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in Critical Mineral
Saving
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Summary

This paper develops a novel text-based approach to identify CRM-saving innovation using patent data and studies how mineral price signals shape the direction of technological change. Using patent data from 1978–2020, we distinguish technologies that rely on CRMs from those that explicitly aim to reduce their use through efficiency improvements, substitution, or recycling. We provide evidence consistent with the induced-innovation hypothesis: higher mineral prices reallocate inventive effort toward CRM-saving technologies, while having little effect on CRM-reliant innovation. The response strengthens over time and is especially pronounced for battery minerals and rare earth elements. These findings are robust to alternative specifications and are reinforced by complementary identification strategies, including a falsification test and the use of plausibly exogenous supply-side price variation.

Keywords: Energy Transition; Critical Raw materials; Patents

JEL Classification: C55; O31; O33; Q55; L72

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Induced Innovation in Critical Mineral Saving Technologies

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1 Introduction

The twin digital and green transition critically depends on a large set of critical raw materials (CRMs), such as lithium, cobalt, nickel, and rare-earth elements, which are essential inputs for batteries, renewable energy technologies, semiconductors, and advanced manufacturing (European Commission, 2020). As demand for these technologies accelerates, global demand for CRMs has surged and is projected to increase sharply over the coming decades, potentially outpacing current and planned supply capacities (IEA, 2024). At the same time, CRM supply chains are highly concentrated geographically and exposed to geopolitical, environmental, and regulatory risks, raising concerns about long-term technological and economic resilience. Recent price spikes, geopolitical tensions and renewed export restrictions on critical minerals have brought the question of whether innovation can endogenously mitigate material scarcity to the forefront of policy debates.

In this context, material-saving innovation – that is, innovation aimed at reducing, substituting, recycling, or improving the efficiency of CRMs – has become a central yet underexplored dimension of the sustainability transition. This issue is particularly salient for countries with limited domestic mining capacity, where technological change rather than resource extraction is likely to play a key role in alleviating material constraints. Understanding whether and how innovation responds to rising CRM scarcity is therefore crucial for policy design.

This paper addresses two related questions. First, how to empirically identify and measure material-saving technological change related to CRMs. Second, whether innovation aimed at reducing the use of CRMs responds systematically to changes in material scarcity, as proxied by supply-side CRM price shocks. By answering these questions, the paper provides new evidence that rising input scarcity redirects technological change away from material-intensive trajectories and toward CRM-saving solutions. These findings are robust to alternative specifications and are reinforced by complementary identification strategies, including a falsification test and the use of plausibly exogenous supply-side price variation.

Our analysis builds on and contributes to three strands of literature. First, we relate to the literature on induced innovation, which emphasizes that technological change responds

endogenously to variations in relative input prices and scarcity. Empirical evidence for energy shows that higher prices stimulate energy-saving innovation and adoption (Popp, 2002; Linn, 2008) and that this response operates primarily through increased inventive activity by incumbent inventors rather than entry of new ones (Dugoua and Gerarden, 2025). At a more aggregate level, Hassler et al. (2021) show that technical change accelerates following large price shocks, such as the oil crises of the 1970s. Responses are heterogeneous: while firms and inventors react along several margins, consumer-side adjustments are weaker (Jacobsen, 2015). While recent work focuses on downstream responses to discrete trade-policy shocks, we study how continuous price variation shapes material-saving innovation across a broad set of CRMs. We extend this literature beyond energy inputs to CRMs. Exploiting within-mineral variation in lagged real prices, we show that increases in CRM prices induce a positive and persistent response in CRM-saving patenting, while no comparable effect is observed for innovations that continue to rely on CRMs. This asymmetric response provides direct evidence that rising material prices redirect innovation toward economizing on scarce inputs.

Second, we connect to the literature on directed technological change, which studies how policy instruments and institutional settings influence the direction of innovation across competing technological trajectories. Acemoglu et al. (2012) show that environmental policies combining taxes and subsidies can redirect innovation from “dirty” to “clean” technologies. Aghion et al. (2016) supports this mechanism and find that higher fuel taxes induce firms to increase clean innovation while discouraging dirty technologies, with strong path dependence reflecting both firm-specific history and aggregate spillovers. Earlier work by Jaffe and Palmer (1997) shows that environmental regulation raises R&D expenditures, although its effect on patenting is less immediate. We contribute to this literature by providing micro-level evidence that material scarcity itself – proxied by price shocks – can redirect the direction of technological change. By distinguishing between innovations that continue to rely on CRMs and those that explicitly aim to reduce their use, we show that scarcity selectively favors material-saving technological trajectories. Recent work further shows that adverse supply shocks to essential and hard-to-substitute inputs – such as export restrictions on rare earth elements – can trigger directed technological change aimed at improving input

efficiency in downstream industries (Alfaro et al., 2025). In this sense, our results support theories of directed technical change driven by relative factor scarcity (Hanlon, 2015), even in the absence of direct policy intervention.

Third, our work relates to the emerging literature on CRMs and innovation. Existing studies analyze CRM-reliant technologies, supply risks, and sustainability challenges (Fifarek et al., 2008; Li et al., 2024), while recent work exploits patent data to study innovation that uses CRMs (Diemer et al., 2022). Systematic empirical evidence on innovation explicitly aimed at reducing dependence on CRMs remains scarce. We contribute by introducing a new, large-scale measure of CRM-saving innovation that shifts the focus from technologies that rely on critical materials to those explicitly aimed at reducing their use. We develop a novel text-based identification strategy that leverages patent titles and abstracts to capture the direction of technological change. Using semantic pattern recognition, we identify CRM-saving patents as those combining references to specific materials with action-oriented language related to material economization, such as reduction, substitution, efficiency improvements, recycling, or reuse. This approach builds on recent work using textual analysis to classify technologies along economically meaningful dimensions (e.g. Autor et al., 2022; Montobbio et al., 2022), and allows us to distinguish between innovations that intensify CRM use and those that actively reduce it. Applying this measure across a broad set of CRMs, we provide the first systematic evidence on the evolution, technological composition, and drivers of material-saving innovation.

The remainder of the paper is organized as follows. Section 2 describes the procedure used to identify CRM-saving patents. Section 3 presents the empirical strategy. Section 4 contains the empirical results, while Section 5 concludes. Additional results and methodological details are provided in a Supplemental Appendix.

2 Identifying CRM-Saving Innovation using patents

2.1 Database construction

We source patent families with English-language titles and abstracts filed at the European Patent Office (EPO) between 1978 and 2020 from PATSTAT Online. Information on applicant entities, namely, their country of location and NACE activity codes, is retrieved from the Orbis Intellectual Property database.¹

To identify patents that may involve CRMs, we select both green and non-green technologies using the CPC (Cooperative Patent Classification) system. For green technologies, we rely on the Y02–Y04S tagging scheme developed by the EPO, which classifies Climate Change Mitigation Technologies (Veefkind et al., 2012), and we further include patents in the H02S category related to photovoltaic power generation. Because substantial raw material use also characterizes non-green technologies, such as those in metallurgy, chemistry, automation, and electronics, we manually select additional CPC classes likely to encompass CRM-related patents.

We define CRMs as raw materials essential for green energy and electric mobility technologies. To identify them, we build on Kowalski and Legendre (2023), who provide a consolidated list of materials critical for key green technologies such as Li-ion batteries, fuel cells, wind turbines, electric traction motors, and photovoltaics. We then expand the group of rare-earth elements (REEs) by listing each element individually, adding 17 materials to the final set.² Because material criticality varies across contexts and countries, our list is not exhaustive and may omit materials important in other settings. The resulting set comprises 48 raw materials, listed in Table 1(a).

¹The Supplemental Appendix provides additional details on data construction, variable definitions, and supporting descriptive evidence.

²REEs comprise 17 chemically similar elements. Scandium is sometimes classified as an REE due to its similar properties (Voncken, 2016). See Table 1(a) and <https://www.usgs.gov/centers/national-minerals-information-center/rare-earths-statistics-and-information>.

2.2 Identifying CRM-reliant and CRM-saving patents

A CRM-reliant patent refers to a process, or product, that depends on CRMs for its functionality, efficiency, or production. We identify the presence of one or more CRMs in a technology using straightforward text analysis techniques previously applied in the literature (Fifarek et al., 2008; Gentzkow et al., 2019; Li et al., 2024). Specifically, we search for the material’s name in the patent title and abstract, as these document’s sections offer insights into the invention’s function, technical process, and the materials used in its manufacturing and operation.

We define CRM-saving patents as technologies aimed at reducing the use of CRMs, either directly or indirectly. Such reductions may arise from cost-cutting, efficiency improvements in production processes, recycling or reuse of secondary materials, or waste minimization. To identify CRM-saving patents, we apply the methodology of Montobbio et al. (2022), which captures reasoning patterns in patent texts through specific semantic structures, to the subset of CRM-reliant patents.

We construct a glossary of terms grouped into three categories: verbal predicates, direct objects, and object attributes. The direct objects correspond to the list of raw materials in Table 1(a). For the predicates and attributes, we adopt a three-step procedure. First, we select context-relevant terms from Montobbio et al. (2022) who deal with labour-saving technologies. Second, we expand this set using ChatGPT-generated suggestions. Finally, we manually review and refine the expanded list. The resulting terms appear in Table 1b and 1c.

Combining the three lists yields $48 \times 16 \times 28 = 21,504$ possible word triplets that may occur – though not necessarily contiguously – within a sentence. A patent is classified as CRM-saving if at least one term from each category appears in the same sentence. While the method may generate false positives and false negatives, we deliberately do not address false negatives to remain conservative. We reduce false positives using the procedure detailed in the Supplement, where we also provide examples of patents retained by our method. In these cases, material savings arise from improved recovery and recycling processes, enhanced extraction and purification techniques, or changes in product design.

2.3 Descriptive statistics

The search for patent families within the green and non-green technological categories yields a total of 3,211,054 documents. Among these, 144,980 patents (4.52%) are labelled as CRM-reliant technologies, as they include at least one CRM in their title and/or abstract. We identify a subset of 1,994 CRM-saving patents before manual screening. After manual verification, this number is further reduced to 765 (0.53% of CRM-reliant patents) over a time period spanning from 1978 to 2020. Henceforth, time refers to the year of patent application or priority date.

When comparing CRM-reliant and CRM-saving patents, a significant difference is observed in the percentage of green patents: only 21.16% of CRM-reliant, while 60.13% of CRM-saving patents. Moreover, only 21% of CRM-reliant patents are classified under metallurgy codes, while this share rises to 62.35% for CRM-saving patents. This large gap suggests that CRM-saving technologies are much more connected to metallurgical processes, as many CRM-saving patents likely involve material substitution, recycling, reprocessing, or other activities related to metallurgy. In contrast, CRM-reliant technologies may use critical materials as inputs but do not necessarily focus on transforming or processing those materials, which might explain their limited association with CPC codes pertaining to metallurgy.

Figure 1a shows the evolution of CRM-reliant and CRM-saving patents from 1978 to 2020, highlighting a steady increase in both categories. Interestingly, when looking at the percentage change from 1978, Figure 1b shows that CRM-saving technologies have a steeper growth curve and greater volatility over the period.

Figures 1c and 1d display the log share of CRM-saving and CRM-reliant patents together with the log real metal price averaged over all CRMs. The co-movement with mineral prices is visibly stronger for CRM-saving patents than for overall CRM-related patenting, suggesting that price fluctuations are more closely associated with shifts toward material-saving technologies than with changes in aggregate CRM-related innovation. This contrast motivates our empirical analysis of differential innovation responses to mineral price shocks.

3 Empirical strategy and data

Following a standard induced innovation hypothesis, we expect CRM-saving technologies to respond differently to mineral price shocks than CRM-reliant technologies. In the context of CRMs, real prices reflect underlying scarcity conditions driven by supply constraints, geopolitical risks, and rising demand from the twin transition. These signals provide incentives for firms to reorient inventive activity toward technologies that economize on scarce materials through substitution, efficiency improvements, recycling, or reduced material intensity. Given the sparsity of CRM-related patents and the fact that mineral prices are determined in global markets, we aggregate the data at the mineral-by-year level (Popp, 2002). This aggregation strategy allows us to exploit variation in mineral-specific price signals while preserving sufficient variation in patenting activity across time.

Let $pat_{j,m,t}$ denote the number of patents of type $j \in \{s, ns\}$ mentioning mineral m in year t , where s refers to CRM-saving patents and ns to CRM reliant patents. Total CRM-related patents mentioning mineral m are $pat_{m,t} = pat_{s,m,t} + pat_{ns,m,t}$, and total CRM-related patenting in year t is $pat_t = \sum_m pat_{m,t}$. Because patents may reference multiple minerals, these counts exceed the number of unique patents.

We estimate separate regressions for CRM-saving and CRM-reliant patents. The dependent variable is the log share of each patent type in total CRM-related innovation, capturing shifts in the composition of inventive activity. Our baseline specification is:

$$\log \left(\frac{pat_{j,m,t}}{pat_t} \right) = \alpha_m + \phi_m t + \sum_{\ell=1}^3 \beta_{\ell} \log P_{m,t-\ell} + \mathbf{x}'_{m,t-1} \boldsymbol{\gamma} + \mathbf{z}'_{t-1} \boldsymbol{\delta} + \varepsilon_{j,m,t}, \quad (1)$$

where α_m are mineral fixed effects, $\phi_m t$ are mineral-specific linear trends, and $P_{m,t-\ell}$ denotes the lagged real price of mineral m , with $\ell \in [1, 3]$. The vector $\mathbf{x}_{m,t-1}$ includes further lagged mineral-specific controls, while \mathbf{z}_{t-1} captures lagged macroeconomic and policy factors common to all minerals.

The coefficients of interest are the distributed-lag elasticities β_{ℓ} , which trace the dynamic response of innovation to mineral prices. Their sum, $\sum_{\ell=1}^3 \beta_{\ell}$, measures the long-run elasticity of CRM-related innovation to a sustained price change.

Mineral specific variables. Mineral-specific variables include real mineral prices, a proxy for the stock of knowledge, and the Herfindahl–Hirschman index (HHI) of production concentration; the latter two are included in the vector $\mathbf{x}_{m,t-1}$.

Mineral price and production data are sourced from the United States Geological Survey (USGS). For mineral prices, we rely on the USGS unit value series, deflated using the Consumer Price Index for All Urban Consumers and reported in 1998 constant U.S. dollars. The unit value represents the average price per physical unit of apparent consumption. The HHI of production concentration controls for geopolitical and supply-security risks arising from concentrated production, which may spur innovation aimed at reducing CRM dependence.

A proxy for the mineral-specific stock of knowledge is included to account for path dependence and cumulative technological opportunities shaping current innovation intensity and direction (Li et al., 2024; Popp, 2001).

Other controls. We include a set of controls capturing time-varying factors common to all minerals in the vector \mathbf{z}_{t-1} . In particular, we use the Index of Global Real Economic Activity of Kilian (2009) as a proxy for the global business cycle, and the log difference of the World Bank real commodity price index as a commodity price factor capturing demand-driven global fluctuations (Alquist et al., 2020; Delle Chiaie et al., 2022).

In addition, we include the Trade Policy Uncertainty index of Caldara et al. (2020), which reflects changes in the global policy environment affecting firms' strategic investment and innovation decisions. Lastly, we rely on the index developed by Noailly et al. (2024) that tracks major policy events and shifts in climate and environmental policy attention that influence firms' incentives to develop cleaner, less resource-intensive technologies.

3.1 Identification assumptions

Identification of the price elasticities comes from medium-run and cyclical deviations of mineral prices around their mineral-specific trends. By absorbing slow-moving structural changes in both prices and innovation, this specification removes long-run co-movements driven by persistent demand shifts, commodity cycles, and broad technological or policy trends.

All mineral prices enter the regression with three lags to reflect the timing of R&D decisions and to mitigate simultaneity concerns. Patent filings in year t result from R&D efforts initiated well before filing and are therefore influenced by past, rather than contemporaneous, price signals. Using lagged prices ensures that identification relies on price movements that are predetermined with respect to patenting outcomes.

All other explanatory variables also enter in lagged form. Mineral-specific controls capture recent market conditions and risk environments observed by firms when forming innovation expectations, while common macroeconomic and policy indicators capture global factors affecting all minerals. Lagging these controls ensures that identification is not contaminated by contemporaneous shocks realized during the filing year.

Under this specification, the estimated short- and long-run elasticities reflect innovation responses to mineral-specific price fluctuations that cannot be explained by persistent structural trends or global demand conditions. As a result, the estimated effects capture the causal response of CRM-related innovation to plausibly exogenous variation in mineral prices.

4 Results

4.1 Main results

Adjusting the sample for lagged variables yields a balanced panel of 20 CRMs over the period 1981–2020 ($T = 38$), for a total of 760 observations.³ We begin with the full-sample estimates reported in columns (1) and (4) of Table 2a, with standard errors clustered at the mineral level.

For CRM-saving patents, the estimated long-run elasticity to mineral prices, $\sum_{\ell=1}^3 \hat{\beta}_\ell$, equals 0.166 and is statistically significant at the 10% level. The response unfolds gradually, with effects small at short lags and increasing over time; the third lag accounts for most of the

³To ensure sufficient observations per cross-sectional unit in the regressions, we aggregate materials with fewer than four patents and sparse data with very frequent zero entries. The resulting categories are: “iron and ferro-alloy metals” (molybdenum, niobium, titanium, vanadium); “non-ferrous metals” (arsenic, cadmium, gallium, germanium, hafnium, indium, selenium, zirconium); and “platinum group metals” (palladium, platinum), following standard material classifications (IEA, 2024, p. 2).

adjustment, indicating a delayed response to scarcity signals. This dynamic pattern mirrors the findings of Popp (2002) for energy-efficiency innovation and extends them to the context of CRMs. The timing and persistence of the effect are consistent with the induced-innovation hypothesis.

By contrast, for CRM-reliant patents the estimated long-run elasticities in column (4) are close to zero or slightly negative, indicating that higher mineral prices do not stimulate innovation that continues to rely on the same inputs.

Variation over time. As suggested by Figures 1c and 1d, the strength of the price-innovation relationship varies over time. Prior to the early 1990s, both CRM-saving and CRM-reliant patent shares are highly volatile and display little systematic co-movement with mineral prices, reflecting the limited scale and fragmented nature of CRM-related innovation in the 1980s. Beginning in the 1990s – and more markedly after the mid-2000s – mineral prices and CRM-saving patent shares exhibit more pronounced and synchronized movements, especially for battery-related minerals. This pattern suggests that meaningful price-innovation linkages emerge only once CRM-saving technologies reach sufficient technological maturity and economic relevance.

We assess this hypothesis in columns (2)-(3) and (5)-(6) of Table 2a, where we re-estimate the baseline specification on subsamples starting in 1990 and 2000. Two results stand out. First, the long-run elasticity of CRM-saving patents with respect to mineral prices increases when restricting the sample to later periods, rising from 0.166 in the full sample to 0.319 in the post-2000 sample. Second, in contrast, the estimated elasticities for CRM-reliant patents remain statistically indistinguishable from zero across all time windows.

Heterogeneity. Given the importance of battery metals and REEs for the energy transition and digital technologies, we allow for heterogeneous price elasticities across these groups of minerals. Table 2b augments the baseline specification with interaction terms between lagged log-prices and indicators for battery minerals and REEs. In columns (2) and (5), we interact prices with a dummy equal to one for minerals that are key inputs in battery production, while columns (3) and (6) include a second interaction term for REEs.⁴

⁴Battery minerals include copper, cobalt, lithium, graphite, manganese, nickel, and phosphorous. See

Results show that the responsiveness of CRM-saving innovation to mineral prices is substantially stronger for battery minerals and, especially, for REEs. Relative to the baseline long-run elasticity of 0.166, isolating battery minerals and REEs raises the elasticity to approximately 0.24 and 0.92, respectively. Comparing columns (2) and (3) with columns (5) and (6), the estimated elasticities for CRM-saving innovation are markedly higher than those for generic CRM innovations.

4.2 Robustness analysis

We conduct a broad set of robustness checks for both CRM-saving and CRM-reliant patent samples. Focusing on the former, Table 3 reports a selected subset of robustness exercises for CRM-saving patents, while the full set of results is reported in the Supplemental Appendix.⁵

Standard errors. In column (1) of Table 3, we assess the sensitivity of our inference to alternative choices of standard errors. We report Driscoll and Kraay (1998) standard errors, which are robust to cross-sectional dependence and serial correlation, and are very similar to those obtained under conventional clustering at the mineral level. In the same column, we also report wild-bootstrap p -values with one-way clustering by mineral. The bootstrap p -value for the long-run elasticity estimate remains below the 10% significance level.

Leads and COVID-19. In column (2), we augment the model with one lead of mineral prices, $\log P_{m,t+1}$, to test whether future price movements are spuriously correlated with current patenting activity, which would indicate reverse causality or omitted common shocks. The lead-augmented model is estimated over the 1981-2019 sample. The coefficient on the lead term is small and statistically insignificant, while the long-run elasticity based on lagged prices remains close to the baseline estimate. Because this specification is estimated on a sample ending in 2019, it also provides an indirect check for the influence of the COVID-19 pandemic. Results excluding 2020 are consistent with those including that year in the

e.g. <https://elements.visualcapitalist.com/the-key-minerals-in-an-ev-battery/>.

⁵The Supplemental Appendix reports additional regression results and robustness analyses that complement the main text. These include alternative lag structures, dynamic specifications, additional controls, nonlinear trend specifications. It also provides further details on the shift-share IV design, including instrument construction and economic motivation.

estimation sample.

Poisson pseudo-maximum likelihood specification. To verify that our results are not driven by the log-share transformation of the dependent variable, we re-estimate the model using the Poisson pseudo-maximum likelihood (PPML) estimator, including the annual total number of CRM-related patents, pat_t , as an exposure term. The PPML estimates reported in column (3) of Table 3 confirm the robustness of our findings, yielding a positive and statistically significant long-run elasticity that is even larger than in the baseline specification.

Market prices. In the absence of comprehensive global price data, our baseline analysis relies on USGS unit values, which are U.S.-specific and may differ from global market prices. To assess the sensitivity of our results to this choice, we collect real price data for selected CRMs from the IMF Primary Commodity Price System. We focus on CRMs with price histories extending back at least to 1990—aluminium, copper, iron, lead, nickel, tin, zinc, cobalt, gold, silver, and PGMs—and estimate the model over the 1993–2020 period. We augment the baseline specification with an interaction term that isolates the price response for this subset of minerals. Results reported in column (4) of Table 3 are positive and statistically significant at conventional levels for both price series, indicating that our main conclusions are not driven by the choice of price data.

4.3 Falsification test

Although the previous analyses show that our results are robust to numerous variations of the empirical specification, an important question remains unanswered: whether our methodology for identifying CRM-saving patents is necessary to isolate technologies whose objective is to reduce the use of CRMs, and whether this category of patents is in any sense unique. To address this issue, we design a “*falsification test*”.

Specifically, we construct an alternative set of patents based exclusively on a manual screening of CPC codes that identify technologies mentioning one or more CRMs and are related to recycling, waste management, material efficiency, and energy-related processes. Importantly, in this case we do not explicitly target CRMs reduction through text analysis. After excluding 376 CRM-saving patents that overlap with this classification, this procedure

yields a sample of 6246 patents, which we label as SMPR patents (Sustainable Metal Processing and Recycling).⁶ SMPR technologies are therefore technologically close to CRM-saving innovations and operate in similar application domains, making them a suitable comparison group for falsification purposes.

We next aggregate the data at the mineral-by-year level, obtaining a sample of the same size as in the baseline analysis, and estimate the same empirical specification as before, with the dependent variable defined as the share of SMPR patents over total CRM-related patents. As shown in column (5) of Table 3, the estimated long-run elasticity is statistically indistinguishable from zero. This result confirms that the price response identified in the baseline analysis is specific to technologies explicitly aimed at reducing CRM use, rather than to broadly related recycling, processing, or sustainability-oriented innovations, and that our text analysis is required to isolate such technologies.

4.4 A shift-share IV approach to induced innovation in CRM technologies

The results discussed so far rely on OLS estimation of the baseline specification, where identification comes from medium-run, mineral-specific deviations in real prices after controlling for trends and global confounders. Mineral prices may nonetheless be influenced by unobserved factors that also affect innovation. For example, the diffusion of electric vehicles may simultaneously raise demand for specific minerals and induce innovation aimed at reducing their use, generating correlations that do not reflect a causal supply-driven response.

We thus implement a shift-share instrumental variables (SSIV) approach that we view as complementary to the baseline OLS design, since it provides an independent source of plausibly exogenous, supply-driven, price variation.

The instrument is based on energy cost shocks, measured by energy CPI inflation, in the top three producing countries for each mineral. Mineral extraction is highly energy intensive,

⁶We select patents classified under CPC codes related to metal recovery from scrap (C22B7), recycling and efficient metal processing (Y02P10/2), solid waste management (Y02W30), material consumption minimization (Y02P80/30, Y02P80/40), bulk chemical processes (Y02P20/5), and battery-related technologies, including recycling of batteries and accumulators (H01M6/52, H01M10/54). In case of overlap, CRM-saving patents are excluded from the SMPR set.

relying on fuels and electricity that are core components of national energy CPIs (Parker, 2024). Because energy inputs represent a substantial share of mining costs, increases in producer-country energy prices raise extraction costs and are passed through to export and world mineral prices (Aramendia et al., 2023; Nuss and Eckelman, 2014). The identifying assumption is that this cost pass-through affects global mineral prices while remaining plausibly exogenous to CRM-saving innovation in downstream consuming countries. By exploiting cross-country heterogeneity in energy inflation among top producers and aggregating shocks using predetermined production shares, the SSIV isolates supply-driven price variation that is orthogonal to demand-side innovation dynamics.

We construct mineral-specific exposure weights using historical production shares from 1980–1999. Country-level shocks are defined as residuals from a first-order autoregressive model for inflation.⁷ Using residuals isolates the unpredictable component of energy cost shocks, as recommended by Borusyak et al. (2025).

Because exposure weights are constructed from 1980–1999 production shares, we estimate the SSIV specification on the 2000–2020 sample. Relative to the baseline specification in column (3) of Table 2, we make two adjustments: we drop the real commodity price index, which partly reflects energy prices and would absorb variation generated by the SSIV, and we rely on a single lag of real prices, instrumented by the corresponding lagged shift-share instrument. The three-lag specification suffers from weak instruments, whereas the parsimonious single-lag model substantially strengthens the first stage, yielding an F-statistic of 26.3.

The three-lag OLS specification yields a long-run elasticity of 0.32 (0.112), while the parsimonious one-lag OLS specification produces an elasticity of 0.13 (0.077), capturing the immediate adjustment while preserving the same qualitative response. Using CRM-reliant patents as the dependent variable yields a small and statistically insignificant coefficient of 0.045. The SSIV estimates imply an elasticity of 1.38 (0.389) for CRM-saving patents and 0.14 (0.058) for CRM-reliant patents. First-stage diagnostics support the validity of the instrument. Overall, the OLS and SSIV results reinforce the conclusion that higher

⁷Energy inflation data are from Ha et al. (2023). Missing observations are filled using headline CPI.

mineral prices causally increase CRM-saving innovation, with limited effects on CRM-reliant technologies. The relatively large magnitude of the SSIV elasticity is investigated in the next section.

4.5 Economic significance

To assess the economic significance of the estimated elasticities, we translate the OLS and SSIV coefficients estimated over the 2000–2020 period into changes in the observed share of CRM-saving innovation. These calculations should be interpreted as comparative statics rather than scenarios: they describe how the observed share of CRM-saving patents would respond to a permanent increase in mineral prices.

We begin with the OLS estimates. Under the three-lag specification, a doubling of mineral prices raises the share of CRM-saving patents from about 2% in 2020 to roughly 2.5%. Using the more parsimonious one-lag specification yields a smaller but still positive effect, increasing the share to approximately 2.2%. Despite differences in magnitude, the two OLS specifications imply qualitatively similar economic effects, indicating that higher mineral prices lead to a modest reallocation of inventive effort toward CRM-saving technologies.

The SSIV approach implies a substantially larger response. Under the SSIV estimates, a doubling of mineral prices raises the share of CRM-saving patents to about 5.2%, with a 95% confidence interval ranging from roughly 2.5% to 8.0%. This effect is considerably larger than the OLS-based estimates, though also less precisely estimated. Taken together, the comparison across OLS and SSIV specifications indicates that mineral price increases induce economically meaningful shifts in the direction of innovation. While the OLS estimates point to moderate adjustments, the SSIV results suggest that supply-driven price shocks can generate stronger responses, which can be interpreted as an upper bound relative to the OLS-based effects.

5 Conclusions

This paper develops a text-based approach to identify CRM-saving innovation using patent data and applies it to study how mineral price signals shape the direction of technological

change. By distinguishing technologies that merely rely on CRMs from those that explicitly aim to reduce their use, we move beyond aggregate measures of CRM-related innovation and focus directly on material-saving inventive effort. Our empirical analysis provides consistent support for the induced-innovation hypothesis. Higher mineral prices reallocate inventive activity toward CRM-saving technologies, while having little effect on innovation that continues to rely on critical materials. The response unfolds gradually, strengthens over time, and becomes more pronounced as CRM-saving technologies mature. We document substantial heterogeneity across minerals, with particularly strong responses for battery metals and rare earth elements, which are central to low-carbon and digital technologies. A falsification test based on a technologically similar set of patents yields no price response, confirming that our text-based identification strategy is essential. Moreover, a shift-share IV approach based on producer-country energy cost shocks delivers qualitatively similar conclusions. Despite these responses, the economic magnitude of the effects remains modest. Even large and persistent increases in mineral prices translate into relatively small changes in the observed share of CRM-saving patents, reflecting the very low baseline prevalence of such technologies. This suggests that market-driven price signals alone are unlikely to generate innovation at a scale sufficient to address long-run supply vulnerabilities associated with the energy and digital transition. Overall, our findings highlight both the potential and the limits of induced innovation in CRMs. While scarcity and price pressures do redirect inventive effort toward material-saving technologies, complementary policy interventions – such as targeted R&D support and incentives – are likely to play an important role in accelerating the development and diffusion of CRM-saving innovations.

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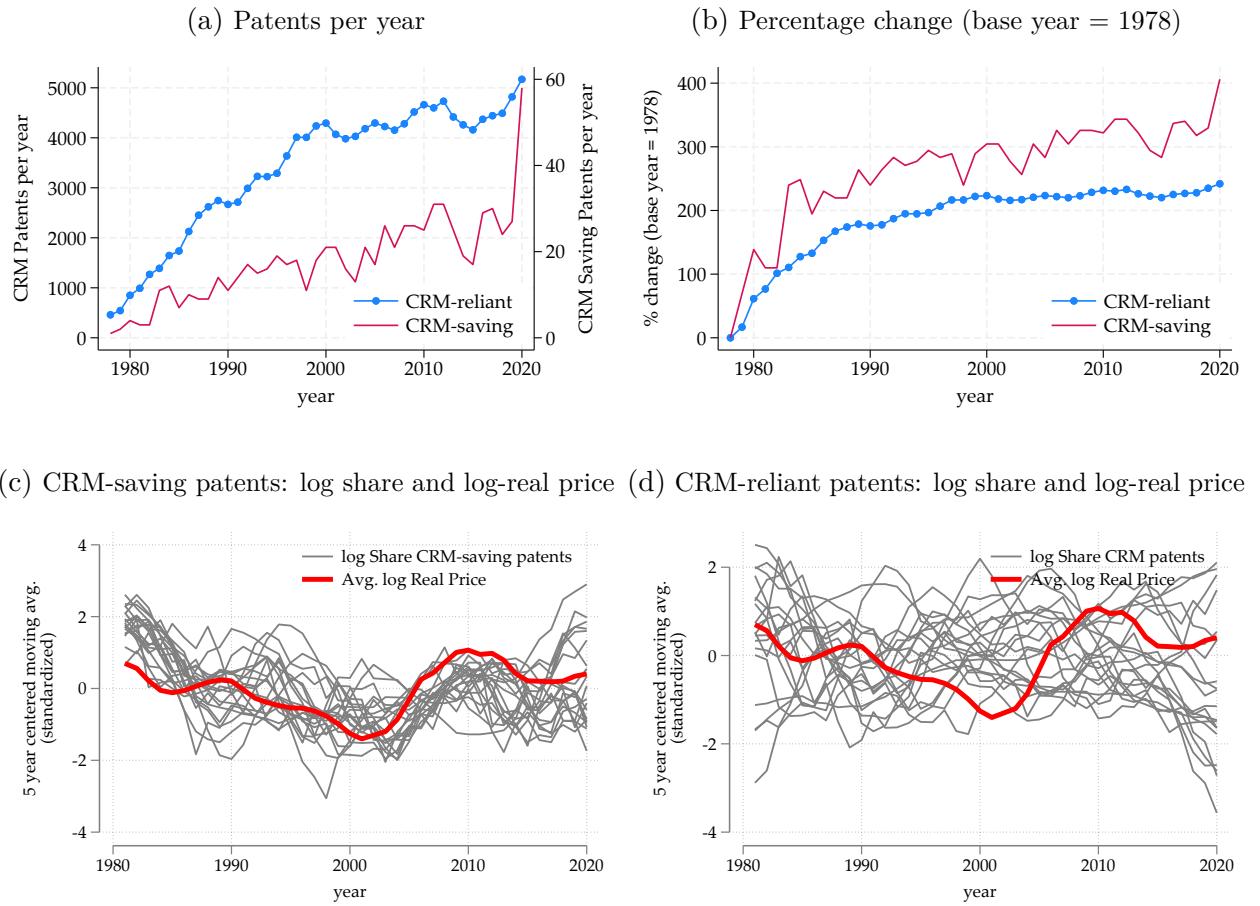
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Table 1: Glossary of words used to identify CRM-saving patents

<i>(a) List of raw materials (direct object, 48 words)</i>
(1) aluminium/aluminum; (2) arsenic; (3) borates; (4) cadmium; (5) chromium; (6) cobalt; (7) copper; (8) gallium; (9) germanium; (10) gold; (11) graphite; (12) hafnium; (13) indium; (14) iron; (15) lead; (16) lithium; (17) magnesium; (18) manganese; (19) molybdenum; (20) nickel; (21) niobium; (22) palladium; (23) phosphorus; (24) platinum; (25) selenium; (26) silver; (27) tin; (28) titanium; (29) vanadium; (30) zinc; (31) zirconium; (32-48) Rare-earth elements (REEs): cerium, dysprosium, erbium, europium, gadolinium, holmium, lanthanum, lutetium, neodymium, praseodymium, promethium, samarium, scandium, terbium, thulium, ytterbium, yttrium.
<i>(b) Verbal predicate (28 words)</i>
avoid; conserve; cut; cutback; decrease; efficiency; eliminate; less; lessen; lighten; limit; lower; minimize; mitigate; optimize; reclaim; recover; recycle; reduce; replace; reuse; save; simplify; streamline; substitute; substitute; trim; upcycle.
<i>(c) Object attribute (16 words)</i>
budget; consumption; cost; depletion; expenditure; expense; footprint; input; investment; outlay; overhead; price; slag; spending; use; waste.

Figure 1: CRM-reliant and CRM-saving patents over time: 1978-2020



Notes: Figure 1b reports the percentage change (or logarithmic growth rate) of the number of patents relative to 1978, which is used as the base year (i.e. $100 \times \log(x_t/x_{1978})$) Panels (1c) and (1d) plot the log-share of CRM-saving and CRM-reliant patents across minerals (thin gray lines) together with the log real metal price averaged over all CRMs (thick red line) starting from 1980. All series are smoothed using a 5-year centered moving average and then standardized to improve readability.

Table 2: The impact of prices on CRM-patents

	<i>CRM-saving patents</i>			<i>Other CRM patents</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel a: variation over time</i>						
	1981- 2020	1990- 2020	2000- 2020	1981- 2020	1990- 2020	2000- 2020
$\log P_{m,t-1}$	-0.029 (0.103)	0.014 (0.104)	-0.009 (0.122)	0.029 (0.029)	0.052 (0.035)	0.050* (0.028)
$\log P_{m,t-2}$	0.072 (0.142)	0.038 (0.153)	0.079 (0.180)	-0.004 (0.015)	-0.014 (0.019)	-0.020 (0.023)
$\log P_{m,t-3}$	0.123 (0.092)	0.205** (0.072)	0.249** (0.098)	-0.008 (0.017)	0.024 (0.025)	0.020 (0.020)
$\sum_{\ell=1}^3 \hat{\beta}_\ell$	0.166* (0.083)	0.257** (0.093)	0.319** (0.116)	0.016 (0.030)	0.062 (0.044)	0.051 (0.041)
Observations	760	620	420	760	620	420
FE	✓	✓	✓	✓	✓	✓
CRM \times trend	✓	✓	✓	✓	✓	✓
controls	✓	✓	✓	✓	✓	✓
<i>Panel b: battery minerals and REEs</i>						
	Baseline	Battery	Battery and REE	Baseline	Battery	Battery and REE
$\sum_{\ell=1}^3 \hat{\beta}_\ell$	0.166* (0.083)	0.121 (0.095)	0.096 (0.095)	0.016 (0.030)	-0.042 (0.034)	-0.041 (0.036)
$\sum_{\ell=1}^3 \hat{\beta}_\ell + \hat{\beta}_\ell^{bat}$		0.244* (0.128)	0.241* (0.128)		0.119* (0.065)	0.120* (0.065)
$\sum_{\ell=1}^3 \hat{\beta}_\ell + \hat{\beta}_\ell^{ree}$			0.918*** (0.078)			-0.046 (0.027)
Observations	760	760	760	760	760	760
FE	✓	✓	✓	✓	✓	✓
CRM \times trend	✓	✓	✓	✓	✓	✓
controls	✓	✓	✓	✓	✓	✓

Notes. The dependent variable is the log share of each patent type in total CRM-related and not-CRM-innovation. The coefficients of interest are the distributed-lag elasticities, which trace the dynamic response of innovation to mineral prices. Their sum measures the long-run elasticity of CRM-related (or not-CRM-related) innovation to a sustained price change. Controls include mineral fixed effects, mineral-specific-linear trends, lagged mineral-specific controls and lagged macroeconomic and policy factors common to all minerals. Panel A reports the distributed-lag elasticities, and their sum, over the whole sample (columns 1 and 4), from 1990 to 2020 (columns 2 and 5), from 2000 to 2020 (columns 3 and 6), by CRM-saving patents (columns from 1 to 3) or not-CRM-saving patents (columns from 4 to 6). Panel B reports the baseline estimates, as well as those that focus on CRM-saving (not-CRM-saving) patents related to batteries and REEs. Cluster-robust standard errors in parentheses. Standard errors are clustered by mineral. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: The impact of prices on CRM-patents: robustness checks

	<i>Std. errors</i> (1)	<i>Leads</i> (2)	<i>PPML</i> (3)	<i>Alt. prices</i> (4)	<i>Falsification</i> (5)
$\sum_{\ell=1}^3 \hat{\beta}_\ell$	0.166** (0.073)	0.137** (0.064)	0.291** (0.119)	0.397*** (0.102)	0.0001 (0.0002)
$\log P_{m,t+1}$		0.025 (0.064)			
$\sum_{\ell=1}^3 \hat{\beta}_\ell + \hat{\beta}'_\ell$				0.267** (0.125)	
p-value ^{boot}	0.078				
Observations	760	740	760	560	760
FE	✓	✓	✓	✓	✓
CRM \times trend	✓	✓	✓	✓	✓
controls	✓	✓	✓	✓	✓

Notes. The dependent variable is the log share of each patent type in total CRM-related innovation in all columns but column 3. In column 3 the dependent is the count CRM-related innovation. Controls include mineral fixed effects, mineral-specific-linear trends, lagged mineral-specific controls and lagged macroeconomic and policy factors common to all minerals. Column 1 reports Driscoll and Kraay (1998) standard errors. In columns (1) “p-value^{boot}” denotes wild-bootstrapped p-values based on 9,999 replications computed using the `boottest` Stata package of Roodman et al. (2019), with one-way clustering by mineral. Column 2 includes one lead of log mineral prices, $\log P_{m,t+1}$. Column 3 employs a Poisson pseudo-maximum likelihood (PPML) estimator. Column 4 additionally employs market-based prices. Column 5 reports a falsification test. Except column 1, the other columns have cluster-robust standard errors in parentheses. Standard errors are clustered by mineral. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: SSIV approach: 2000–2020

	CRM-saving patents		Other CRM patents	
	(1) OLS	(2) SSIV	(3) OLS	(4) SSIV
$\hat{\beta}_1$	0.131* (0.077)	1.38*** (0.389)	0.045 (0.030)	0.135** (0.058)
First stage coeff.		1.06 (0.207)		1.06 (0.207)
KP F-stat.		26.26		26.26
SY 10% C.V.		16.38		16.38
obs.	420	420	420	420
FE	Y	Y	Y	Y
CRM \times trend	Y	Y	Y	Y
controls	Y	Y	Y	Y

Notes: robust standard errors in parentheses. * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. “controls” indicates that we include all mineral-specific and macroeconomic explanatory variables, except the commodity price factor.

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