sales, solar systems, solar technologies, solar technology, solar thermal, solar wafer, solar wafers*.

Wind power: *offshore wind, onshore wind, wind capacity, wind energy, wind equipment, wind farm, wind farms, wind generation, wind installation, wind plant, wind plants, wind power, wind project, wind projects, wind resource, wind resources, wind turbine, wind turbines*.

G Illustrative Transcript Excerpts

Table A6: Examples of Discussion on Risks Related to Critical Minerals

Company	Year-Month	ISO	Excerpts
Rockwood Holdings, Inc.	2010M04	USA	or is it the case that there is like too much volatility in terms of demand and the euro being a headwind, and *copper* prices **fluctuating**, and other things happening that you could n't achieve peak margins ?
Evonik Industries AG	2013M10	DEU	on the *lithium* ion battery case, i can confirm that all **risks**, which we can anticipate, we have provided for.
The Goldman Sachs Group, Inc.	2015M10	USA	*copper* and natural gas were both down approximately 10 %. the price slump led the market to focus on the credit **risk** of commodity producers, trading houses and those economies with significant commodity exports. these concerns drove an increase in credit spreads, particularly across the energy sector.
Volkswagen AG	2018M03	DEU	and my last question is relating to the battery contracts you have already signed so far. are you actually assuming the raw material price **risks** for those batteries ?meaning *cobalt* prices, *nickel* and manganese, is that your **risk** or is it the battery supplier taking that **risk** ?
General Motors Company	2018M07	USA	steel prices, we can see clearly they were sharply higher in the quarter, and they remain high. at the same time, the prices for some of the other metals that you 're **exposed** to such as aluminum or *copper*, while they were also sharply higher in q2, they appear to have significantly moderated after the quarter end
Barloworld Limited	2019M11	ZAF	bartrac continues to deliver strong results despite the challenging regulatory framework, but also **fluctuating** *cobalt* prices that we 've seen during the period, with the associate income moving from zar 251 million to zar 268 million.
Allegion plc	2020M04	IRL	i mean it can and how **sticky** you think the pricing will be ?yes. basis of the current cost for steel, zinc, *copper*, brass, et cetera, that will continue throughout the course of the year, yes. okay. that 's helpful.
Adani Green Energy Limited	2021M10	IND	there is a **possibility** of variation in the prices of wind also like solar, ashwin, because it is 100 % again a commodity driven business. the same *copper*, same aluminum, same steel and everything, same cement. so there is a **possibility**, like in case of any other business, there 's a **possibility** of variation.
BorgWarner Inc.	2021M11	USA	our typical pass throughs, when you look at the blend of all the pass through mechanisms we have contractually as it relates to steel, aluminum, *nickel*, *copper*, the things that we 're most **exposed** to the contractual pass throughs are about 50 % on a fully blended basis.
Worley Limited	2022M02	AUS	we are going to have renewables, you 're going to have offshore wind. you 're going to have to use water more efficiently. we know that you 're going to have to have more *copper*, more *nickel*, more *lithium*. so is there a **risk** ?yes.
Munters Group AB (publ)	2022M07	SWE	we have next question from the line of anders roslund with pareto securities. i have a question about your capacity increases. now you 're building new factories in the u.s. for data centers and also new capacity in europe for *lithium* batteries. how will that impact ?are there any **risks** that you run into more production problems ?
Vedanta Limited	2022M07	IND	we have started dynamic commodity hedging for proactive **risk** management amidst unprecedented price volatility. in july '22, we commenced operation on *nickel cobalt* goa plant, and liberia iron ore mine
Wärtsilä Oyj Abp	2023M01	FIN	we have *lithium* going up 50 % since summer. how do you assess the **risk** of that further price increases are now needed to cover your cost on the energy storage ?

Notes: This table displays example snippets of transcripts discussing risks related to critical minerals, along with information about the company name, the time of conference calls, and the 3-digit ISO codes of the countries where the companies are headquartered. Words referring to *critical minerals* are in *italics*, while synonyms for **risk or uncertainty**, as derived from the Oxford Dictionary (excluding 'question,' 'questions,' and 'venture'), are in **bold**.

Table A7: Examples of Discussion on Sentiments Related to Critical Minerals

Company	Year-Month	ISO	Excerpts
Nanophase Technologies Corporation	2011M08	USA	*cerium* oxide is a common *rare-earth* material that, while **abundant**, can be difficult to extract. today, virtually all *rare-earth* metals are exported from china, which began imposing severe export limitations during the second half of 2010 and continue through today.
Hitachi, Ltd.	2012M07	JPN	for high functional materials and components, revenue was also flat at 99 %. hitachi cable withdrew from the unprofitable businesses. furthermore, *copper* prices declined, **leading** to a decline in revenues. but overall **profitability** increased because of the cost reduction efforts underway. next is our automotive systems.
Harman International Industries, Incorporated	2012M11	USA	on the *neodymium*, is there a number there in terms of year over year how much of a **benefit** there was from the unwinding of the costs last year ?yes, david. we had one.
Sika AG	2016M02	CHE	the rest of the pacific side of latin america, it was facing the problem of the raw materials. the commodity problem, *copper*, silver, oil, coke, has been facing a serious problem. the government has been **stable**, excluding ecuador. ecuador, the situation is difficult.
Innergex Renewable Energy Inc.	2018M11	CAN	how do you guys think about the potential for a global recession occurring and impact on power prices and demand for *copper* overall ? [..].but i think in general, the demand for *copper* seems to be **strong** based on the fact that a lot of the electricity cars and component will utilize *copper*. so my understanding is that *copper* demand for the future will be **strong**. a
Bayerische Motoren Werke Aktiengesellschaft	2019M03	DEU	and the **positive** piece of news is that with the generation 5, for the first time, we will have e engines free of *rare-earths* that still have the same degree of **efficiency**.
Umicore SA	2020M02	BEL	finally, *cobalt* prices were depressed to less than half 2018 levels, and this was exacerbated by the inflow of cheap *cobalt* products originating from unethical sourcing. against the backlog against the backdrop of declining ev demand in the second half, we managed to grow our sales of nmc cathode materials,
S&P Global Inc.	2021M04	USA	you also have *lithium* in the batteries. so these are areas where we also see a lot of **opportunities** for the benchmarks to be used from a combination of new power grids, from the metals that are in them, from the clean energy that is going to be clean transition energy.
Varex Imaging Corporation	2021M08	USA	. i mean, you find sometimes *coppers* were there is a shortage of *copper* or shortage of aluminum and castings. and it 's a daily discussion with suppliers and making sure we have a **good** handle on their delivery dates and what they 're doing.
Volvo Car AB (publ.)	2021M11	SWE	and i wanted to ask you around the raw material supply for your battery electric vehicles. i wondered how concerned you are that shortages of *cobalt* and *lithium* might hamper your transition to pure electric in the coming years ?obviously, everyone at the moment is, how can there be **easy** next target
Alexandria Real Estate Equities, Inc.	2022M04	USA	in addition to fuel, the war has reduced the supply of critical semiconductor materials such as palladium and *nickel*, exacerbating the chip shortage, which affects such things as building control systems and emergency generators, the latter of which can now take up to a year to deliver.
Ameresco, Inc.	2022M05	USA	are you **able** at this point to write a contract that, for example, allows you to pass through any volatility on, say, *lithium* carbonate pricing or *cobalt* pricing or something like that ?how are you coming at insulating yourself from the volatility that exists in inputs for those products ?

Notes: This table displays example snippets of transcripts expressing sentiments related to critical minerals, along with information about the company name, the time of conference calls, and the 3-digit ISO codes of the countries where the companies are headquartered. Words referring to *critical minerals* are in *italics*, while expressions denoting **positive** and negative tones according to Loughran and Mcdonald (2011) are respectively highlighted in **bold** and underlined.

Table A8: Examples of Discussions on Critical Mineral Price Shock Mitigation

Company	Year-Month	ISO	Excerpts
Panel A: Circular Economy Solutions			
Tesla, Inc.	2014M02	USA	and i 'd actually point out also though that *lithium* ion battery packs are **recycled** today. there 's a **recycling** facility in vancouver and one in belgium for u.s. and europe, and they have quite a bit of value.
Toyota Tsusho Corporation	2018M05	JPN	jpy 140 billion will be allocated to resources & environment areas. project in this area include renewable energy, *lithium* and other metal **recycling**.
EnerSys	2019M02	USA	primarily due to the previously announced market **reduction** in china, due to china tower shift from lead acid to **repurposed** *lithium* batteries.
Apple Inc.	2019M10	USA	and we 've added *rare-earth* elements to our list of **recycled** materials with the introduction of iphone 11. we 're disassembling, **recycling** or **refurbishing** millions of devices every year
Samsung SDI Co., Ltd.	2022M10	KOR	making equity investments into **recycling** business partners centering around *nickel*, *lithium*, and *cobalt* for now.
Panel B: Material Reduction and Substitution			
Tesla, Inc.	2018M05	USA	being on a path to **reduce** *cobalt* usage, for instance, has been something we 've been working on for literally several years now. and this has been extremely helpful in the overall cost per kilowatt hour, especially with recent commodity price movements.
Contemporary Amperex Technology Co., Limited	2021M05	CHN	t catl 's *cobalt* **free** battery was under smooth development and is a new and disruptive product, and the company 's senior management also explained that they are developing rare metal **free** (*nickel* **free** and *cobalt* **free**) batteries
Nissan Motor Co., Ltd.	2022M07	JPN	the third challenge is the escalating raw material cost. we are focusing first on mitigating the impact by **reducing** the usage of precious metals. for example, by developing a new generation of catalysts that use fewer precious metals and also developing *cobalt* **free** batteries.
Panel C: Hedging or Stockpiling			
Molycorp, Inc.	2012M02	USA	do you have the capability, let 's say if the magnet growth is there to produce up to 40,000 metric tons and **stockpile** say the *cerium* and the *lanthanum*
Stoneridge, Inc.	2012M08	USA	we do have *copper* escalation clause, but we think that clause is too long, so this year we are **hedged** out on *copper*.
Sandvik AB (publ)	2020M04	SWE	the raw material **hedges**, which is mainly *nickel* and a little bit of molybdenum, is normally around sek 400 million to sek 500 million.
Sumitomo Metal Mining Co., Ltd.	2022M02	JPN	higher *nickel* and *cobalt* prices made a big contribution and **inventory** valuation improved in both *copper* and *nickel* entities.
Panel D: Pass through Cost to Customers			
Gentherm Incorporated	2021M04	USA	so we are obviously facing the inflationary pressure that *copper* has. about 40 % is **passed through**.
Aptiv PLC	2021M05	IRL	we 're about 80 % **pass through** on *copper*. so *copper* increases, changes in *copper* prices, both positive and negative, we **pass through** to **customers**.
Garrett Motion Inc.	2021M07	CHE	we recovered a majority of the increase from our **customer pass through** agreements, especially for *nickel*, and continue to actively manage our supply base and cost recovery mechanisms to minimize the impact of materials cost inflation.
TECO Electric & Machinery Co., Ltd.	2021M08	TWN	so, most of the material price increases was basically partially **passed** on to **customers**. the whole motor industry was suffering from the rise of price of *copper*, iron, and aluminum.
Ameresco, Inc.	2022M05	USA	are you able at this point to write a contract that, for example, allows you to **pass through** any volatility on, say, *lithium* carbonate pricing or *cobalt* pricing or something like that ?
Neogen Chemicals Limited	2022M08	IND	we witnessed significant increase in the prices of raw materials linked to *lithium*, which the company was able to **pass** on to the **customers**, resultantly protecting the absolute ebitda.

Notes: This table displays example snippets of transcripts discussing methods for mitigating price shocks of critical minerals, along with information about the company name, the time of conference calls, and the 3-digit ISO codes of the countries where the companies are headquartered. Words referring to *critical minerals* are in *italics*, while wording patterns indicating the **mitigating method** are in **bold**.