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Abstract

In this paper, we present a critical raw materials index (CRMI) that represents the price dynamics of the raw materials required for the low-carbon transition. Using a unique market and trade dataset covering 29 critical raw materials from 2012 to 2023, we construct a weekly trade weighted price index following a robust methodological framework. The relevance of our index is demonstrated through a validation process including a plausibility analysis and a comparability analysis. In addition, a sensitivity analysis provides empirical evidence of the robustness of our index to alternative data treatment, weighting factors and weighting schemes. Our framework offers policymakers a useful price benchmark to track the underlying metal market dynamics required by the growing clean energy sectors.

JEL: C43, Q3, Q4, Q54.

Keywords: Critical Raw Materials Index (CRMI), Energy Transition, Index Construction, Metal prices.

1. Introduction

In this paper, we present a critical raw materials index (CRMI) that represents the price dynamics of the raw materials required for the low-carbon transition. Using a unique market and trade dataset covering 29 critical raw materials from 2012–2023, we construct a weekly trade weighted price index following a robust methodological framework. Focusing on the raw materials critical for the low-carbon transition, the CRMI provides a benchmark to track the dynamics underlying the growing clean energy sectors, e.g., electric vehicles, electricity networks, grid battery storage, hydrogen, solar photovoltaics (PVs), and wind.

Climate change mitigation is a crucial issue for policymakers and critical raw materials play a key role in the energy transition. Indeed, a growing use of renewable energy is a nonavoidable

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alternative to the use of carbon-intensive fossil fuels, and this growth depends on the availability of a set of raw materials such as copper, cobalt, graphite, or rare-earth elements. Unfortunately, critical raw materials are scarce and not equally distributed around the world in terms of extraction, refining and trade. Consequently, this market exhibits some oligopoly dynamics (IRENA, 2023; European Commission, 2024) that are exacerbated by the recent rise in trade restrictions, resource nationalism, or regulatory measures for those raw materials (Kowalski and Legendre, 2023; Nobletz et al., 2024).

For example, China's rare earth export controls have had significant impacts on the global supply chain. In particular, the 2010 China–Japan crisis led to price bursts of rare earth elements (Seaman, 2019; Liu and Paton, 2022). Other recent geopolitical tensions between China and the US have fueled fears in the metal market. Indeed, in response to US protectionist policies, China announced trade restrictions on germanium, gallium (Harper, 2023; Weaver, 2022), and graphite (Benson and Denamiel, 2023), which are needed for the production of solar PVs and electric vehicles. These types of restrictions could lead to potential supply and demand bottlenecks, exponential price increases (Boer et al., 2024) and difficulties in financing the clean energy transition. The consequences would be all the more relevant for the poorest households (Seck et al., 2022; Hache and Louvet, 2023).

Recently, only a few studies have investigated metal price dynamics and their relationships with economic activity. In addition, empirical papers about critical metals are mostly restricted to specific metals, such as rare-earth elements (Reboredo and Ugolini, 2020). Therefore, the literature lacks a price index that is representative of the critical materials market, which is required to carry out empirical studies in the low-carbon economy field. Moreover, such an index would be a valuable tool for policymakers to monitor developments relative to the demand and supply in this market. Specifically, a critical metal price index could be used to construct scenarios that consider critical materials for clean energy technology trajectories that impact climate change paths. More broadly, such an index would help to monitor market tensions and take the appropriate measures to secure supply chains.

Our goal is to propose a new index that provides a signal of the state of the critical raw materials in the world market. This contribution is based on two innovations: data variable selection and the index construction method. On the one hand, the components of the index were sourced in an original way: materials were selected on the basis of their criticality to the energy transition, and the weights were calculated on the basis of export volumes that were carefully selected. On the other hand, data processing and the aggregation of the various components of the index were carried out within a rigorous methodological framework, including the management of missing and extreme values and the calculation of the weights. Finally, a sensitivity analysis to changes in assumptions related to data collection and processing, as well as to the aggregation of the index components, was carried out to assess the robustness of the index.

The rest of this paper is organized as follows. Section 2 reviews the literature on critical raw materials, with a particular emphasis on their pricing determinants. Section 3 offers a review of the methodology for CRMI construction. Section 5 describes the dataset and the main empirical results. Specifically, the construction process is detailed, including the definition and measurement of the index. Section 6 presents two exercises aimed at ensuring the validity of the CRMI. Section 7 presents a sensitivity analysis performed to evaluate the robustness of the CRMI. Finally, Section 8 concludes the paper.

2. Literature Review

Among raw materials, metals are receiving increasing attention in the literature. As in the case of oil, the study of mineral price dynamics has aroused interest in terms of their impact on both companies and governments. To optimize production cost management, company managers need to understand and anticipate variations in metal prices. The same applies to public decision-makers, who need to consider fluctuations in mineral prices to develop effective economic policies, particularly in the areas of international trade, industry and energy, as well as to meet the challenges of national defense. Business managers and policymakers must also ensure the security of supply by implementing strategies to diversify supply sources and reduce the risk of shortages. In this context, the economic literature has been enriched by works on precious metals (e.g., silver and platinum) but also on ferrous base metals (e.g., iron and steel) or nonferrous base metals (e.g., aluminum and copper). Most of these contributions have focused on examining the factors that determine the prices of these metals on subsets of metals according to demand or supply determinants. The literature on the determinants of metal prices has focused on this duality, exploring the economic, geopolitical and environmental drivers of metal prices. More specifically, empirical evidence indicates that global economic growth, interest rates, exchange rates and monetary policies influence the demand for metals. Conflicts, economic sanctions and geopolitical tensions can impact the metal supply. Finally, environmental regulations, natural disasters and climate change concerns can also impact metal supply and demand. Important contributions include Klotz et al. (2014) and Li et al. (2023), who studied the determinants of demand in the metal market, whereas Wanner et al. (2014) and Baffes and Savescu (2014) focused on the determinants of supply. There are also contributions in the literature concerning supply and demand shocks and their impacts on prices (Hu et al., 2017; Ehrlich, 2018). The literature on metal price dynamics is also based on either a microeconomic or a macroeconomic approach. The former examines the role of market concentration (Bucciarelli et al., 2024), production constraints (IEA, 2023) and market structure (OTC) (IRENA, 2023). The latter investigates the role of geopolitics, which has been the cause of the sharp increase in the prices of certain metals (Seaman, 2019; Farchy et al., 2022; Harper, 2023; Weaver, 2022; Benson and Denamiel, 2023; Liu and Paton, 2022), emphasizing that this effect differs from one metal to another (Chen et al., 2022; Li et al., 2023). Other contributions have examined the interactions between metal prices and the prices of other commodities, such as oil or gold (Reboredo and Ugolini, 2020).

Recently, the empirical literature has been enriched by studies on the price dynamics of critical metals. These metals cover a wide range of very diverse metals, including rare earths, aluminum and copper. The definition of critical materials varies according to the context. The notion of criticality is related to four levels of risk: geological, economic, strategic and environmental (Hache and Carcanague, 2022). In particular, driven by the importance of the fight against global warming, researchers have studied the price dynamics of certain metals needed for the transition to a low-carbon economy. In this context, the literature has been enriched by empirical contributions analyzing the relationships between critical metals for environmental risk and green energy indices (Baldi et al., 2014; Bouri et al., 2021; Sohag et al., 2023). However, these contributions each focused on one or more given metals. Hu et al. (2017) only considered copper, Reboredo and Ugolini (2020) only considered rare earths, and Wang et al. (2023) only considered nickel. Above all, very few contributions have focused on the metals needed for the transition to a low-carbon economy. The few studies that do so are limited to a few metals separately and often to rare earths and not as a whole. A few exceptions are the contributions of Seck et al. (2022) and Boer et al. (2024), which examined whether metals for the energy transition could constitute a bottleneck for zero net emissions. In particular, Seck et al. (2022) studied the evolution of cobalt demand on the basis of several climate and mobility scenarios and showed that the cobalt supply will probably not be sufficient to meet the growth in demand for this metal, which is needed to manufacture the batteries used in electric and hybrid vehicles. Using a more econometric approach, Boer et al. (2024) studied the impact of copper, nickel, cobalt and lithium prices in an analysis of structural scenarios. Their results indicated that the prices of these four metals could not only return to their historical highs but also remain there for very long periods, which could hinder the transition to a low-carbon economy. The recent literature has therefore been enriched by this study, which is a significant contribution to the field of research dedicated to the fight against global warming. However, this list of metals is only a subset of those critical to the energy transition. This gap in the literature is linked to several limitations in terms of data, which stem from the fact that the critical metals market is an OTC market and from the plurality of definitions of critical metals. On the one hand, issues related to the collection of prices and volumes are typical of OTC markets. Missing values and the opacity of the trading system mean that the data are not always reliable and that there is a need for data processing, including data imputation and the management of extreme values. On the other hand, as the definition of critical metals is not unanimous, the selection of a complete list of critical metals for the energy transition is not trivial. Among the possible solutions, the construction of a price index of critical metals for the energy transition would make it possible to smooth out the problems associated with each metal in particular while offering a reference that could serve as a basis for prospective and empirical studies in the field of the energy transition.

3. Methodology

The CRMI was constructed using the methodology for composite indicators from Nardo et al. (2008)'s framework. This composite indicator construction process, resulting from the collaboration between the Organisation for Economic Co-operation and Development (OECD) and the Joint Research Center (JRC) of the European Commission, is a reference in the literature related to the consequences of climate change. For example, Lèbre et al. (2020), Sciarra et al. (2021), and Papathoma-Köhle et al. (2022) used this methodological framework to construct indicators related to energy transition metals, sustainable development and wildfire vulnerability, respectively. Specifically, this framework consists of two steps: (i) data treatment and (ii) weighting. These steps are described in Subsections 3.1 and 3.2, respectively .

3.1. Data treatment

In his seminal paper, Rubin (1976) noted that ignoring missing data can lead to, in addition to a loss of precision, significant biases in the analysis models. Various strategies exist to handle missing data, either by deletion or by imputation. The selection of the appropriate method depends on the nature of the missingness mechanism, which can be random or not random. Little and Rubin (1987) proposed a typology distinguishing three categories: (i) missing completely at random (MCAR), (ii) missing at random (MAR), and (iii) missing not at random (MNAR).

Specifically, a dataset is considered to be MCAR if the probability of absence is identical for all observations. This situation is rare but can occur when missing data are due to random events unrelated to the variables studied. The MCAR hypothesis can be inferred via Little (1988)'s test. The data are MAR if the probability of absence depends on one or more other observed variables. In this case, imputation by regression on the predictors of missingness is possible and allows us to correct the bias. The MAR hypothesis can be tested via Diggle (1989)'s approach. Alternatively, the data are MNAR if the probability of absence depends on the variable itself. This situation is problematic because it introduces a bias that cannot be corrected by standard imputation methods. A sensitivity analysis can be useful for assessing the impact of MNAR missingness on the results.

Since the 1980s, the management of missing data has given rise to abundant literature in all scientific fields. In economics, data gaps can stem from various reasons, including trading suspensions and a lack or irregularity of economic activity. More recently, some contributions in macroeconomics have studied the impact of missing values on nowcasting accuracy (Giannone et al., 2008) or financial development index construction (Svirydzenka, 2016). Currently, this subject is still very topical, both theoretically and empirically (i.e., Bai and Ng (2021) and Jin et al. (2021)).

Different methods of data imputation coexist in time series analyses. If missing data are not MCAR, then simply deleting the relative observations is not an option. Data imputation is necessary and depends on the statistical properties of the time series and the economic context. When the data are stationary, replacing the missing value at time t with the last observed value at time t^* (i.e., the last observation carried forward method) is widely used. Alternatively, a common technique is to replace all missing values with a linear combination of observations, such as the mean of nonmissing values. More formally, let $P = (p_{it}) \in \mathbb{R}_+^{N\times T}$ be the matrix of prices, where p_{it} is the price of mineral i at time t, with $i \in \{1, ..., N\}$ and $t \in \{1, ..., T\}$. Let $M = (m_{it}) \in \{0, 1\}^{N\times T}$ be the shadow matrix of P, so that $m_{it} = 1$ if p_{it} is missing, and $m_{it} = 0$ otherwise. Then, the last observation carried forward method data imputation can be written as follows:

$$(p_{it}) = \begin{cases} \{p_{it}\} & \text{if } m_{it} = 0 \\ \{p_{it^*} | m_{it} = 0, t^* < t\} & \text{if } m_{it} = 1 \end{cases}. \tag{1}$$

In the special case where only one value is missing at time t, then $t^* = t - 1$ such that $p_{it} = p_{it^*} = p_{i(t-1)}$.

Instead of using all available observations, it is also possible to restrict the set of observations to a sample to perform a local aggregation. Alternatively, missing values can be extrapolated via a (local) regression of a linear or autoregressive model.

In summary,, managing missing data is therefore a necessary and crucial step in ensuring the quality of the database used for research in economics. The choice of the appropriate method depends on the type of missingness and the nature of the variable. Finally, this choice must be made with a full understanding of the reasons for the underlying missing values and motivated by an economic rationale.

Using the last observation at time $t - 1$ as a substitute when the data at time t are missing is common in economics. Other imputation techniques exist, including mean imputation. Mean imputation is also common for handling missing data. It involves replacing missing values with the mean of the observed values for the same variable. Such data imputation is debatable from an economic perspective, but from a statistical point of view, the technique is simple to implement and preserves the mean of the variable. In the context of time series, the mean imputation consists of calculating a moving average. Considering the $k - 1$ values observed over a time window from $t - k$ to $t - 1$, the mobile average imputation can be written as follows:

$$(p_{it}) = \begin{cases} \{p_{it}\} & \text{if } m_{it} = 0 \\ \{\overline{p_{it}}\} & \text{if } m_{it} = 1 \end{cases}, \tag{2}$$

where $\overline{p_{it}}$ is the mean value of the elements $\{p_{it} | m_{it} = 0 and t \in [t - k, t - 1]\}$.

Extreme values are often present in economic databases. If these values are interpreted as outliers, then it is important to remove them or at least reduce their influence. Indeed, outliers can have a significant effect on the robustness of the estimations. Two approaches can be used to improve the quality of the data and thus make the statistical analyses more reliable: trimming and winsorization. From a given quantile threshold q_α, trimming removes the extreme values from the dataset, whereas winsorization replaces those extreme values with the α percentile value.

In the context of market data analysis, considering extreme variations as noise is debatable. Indeed, those variations are more likely to be related to economic events than accounting errors. Therefore, winsorization is better adapted than trimming, as replacing extreme data values with percentile values reduces the influence of these values without completely omitting them. More formally, winsorization can be written as follows:

$$(p_{it}) = \begin{cases} \{p_{it}\} & \text{if } |p_{it}| \leq q_\alpha^i \\ \{q_\alpha^i\} & \text{if } |p_{it}| > q_\alpha^i \end{cases}, \tag{3}$$

where q_α^i is the α percentile value of the element i.

Data aggregation usually requires normalization because indicators often have different sets of definitions. Additionally, analysis often focuses on returns, not raw prices, further reducing the need for normalization.

However, combining elements from different probability distributions can be challenging in statistics, and normalization methods such as standardization (z score) can help address this issue. Here, the normalized data can be written as follows:

$$(p_{it}) = \{(p_{it} - \mu_{p_{it}})/\sigma_{p_{it}}\}, \tag{4}$$

where $\mu_{p_{it}}$ and $\sigma_{p_{it}}$ are the mean and the standard deviation of raw prices p_{it}, respectively.

3.2. Weights

In economics, weights significantly impact the final indicator in a benchmarking framework, and various methods are used to assign weights. These methods range from using market data to statistical analysis, but they all reflect a judgment about which factors are most important. While some rely solely on statistics, others incorporate expert opinions on influential components. Alternatively, other indicators are based on equal weighting. Equal weighting in composite indicators treats all variables as equally important. This approach is simple, but it can mask a lack of deeper justification and lead to a nonrepresentative indicator.

Capping weights are an optional step when constructing a composite indicator. A capped composite indicator limits the influence of any single element within the indicator. Even if an element dominates the market, its weight in the indicator is capped at a predetermined maximum. The process consists of four steps: (i) each element's weight is based on a given economic factor (e.g., its market share), (ii) if any element's weight surpasses a set limit (i.e., threshold being equal to ω_{max}), then its weight is reduced to ω_{max}, (iii) the excess weight is then divided equally or proportionally among the remaining elements, and (iv) if this redistribution causes other elements to exceed the cap, then Steps (ii) - (iv) are repeated until all the elements stay within the weight limit. The weights can be written as follows:

$$\omega_i(t) = \frac{EF_i(t)}{\sum_{i=1}^{N} EF_i(t)}, \tag{5}$$

where $\omega_i(t)$ and $EF_i(t)$ represent the weight and the economic factor of element i at time t, respectively. By definition, we have $\forall i \in \{1, ..., N\}$, $\omega_i(t) \in [0, 1]$ and $\sum_{i=1}^{N} \omega_i(t) = 1$.

Capping a composite indicator has advantages and disadvantages. On the one hand, capping prevents a single element from swaying the overall indicator. In addition to the fact that capping the weights of an indicator ensures the representativity of an entire set of elements, it can also promote its stability by mitigating the influence of any single element. Indeed, capping reduces the indicator's sensitivity to extreme observations relative to a single element having a very large weight. On the other hand, cap weighted indicators do not always accurately reflect the real set of elements. For example, most traded raw materials do, in fact, have greater influence on the commodity market than others do. Furthermore, capping weights have an impact on the distribution of weights. Reducing the weights of elements whose weights exceed a certain threshold implies increasing the weights of other elements. The way in which weights are redistributed (equidistributed or proportional) is therefore crucial.

The way a composite index prioritizes its subindicators is determined by the weights assigned to each of them. Several weighting methods coexist to construct price indices. Trade weighting, which is commonly used for commodity price indices, assigns higher weights to components with a larger share in overall trade. Equal weighting, where each subindicator has the same weight, is also an option. In addition, capping the weights within a specific range can be useful to avoid situations where a single dominant factor overly influences the entire index. Furthermore, the way to redistribute the surplus to other weights can depend on the other weight values or not.

The choice of weighting method significantly impacts the final value of the composite index. By comparing different versions of the same index calculated with various weighting methods, one can explore how the variability in weights affects the overall score. This analysis helps to evaluate the sensitivity of the index to these weighting choices and ultimately strengthens its robustness.

4. Constructing an energy transition metal price index

The forthcoming section is dedicated to the development of a comprehensive and robust price index representative of the critical metals market. The index construction is divided into three key steps. First, we define the components that constitute the index, outlining the critical raw materials to be considered and their trading codes. Second, we describe the sample selection in terms of time coverage and frequency. Third, we discuss the different weighting factors and weighting schemes that can be used to aggregate components of a price index.

4.1. Data selection process

To identify the metals and minerals critical for the energy transition, it is important to clarify several definitions, including the distinction between minerals, metals and materials. Minerals are naturally occurring inorganic elements or compounds with unique chemical compositions and crystal structures that serve as the building blocks of rocks (aggregates of minerals) and ores (economic rocks). Metals are a subset of minerals with specific chemical elements or alloys characterized by properties such as luster, malleability, ductility and conductivity. Metals are extracted from ores, refined and used in various applications (ICMM, 2024). Materials, in turn, include a wider range of substances than metals do, including ceramics, polymers and composites. In most applications, the term "minerals" refers to the extraction stage, whereas "metals" and "materials" refer to the refining stage. In this study, we use the broader terms "metal" or "material."

Regarding key materials for energy transition technologies, we used the International Energy Agency's (IEA) Critical Minerals Data Explorer 2024a. This database makes publicly available global demand projections for critical energy transition metals. We retrieved 29 metal price series from the 31 reports in the IEA database. In fact, we have no data for "boron", and the data found for zirconium are of insufficient quality to be included. We cover six sectors: electric vehicles (11), electricity networks (2), grid battery storage (7), hydrogen technologies (6), solar PVs (15), and wind (10). Table 1 underlines the metals in the clean energy sectors.

Importantly, not all of these metals are considered "critical" by countries. The concept of metal criticality is not universal. A metal is considered "critical" if it is of high economic importance and/or faces a high risk of supply disruption due to factors such as geographical concentration, limited reserves or lack of affordable substitutes. Furthermore, criticality extends beyond the energy transition sectors to strategic industries such as digital technology, aerospace and defense (European Commission, 2023). For example, a smartphone can contain up to 50 different metals, each contributing to its compact size, lightweight and functionality (ibid). Consequently, this study focuses on metals that are critical to the clean energy sectors and related technologies. Of the 29 metals selected, 23 are identified as critical for the European Union (European Commission, 2023), and 26 are identified as critical for the United States (U.S. Geological Survey, 2022)(Table A, Appendix).

Table 1: Metals in the clean energy sectors

Electric Vehicle (EV):	Cobalt, Copper, Dysprosium (REE), Graphite, Lithium, Manganese, Neodymium (REE), Nickel, Praseodymium (REE), Silicon and Terbium (REE);
Electricity Networks:	Copper and Aluminium;
Grid battery storage:	Cobalt, Copper, Lithium, Manganese, Nickel, Silicon and Vanadium;
Hydrogen technologies:	Cobalt, Copper, Iridium (PGM), Nickel, Platinum (PGM), Yttrium (REE) and Zirconium**;
Solar PV:	Arsenic, Cadmium, Copper, Gallium, Germanium, Indium, Lead, Molybdenum, Nickel, Selenium, Silicon, Silver, Tellurium, Tin and Zinc;
Wind:	Boron*, Chromium, Copper, Dysprosium (REE), Manganese, Molybdenum, Neodymium (REE), Nickel, Praseodymium (REE), Terbium (REE) and Zinc.

Notes: The list of critical metals for the clean energy transition sectors is provided by the IEA (2024a). Please note that REE stands for rare earth elements, PGM for platinum group metals and PV for photovoltaics. Finally, * indicates that we were unable to find the data, while ** indicates that the quality of the data was insufficient to be included in our index.

Regarding the price series selected for each metal, we evaluated approximately one hundred series. To differentiate between them, we applied several "selection rules."

First, we favored metal series that are traded on a global exchange. When these series were unavailable, we turned to the Chinese export price series, noted as free on board FOB). Indeed, not all metals are traded on global exchanges, as many are traded over the counter (OTC). The Shanghai Metal Market is the major price reporting agency (PRA) for minor metals, and their prices serve as a benchmark for financial investors. The SMM provides metal prices for China and its provinces, as well as its export metal prices. We select export prices when possible to better account for worldwide dynamics while excluding Chinese internal demand factors. This latter point is important, as China produces many metals, but a substantial share of this production is consumed domestically.[1] Additionally, we focused on Chinese export prices rather than foreign import prices (i.e., cost, insurance, and freight price (CIF)), as the metal market is characterized by strong market concentration, and China is one of the biggest actors. For example, China extracts 43% of the rare earth elements and even refines 70% of the latter globally (European Commission, 2023). Therefore, we prefer to rely on the producer side, especially as the data provided by the SMM have better quality, with series having daily price variations, compared with foreign import series.

Second, after differentiating on the basis of whether the metal is traded on a global exchange or if it is a Chinese export price, we further discriminate between series on the basis of their daily price variations and/or their historical coverage. In simple terms, we prefer series that exhibit daily price variations and have long historical coverage. For example, regarding the rare

[1] The pricing dynamics between Chinese export prices of metals and domestic prices are aligned. The discrepancy in nominal values is because transactions involving metals abroad are predominantly conducted in US dollars, whereas domestic exchanges are conducted in renminbi.

earth series, we had the choice between the rare earth FOB prices in oxide or metal form. We selected the rare earth elements in oxide form, as these series have a higher trading volume than their counterparts do (Proelss et al., 2018).

Third, we also discriminated between series on the basis of the providers. For instance, we had two silver prices that share exactly the same dynamics, but one series is provided by the London Bullion Market Association (LBMA) and one by Handy & Harman (a manufacturer of silver). We preferred the series from the LBMA as it is an independent precious metal authority.

Finally, the final criterion for selecting our series is based on the shape of the metal traded. We favored a metal shape that is closest to its utilization in clean energy technology. To illustrate, we had several series of silicon with different degrees of purity, i.e., #2202, #3303, #441, and #553. As the silicon used in solar PVs is the highest purity silicon at 99.99% (SCRREEN, 2020), we chose the series with the purity level that comes closest to this value, which is #2202 with 99.58%. The only exception to our selection criteria is for lithium, where we selected the Chinese domestic price, as we do not have access to the FOB prices, and the series traded on the LME only starts in 2021. All the series discriminated are disclosed in Table B in the Appendix.

All of the selected metal prices are spot prices. Spot prices provide greater insights into the real drivers of the markets by avoiding speculative behaviors (IRENA, 2023). Additionally, many series simply do not have future prices because, as previously mentioned, many metals are not traded on a global exchange, e.g., graphite or rare earth elements. Furthermore, the frequency of our metal series is mostly daily prices. The exception is graphite, which is available weekly. While we could have constructed an index with a daily frequency by excluding the graphite price series, we preferred to keep this metal and construct our index on a weekly frequency. This choice is justified for several reasons. First, a weekly frequency better matches the characteristics of metal prices. Indeed, many minor metals do not experience daily price fluctuations because of the limited number of exchanges. Second, keeping the graphite series is necessary because this metal is crucial in the construction of EV batteries. Finally, constructing a weekly index allows us to handle the time-shifting problems between different exchange places/price reporting agencies and to avoid autocorrelation issues. Moreover, the index is constructed using the return of the weekly metal prices, enabling us to handle different currencies effectively. Indeed, all series are in USD, except for lithium, which is in Renminbi. Table 2 lists all the selected metal series.

Finally, to construct an index (as described in Section 3) that properly represents the metal market, we need to weigh the metal components of the index in terms of their trading volumes. This step is necessary because the metal market is characterized by strong heterogeneity; e.g., the trading volume of copper is not the same as that of dysprosium. However, we do not have these data, especially for minor metals that are traded over the counter. We have therefore approximated trade volumes by using global export flows for each metal. The choice of export flows rather than import flows is in line with our focus on the producer side and ensures consistency with our previous data selections.

The global export flows of the metals have been exported from the BACI database, constructed and updated annually by Gaulier and Zignago (2010). This database represents a refinement of the UN Comtrade database. The UN Comtrade database is the most comprehensive worldwide trade database containing detailed import and export statistics. However, this latter database is also subject to several well-known limitations, including the presence of outliers, missing values and asymmetrical bilateral relationships between import and export values. The BACI database addresses these shortcomings by addressing the issue of missing values, matching export and import data and standardizing unit values (Gaulier and Zignago, 2010). This latter aspect is of particular significance, as to ascertain the metal weight on the index, the volume of the export metal product is divided by the total volume of the export of all metals. Consequently, it is essential to employ the same unit of measurement.

To identify the product codes for each metal, we employed the Harmonized System (HS) Codes, specifically HS17. The Harmonized System is an internationally standardized product classification system maintained by the World Customs Organization (WCO). The system is employed to identify products for exports and imports, assess the associated duties and taxes, and compute trade statistics (ITA, 2024). Each HS code is a multidigit number, with a maximum of six digits. The first two digits represent the chapter, which serves to indicate a broad category of goods. The subsequent two digits represent the heading, which provides a more specific classification. Finally, the last two digits represent the subheading, which provides the most detailed product lines.

To ensure maximum precision for each metal, we used the six-digit HS codes that most closely match the metal price series (Table 3 for the HS codes per metal). The codes were chosen on the basis of three criteria.

First, if the form of the metal traded is known, we chose the product code that includes that form. For example, the traded forms of the aluminum price series are ingots, bars and sows. Therefore, we selected the HS codes 760120, 760410 and 760429, which include ingots (i.e., the unwrought form) and bars. In this example, as we have several code products for one metal, our export volume is the average of all selected HS codes.

Second, when the form of the metal traded is unknown, we used other characteristics, such as the metal content or purity, to identify the appropriate code. For example, we did not know the form of the traded silicon, but we knew that its content is 99.58%. Therefore, we chose the HS code "Silicon: containing less than 99.99% silicon by weight". When the choice was not straightforward, we used external resources. We know that gallium and germanium are traded at high purity levels, suggesting unwrought forms. This information comes from "Western Minmetals", a company specializing in these metals, and is cross-checked with the

Zauba database, which lists all exports and imports to India, along with the associated HS codes. Overall, where possible, we tended to select the HS code that includes the unwrought form of the metal. This form is commonly traded, falls in the middle of the supply chain (neither in the initial extraction phase nor in the final refining phase) and allows for a better comparison with other metals. For a correct representation of the market, it is appropriate to consider the volume of metal exchanged at the same stage of the value chain.

Finally, for several minor metals with limited exchanges, we have no choice of HS code, as there is only one code. This is notably the case for rare earths, tellurium and selenium.

By following these criteria, we ensure that our choice of HS codes accurately reflects the trading forms and characteristics of the metals, thus facilitating accurate and meaningful analysis of their price series.

In summary, in this section, we explained how we defined a critical metal for the energy transition. We then explained the data selection process for the metal price series. Finally, we explained how we identified the "right" HS code of metal transactions to effectively weight the index.

Table 2: Metals in the index

Name	Series	Tickers	URL	Type	Currency	Unit	Freq.	Provider	Database	Start date
Aluminium	LME-Aluminium 99.7% Cash U$/MT	LAHCASH(P)	link	Spot	USD	t	D	LME	Datastream	31/07/1957
Arsenic	China Arsenic Metal 99% FOB	ARCNJQLL AMTL	NA	Spot, FOB	USD	t	D	NA	Bloomberg	02/07/2004
Cadmium	Europe Cadmium Ingot 99.99% In warehouse Rotterdam	CMEUSLKG AMTL	link	Spot	USD	lb	D	Asian Metal	Bloomberg	01/02/2006
Chromium	China Chromium Metal 99% FOB	C9CNRLJI AMTL	link	Spot, FOB	USD	t	D	Asian Metal	Bloomberg	12/01/2001
Cobalt	LME-Cobalt Cash	LCOCASH(P)	link	Spot	USD	t	D	LME	Datastream	22/02/2010
Copper	LME-Copper Grade A Cash U$/MT	LCPCASH(P)	link	Spot	USD	t	D	LME	Datastream	30/01/1957
Dysprosium	China Dysprosium Oxide 99% FOB	DMCNGTMR AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	20/04/2001
Gallium	China Gallium Metal 99.99% FOB	GACNDQSD AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	12/01/2001
Germanium	China Germanium Metal 99.99% FOB	GECNMVKY AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	12/01/2001
Graphite	Graph spherical 99.9 FOB China	MGRA036(P)	link	Spot, FOB	USD	t	W	Fastmarkets MB	Datastream	30/03/2012
Indium	China Indium Ingot 99.99% FOB	IUCNNWTD AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	12/01/2001
Iridium	JM Iridium London U$/Troy Oz	JMIRIEU(P)	link	Spot	USD	t oz	D	JM	Datastream	01/07/1992
Lead	LME-Lead Cash U$/MT	LEDCASH(P)	link	Spot	USD	t	D	LME	Datastream	05/07/1993
Lithium	Lithium Metal =99%, Battery Grade	SMINLTM(P)	NA	Spot, Domestic.	CNY	t	D	SMM	Datastream	01/06/2012
Manganese	SMM Electrolytic Manganese Metal Spot Price Daily	SMM-EMM-USD	link	Spot, FOB	USD	t	D	SMM	Reuters	01/06/2012
Molybdenum	Europe Molybdenum Oxide 57% In warehouse Rotterdam	MBEUDGDZ AMTL	link	Spot	USD	lb	D	Asian Metal	Bloomberg	26/10/2005
Neodymium	China Neodymium Oxide 99% FOB	NDCNDLXH AMTL	link	Spot, FOB	USD	t	D	Asian Metal	Bloomberg	20/04/2001
Nickel	LME-Nickel Cash U$/MT	LNICASH(P)	link	Spot	USD	t	D	LME	Datastream	20/07/1993
Platinum	JM Platinum London U United States Dollar Per Troy Ounce	JMPLTER(P)	link	Spot	USD	t oz	D	JM	Datastream	01/07/1992
Praseodymium	China Praseodymium Oxide 99% FOB	PECNTBXR AMTL	link	Spot, FOB	USD	t	D	Asian Metal	Bloomberg	04/02/2005
Selenium	Europe Selenium Powder 99.9% In warehouse Rotterdam	S8EUUTZG AMTL	link	Spot	USD	lb	D	Asian Metal	Bloomberg	21/12/2005
Silicon	China Silicon Metal 2-2-02 FOB	S6CNPPWK AMTL	link	Spot, FOB	USD	t	D	Asian Metal	Bloomberg	20/10/2011
Silver	LBMA Silver Price USD/t oz DELAY	SILVUSL	link	Spot	USD	t oz	D	ICE	Datastream	02/01/1968
Tellurium	Europe Tellurium Metal 99.99% In warehouse Rotterdam	TEEUUQPU AMTL	link	Spot	USD	kg	D	Asian Metal	Bloomberg	16/05/2008
Terbium	China Terbium Oxide 99.9% FOB	TBCNFWBZ AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	04/02/2005
Tin	LME-Tin 99.85% Cash U$/MT	LTICASH(P)	link	Spot	USD	t	D	LME	Datastream	31/01/1957
Vanadium	China Vanadium Pentoxide Flake 98%min In warehouse Rotterdam USD/lb V2O5	VNEUJOQT AMTL	link	Spot	USD	lb	D	Asian Metal	Bloomberg	30/11/2005
Yttrium	China Yttrium Oxide 99.999%min FOB USD/kg	YTCNNKUM AMTL	link	Spot, FOB	USD	kg	D	Asian Metal	Bloomberg	27/08/2010
Zinc	LME-SHG Zinc 99.995% Cash U$/MT	LZZCASH(P)	link	Spot	USD	t	D	LME	Datastream	31/01/1957

Notes: This table pictures all the metal prices included in the CRMI. In the column on units, 't' stands for tonnes, 'kg' for kilograms, 'gm' for grams, 'lb' for pounds, and 't oz' for troy ounces. In the frequency (Freq.) column, 'D' stands for daily prices and 'W' stands for weekly prices.

Table 3: HS17 Codes by Metal

Series	**Unit**	**Form**	**HS17**	**Rule**
Aluminum	t	Ingots, t-bars, and sows	760120, Aluminum: unwrought, alloys; 760410, Aluminum: (not alloyed), bars, rods and profiles; 760429, Aluminum: alloys, bars, rods and profiles, other than hollow	A
Arsenic	t	Unknown, but high-purity metal	280480, Arsenic	B
Cadmium	lb	Ingots	810720, Cadmium: unwrought, powders	A
Chromium	t	Unknown, but high-purity metal	811221, Chromium and articles thereof: unwrought chromium, powders	B
Cobalt	t	Cathodes (broken or cut), ingots, briquettes, rounds and coarse grain powder	810520, Cobalt: mattes and other intermediate products of cobalt metallurgy, unwrought cobalt, powders	A
Copper	t	Cathodes	740311, Copper: refined, unwrought, cathodes and sections of cathodes	A
Dysprosium	kg	Oxide	284690, Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or of mixtures of these metals	C
Gallium	kg	Unknown, but high-purity metal	811292, Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium: articles thereof, unwrought, including waste and scrap, powders	B
Germanium	kg	Unknown, but high-purity metal	811292, Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium: articles thereof, unwrought, including waste and scrap, powders	B
Graphite	t	Spherical graphite	250410, Graphite: natural, in powder or in flakes	A
Indium	kg	Ingots	811292, Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium: articles thereof, unwrought, including waste and scrap, powders	A
Iridium	t oz	Sponges and ingots	711041, Metals: iridium, osmium, ruthenium, unwrought or in powder form	A
Lead	t	Ingots	780110, Lead: unwrought, refined	A
Lithium	t	Unknown, but battery grade	283691, Carbonates: lithium carbonate	B
Manganese	t	Unknown, but electrolytic manganese	282090, Manganese oxides: excluding manganese dioxide	B
Molybdenum	lb	Oxide	282570, Molybdenum oxides and hydroxides	A
Neodymium	t	Oxide	284690, Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or mixtures of these metals	C

Nickel	t	Cathodes (full plate and cut), pellets, briquettes and rounds	750210, Nickel: unwrought, not alloyed; 750610, Nickel: plates, sheets, strip and foil, not alloyed; 750620, Nickel: plates, sheets, strip and foil, of nickel alloys	A
Platinum	t oz	Sponges and ingots	711011, Metals: platinum, unwrought or in powder form	A
Praseodymium	t	Oxide	284690, Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or mixtures of these metals	C
Selenium	lb	Powder	280490, Selenium	C
Silicon	t	Unknown, but #2202 indicates 99.58% silicon content	280469, Silicon: containing by weight less than 99.99% silicon	B
Silver	t oz	Various shapes	710610, Metals: silver powder; 710691, Metals: silver, unwrought, (but not powder); 710692, Metals: silver, semimanufactured	B
Tellurium	kg	Ingot	280450, Boron: tellurium	C
Terbium	kg	Oxide	284690, Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or of mixtures of these metals	C
Tin	t	Ingots	800110, Tin: unwrought, not alloyed	A
Vanadium	lb	Pentoxide Flake	282530, Vanadium oxides and hydroxides	A
Yttrium	kg	Oxide	284690, Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or mixtures of these metals	C
Zinc	t	Ingots, jumbos	790111, Zinc: unwrought, (not alloyed), containing by weight 99.99% or more of zinc	A

Notes: The table displays the HS17 codes selected for different metals. We aligned the traded forms of these metals, as indicated in the price series, with their corresponding HS codes. The codes were chosen on the basis of three criteria:

- **(A) Known Form**: When the shape of the traded metal is known, the selected product code corresponds to that form. For example, if a metal is traded as an ingot, the relevant product code includes unwrought forms.
- **(B) Unknown Form:** In cases where the exact form is unknown, we use other characteristics to identify the appropriate code. For example, in the silicon series, although the form is unclear, the silicon content is known to be greater than 99.58%. Therefore, we use the code for "Silicon: containing by weight less than 99.99% silicon."
- **(C) Single Code:** In cases where only one product code is available, the selection is straightforward. This is the case with rare earth elements, where a single code covers all rare earth exchanges.

4.2. Data sample

Owing to data availability issues across time and metals, there is a tradeoff between building an index covering a large period of time and building an index including all metals that are necessary for the energy transition.

The extent of missing data (see Table 4) varies considerably across time and metals. On the one hand, more data are available for a larger sample of metals in the second half of the sample from 2012 onward rather than earlier in the sample. On the other hand, data coverage is strong for metals such as aluminum, cobalt, copper, iridium, lead, lithium, nickel, platinum, silver, tin and zinc. It is weaker for arsenic, manganese, chromium, gallium, germanium, indium, silicon and tellurium, especially before 2012.

In some cases, such as aluminum, cobalt, copper, nickel, platinum and silver prices, data are missing because they were not collected before 2006 on a comprehensive basis. In other cases, such as cadmium iridium, selenium, and tellurium prices, a lack of data indicates that markets may have emerged in the early 2000s. In other cases, after 2012, missing values may be related to events related to a specific market, such as a quotation interruption.

As most of the metal prices are not volatile, choosing to aggregate daily prices onto weekly prices is an interesting option, in addition to the aforementioned points presented in the preceding section 4.1. In doing so, data availability increases without losing too much information, enabling better arbitrage. Indeed, the number of missing values decreases via the smoothing of the data prices without eclipsing market events. Table 5 reports the data availability for the whole sample at the weekly frequency.

Table 4: Percent of critical materials with data availability - Global sample - Daily frequency

	2000-2005	2006-2011	2012-2017	2018-2023
Aluminium	0	33	100	100
Arsenic	9	52	92	92
Cadmium	0	47	94	91
Chromium	22	52	92	91
Cobalt	0	27	100	100
Copper	0	33	100	100
Dysprosium	15	51	93	92
Gallium	22	52	92	92
Germanium	11	52	92	92
Indium	22	52	92	92
Iridium	0	33	100	100
Lead	0	33	100	100
Lithium	0	0	93	100
Manganese	0	0	86	92
Molybdenum	1	47	94	92
Neodymium	15	51	93	92
Nickel	0	33	100	100
Platinum	0	33	100	100
Praseodymium	3	51	93	92
Selenium	0	47	93	91
Silicon	0	3	92	91
Silver	0	33	100	100
Tellurium	0	32	92	92
Terbium	3	51	93	92
Tin	0	33	100	100
Vanadium	1	47	95	92
Yttrium	0	19	93	92
Zinc	0	33	100	100
Graphite	0	0	96	100

Notes: This table provides each critical materials availability per lustrum since 2000. Data availability is calculated as the average of daily observations by periods. Percentage values are rounded up.

Focusing on a data sample from June 2012 to October 2023 with a weekly frequency, this results in a dataset of 29 metals and 593 observations per mineral. The remaining missing values appear to be missing not at random. Following the econometric approach of Diggle (1989), we find that the probability of absence depends on the variable in question. Hence, deleting observations is not an option; missing data must be imputed.

Various methods exist for imputing these missing values, each with advantages and disadvantages. In this context, the last observation carried forward (LOCF) method, as described in Eq. (1), is the most appropriate. From an economic point of view, the best approximation of a metal's price at time t is its price at time $t-1$. In addition, from an econometric perspective, it is a simple and precise way to impute missing values in the case of a stationary process; it also preserves variance and reduces attrition bias (see Section 4 for further details). Therefore, missing values are replaced by the last observed value before the missing point.

Table 6 reports the descriptive statistics of the final sample. The results indicate that the critical material returns have several similarities. The mean of returns is very close to 0, as is the median. The distribution of returns is therefore centered at 0 and shows little asymmetry. Next, the standard deviations are much larger than the means but of the same order of magnitude for all the critical materials. On the other hand, the extreme values are very large compared with the first two return moments. For all the critical materials, the assumption of a normal

Table 5: Percent of critical materials with data availability - Global sample - Weekly frequency

	2000-2005	2006-2011	2012-2017	2018-2023
Aluminium	0	34	100	100
Arsenic	24	97	97	96
Cadmium	0	97	98	95
Chromium	81	97	97	96
Cobalt	0	27	100	100
Copper	0	34	100	100
Dysprosium	73	96	97	96
Gallium	81	97	97	96
Germanium	28	97	97	96
Indium	81	97	97	96
Iridium	0	34	100	100
Lead	0	34	100	100
Lithium	0	0	93	100
Manganese	0	0	91	98
Molybdenum	3	98	98	96
Neodymium	73	96	97	96
Nickel	0	34	100	100
Platinum	0	34	100	100
Praseodymium	14	96	97	96
Selenium	1	98	98	96
Silicon	0	4	97	96
Silver	0	34	100	100
Tellurium	0	59	98	96
Terbium	14	96	97	96
Tin	0	34	100	100
Vanadium	2	98	98	96
Yttrium	0	22	97	96
Zinc	0	34	100	100
Graphite	0	0	96	100

Notes: This table provides each critical materials availability per lustrum since 2000. Data availability is calculated as the average of weekly observations by periods. Percentage values are rounded up.

distribution of returns would be inappropriate. Overall, the critical material returns appear to be homogeneous in cross-section, and all exhibit high volatility on average, with extreme price variations.

Figure 1 shows the correlation between each pair of critical material returns. A correlogram representation illustrates the relationships among related time series. The global level of correlation is low, except for the pairs neodymium – platinum, dysprosium – tellurium and silicon – platinum. These dependencies can be notably explained by industrial co-usage. For example, in high-tech industries such as electronics and advanced automotive technology, neodymium and platinum can be used together in various components. Neodymium is used in magnets for electric motors, and platinum is critical in catalytic converters or fuel cell technology in hybrid or electric vehicles. These overlapping industries can create synchronized demand shifts, contributing to the correlation.

Table 6: Descriptive statistics after data imputation

	Obs.	Mean	Median	St. Dev.	Min	Max
Aluminium	593	0.0005	0.0004	0.0241	-0.0862	0.1375
Arsenic	593	-0.0008	0.0000	0.0152	-0.0853	0.1974
Cadmium	593	0.0014	0.0000	0.0233	-0.1304	0.1250
Chromium	593	-0.0004	0.0000	0.0148	-0.0829	0.1303
Cobalt	593	0.0007	0.0000	0.0310	-0.1523	0.1317
Copper	593	0.0004	0.0007	0.0218	-0.0987	0.0914
Dysprosium	593	-0.0015	0.0000	0.0256	-0.1577	0.1593
Gallium	593	0.0006	0.0000	0.0278	-0.1052	0.1268
Germanium	593	0.0005	0.0000	0.0120	-0.0502	0.0872
Indium	593	-0.0008	0.0000	0.0229	-0.0909	0.1174
Iridium	593	0.0029	0.0000	0.0276	-0.0758	0.4089
Lead	593	0.0005	-0.0002	0.0255	-0.0788	0.1097
Lithium	593	0.0027	0.0000	0.0218	-0.1132	0.1564
Manganese	593	-0.0005	0.0000	0.0319	-0.2118	0.1766
Molybdenum	593	0.0013	0.0000	0.0340	-0.1308	0.1297
Neodymium	593	-0.0003	0.0000	0.0295	-0.1187	0.1750
Nickel	593	0.0012	0.0007	0.0478	-0.2563	0.8005
Platinum	593	-0.0004	-0.0003	0.0270	-0.2324	0.0918
Praseodymium	593	-0.0004	0.0000	0.0241	-0.1039	0.1333
Selenium	593	-0.0024	0.0000	0.0341	-0.1837	0.2803
Silicon	593	0.0005	0.0000	0.0352	-0.1232	0.4874
Silver	593	0.0001	-0.0002	0.0316	-0.2499	0.1238
Tellurium	593	-0.0012	0.0000	0.0223	-0.1684	0.1612
Terbium	593	-0.0006	0.0000	0.0304	-0.1294	0.1509
Tin	593	0.0009	0.0009	0.0301	-0.1371	0.1435
Vanadium	593	0.0008	0.0000	0.0339	-0.1379	0.1498
Yttrium	593	-0.0047	0.0000	0.0309	-0.2041	0.1391
Zinc	593	0.0008	0.0026	0.0280	-0.0970	0.1376
Graphite	593	-0.0010	0.0000	0.0116	-0.1242	0.0596

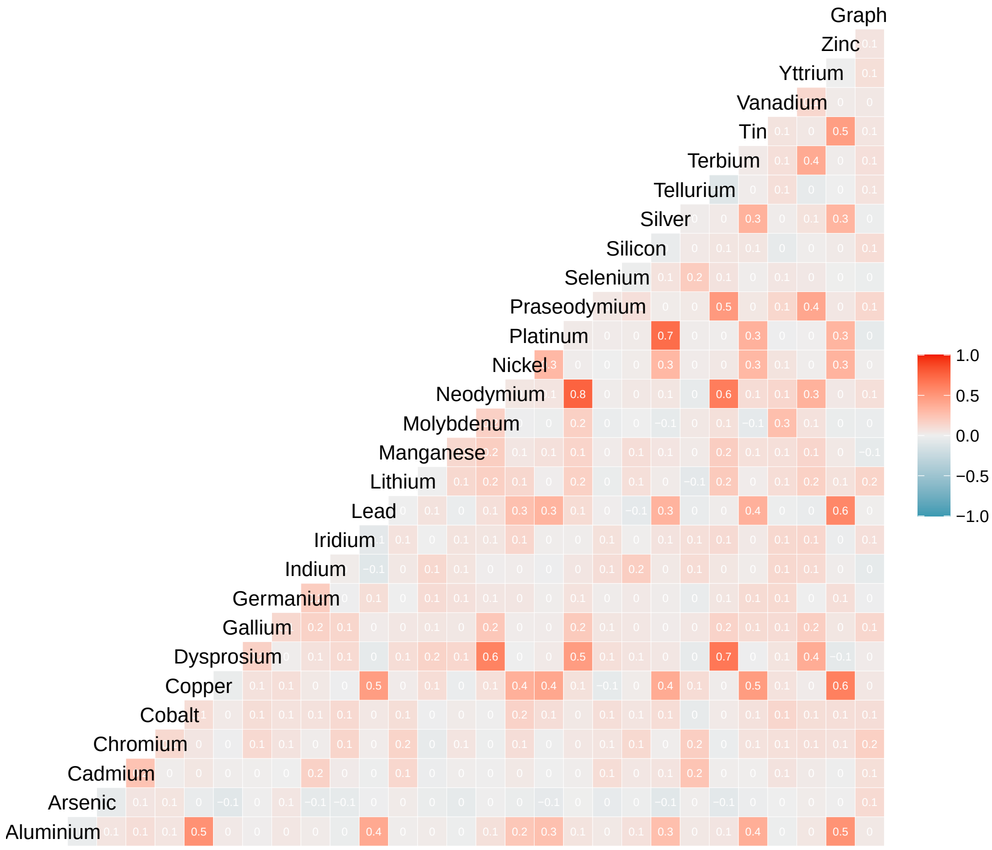
Notes: This table reports descriptive statistics of critical materials returns after data imputation (LOCF method).

4.3. Weighting schemes

As discussed above, we weighted the metals by their export trading volumes. However, these trade volumes are not equally distributed: some materials, such as copper and aluminum, are much more traded than neodymium and dysprosium. In addition, critical material returns exhibit extreme values (see the descriptive statistics in subsection 4.2). Consequently, the weights need to be capped to ensure the stability of the index, mitigating the influence of any single material. Moreover, as some materials are far more traded than others are, capping weights also ensure the representativity of the entire set of critical materials. Hence, following the methodological framework related to the design of the weighting scheme (see subsection 3.2), the best option is to choose weight capping. Specifically, this weight capping is performed with a threshold of 20%, with a proportional redistribution of the weights to avoid altering the distribution of the weights.

Figure 2 shows the distribution of weights allocated to each metal according to their export trading volume. The distribution of weights is very uneven: copper and aluminum alone account for 35% of the total index weighting. Next, platinum, cobalt, tin, nickel, silver and zinc account for approximately 5-10% of the index, whereas the remaining metals have a lower weighting. This weighting scheme is consistent with export trade data and highlights the importance of capping for the representativeness of the index.

Figure 1: Correlogram of critical material returns



Notes: This figure illustrates the correlations of critical materials returns. Pearson correlation coefficients are reported in white, whereas positive (resp. negative) values are depicted in red (resp. blue).

5. The CRMI - The Critical Raw Materials Index

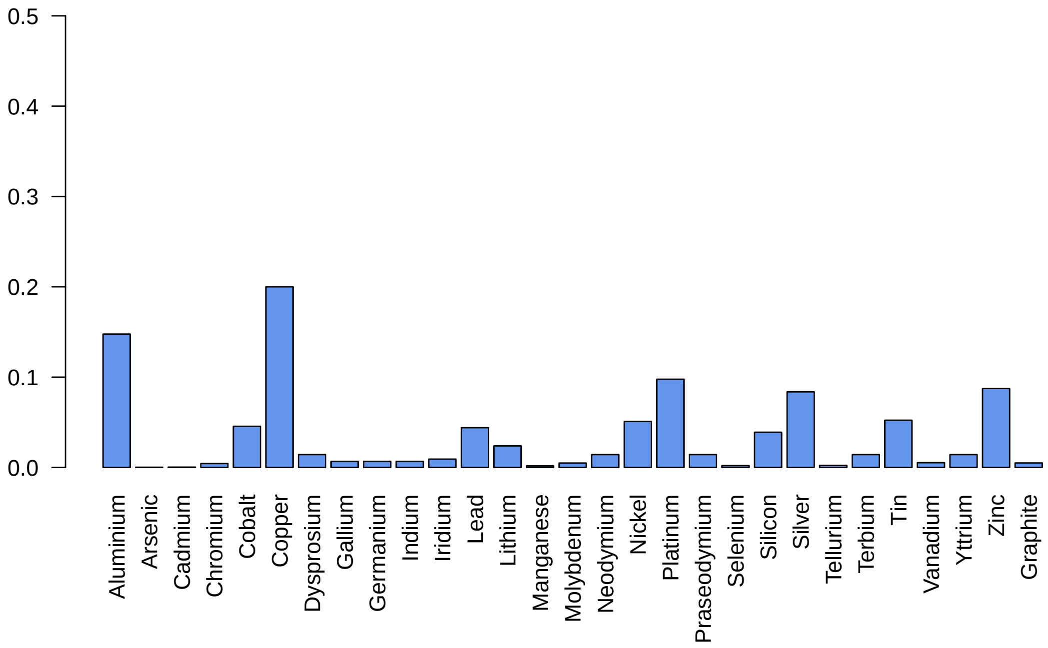
The most common methodology for constructing a commodity price index involves a weighted linear average of the returns associated with each raw material price series. This approach assigns weights $w_i(t)$ to each raw material i at time t on the basis of its relative importance within the market, typically determined by market share or production volume. Using the weights previously computed from metal export volumes and the commodity returns series, the $CRMI(t)$ growth rate at a given time period t can be expressed as:

$$\Delta CRMI(t) = \sum_{i=1}^{N} \omega_i(t) \times R_i(t), \tag{6}$$

where $\omega_i(t)$ and $R_i(t)$ represent the weight and return of mineral i at time t, respectively.

This linear functional form is particularly advantageous when dealing with commodity return data containing a significant number of zero or near-zero observations. Unlike some alternative aggregation methods, linear functions exhibit less sensitivity to extreme values, ensuring a more robust representation of the underlying price dynamics (e.g., weighted arithmetic mean vs. weighted geometric mean).

Figure 2: Trade weighting and capping



Notes: This figure illustrates the distribution of weights across metals. The weights are computed from the volume of trade of each mineral. Weights are limited to a maximum of 20% of their total value, and any excess is distributed proportionally among the remaining weights.

A common practice is to set the index value for a specific year (e.g., 2012) equal to 100. This rescaling facilitates easier comparison and interpretation of the index across different time periods. By analyzing the changes in the index over time, one can readily identify trends in overall mineral prices. In matrix form, we can rewrite Eq. (6):

$$\mathbf{CRMI_{2012}} = 100 \times (1 + \boldsymbol{\omega}^{\boldsymbol{T}}\mathbf{R}), \tag{7}$$

where $\boldsymbol{\omega}$ and $\mathbf{R}$ represent the weight and return vectors, respectively.

Following this methodological approach, we compute the CRMI and convert it to base 100. Figure 3 presents the CRMI at a weekly frequency from 2012 through 2024.

Figure 3: The CRMI from 2012 to 2024

Notes: This figure illustrates the CRMI (base 100 = 2012). The weighting methodology is as follows: trade-weighted, a cap of 20% and a proportional redistribution of weights.

The index is characterized by several spikes corresponding to key events related to the critical materials market. First, the 2012–2016 period was characterized by a general decline in commodity prices. During this period, critical materials were no exception among commodities. Consistently, the CRMI significantly decreases by approximately 40%. This drop can be attributed to slowing economic growth and reduced aggregate demand in major economies such as China, compounded by the drop in oil prices in mid-2014. During this period, the CRMI experienced a significant decline of approximately 40%. This can be attributed to the slowing economic growth and reduced aggregate demand in major economies such as China (Cashin et al., 2017), compounded by the drop in oil prices in mid-2014 (Stocker et al., 2018). China's economic slowdown, caused by a shift from export-led to domestic demand and from manufacturing to services, has negatively impacted global markets, particularly metal markets. The decline in Chinese demand for copper, a key metal used in buildings and infrastructure, led to a significant drop in copper prices (Norland, 2016). Additionally, the decline in oil prices, driven by factors such as increased US shale oil production and policy changes by OPEC, further impacted the metal markets because of their energy-intensive production (Stocker et al., 2018). The global economy's recovery from 2016 to mid-2018 was subsequently driven by strong domestic demand in major economies such as the United States, the Euro area, Japan, and China (IMF, 2017). This recovery was further supported by significant advancements in clean energy technology, particularly solar energy, which experienced a surge in investment, especially in China (Louw, 2018). This combination of factors led to a significant increase in metal prices, as reflected in the CRMI, which rose by approximately 60% during this period. Next, the spikes of the CRMI during the period of 2018–2020 are related to the trade tensions between the US and China. Specifically, the trade war between the US and China escalated in 2018, with both countries imposing tariffs on each other's goods (Reuters, 2020). This led to heightened uncertainty, slower growth, and reduced demand for industrial metals, particularly in China (Itakura, 2020). The depreciation of the yuan relative to the dollar made dollar-priced metals more expensive for Chinese buyers, further reducing demand (Hobson, 2019). As a result, the CRMI prices fell significantly from mid-2018 to 2020. Recently, the spikes over the period 2020–2022 correspond to the COVID -19 pandemic and the Russian–Ukrainian war. First, a sharp drop in critical material prices was experienced due to a sudden collapse in demand during the pandemic. Conversely, the Russian–Ukrainian war and the end of the pandemic are associated with a significant increase in critical material prices due to increased uncertainty, supply chain disruption, and sanctions-induced shortages of materials supplied by Russia (Baffes and Nagle, 2022). Since then, the CRMI has fallen significantly because of an oversupply of various metals and weakening demand, particularly in the EV market. This is particularly the case for the price of lithium, which has fallen by half since 2022 and 2023 (McClelland, 2024). These effects have been exacerbated by the overall slowdown in demand in response to monetary tightening in advanced economies (Jeetendra and Kaltrina, 2024).

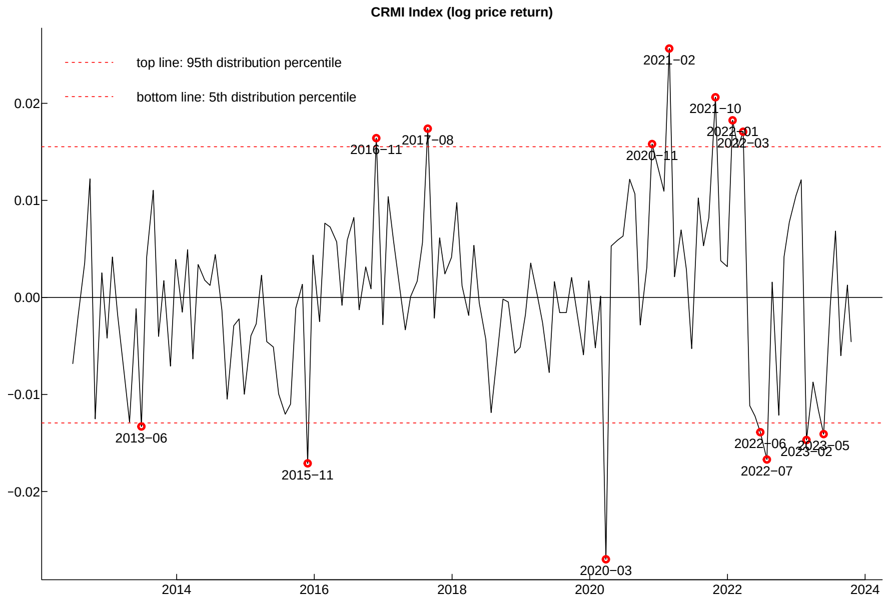
6. Validation

Following Caldara and Iacoviello (2022)'s index validation approach, this section presents two exercises aimed at ensuring the validity of the CRMI. First, we verify that the CRMI provides a plausible quantification of the historical evolution of critical material prices. Second, we compare the CRMI with similar economic time series.

6.1. Plausibility

The first objective of the validation section is to analyze whether the price dynamics of the Critical Raw Material Index correctly reflect changes in the dynamics of the critical metals market. Our plausibility test relies on the logic that extreme values in the index must capture the most important events related to the critical metals market of the past 10 years, in the way these events were perceived by the contemporaries. We identify surprises having a negative or positive effect on the index as the 5th and 95th percentiles of the returns distribution, respectively. Figure 4 illustrates the event analysis based on the graphical analysis of surprises.

Figure 4: Critical Raw Material Index (log price returns)



Notes: The log-returns of the CRMI are analyzed at a monthly frequency to enhance the readability of extreme events. These extreme events are defined as the values exceeding the dashed red lines, which represent the 95th and 5th percentiles of the return distribution.

The CRMI has undergone significant changes in response to both external global events and internal market dynamics. In June 2013, the Federal Reserve signaled the potential tapering of its quantitative easing (QE) program, which had a negative impact on market conditions. The Paris attacks in November 2015 also had a notable negative effect on market sentiment. Conversely, the election of Donald Trump in November 2016 increased the return of the index. In August 2017, China's environmental crackdown drove up the prices of several rare earth metals and aluminum. Tighter environmental regulations and the closure of illegal smelters reduced production, leading to this price spike (Daly, 2017). The COVID-19 pandemic in March 2020 caused a sharp decline in the index, whereas the election of Joe Biden in November 2020 marked another "positive return event". February 2021 was significant, as China began a stockpiling strategy following the CHIPS and Science Act in the United States in January 2021 (CRS, 2023; Cobalt Institute, 2022; Mayger and Dai, 2021). In January 2022, sanctions against Russia led to a spike in aluminum prices (Onstad, 2022). The Russian–Ukrainian war and the nickel crisis in March 2022 further disrupted markets. In June 2022, China's economic slowdown, combined with weaker industrial demand, rising interest rates and inflation in developed economies, had a markedly negative impact on the index (Jones, 2022). This trend continued until July 2022, reflecting the ongoing challenges in the global market.

These results are encouraging, as the extreme movements in the index can be attributed to identifiable events, either due to global economic shocks or internal disruptions within the metal markets. This is consistent with recent findings in the financial literature.

6.2. Comparability

The second objective of the validation section is to compare our index with other financial products and assess its comparative advantages. We start by comparing our index with the IMF's Energy Transition Metal (ETM) index, which, to the best of our knowledge, is the price index most closely related to the CRMI. Our analysis shows that our index addresses several limitations inherent in the construction of the ETM Index. Empirically, we show that the CRMI captures different information than the ETM does. Additionally, we discuss the comparative advantages of our index with the new IEA energy transition mineral price index. We then compare the CRMI with oil prices to ensure that metal prices are not driven entirely by the oil market. This comparison confirms that our index does not simply reflect fluctuations in oil prices.

Table 7: Comparing the construction of the CRMI and ETM Index

	CRMI	**ETM**	**Remark**
Metals coverage	29	16	In ETM, several key metals are missing.
Selection	IEA (2024)	Ad-hoc	In ETM, ad-hoc selection of metals.
Frequency	Weekly	Monthly	ETM has a lower frequency than CRMI.
Starting date	2012 M6	2012 M6	NA.
Base	100: 2012	100: 2016	NA.
Currency	USD / CNY	USD	NA.
Methodology	Trade-weighted with a cap (prop)	Trade-weighted	In ETM, no capping strategy.
Trade database	BACI	UN Comtrade	BACI enhances UN Comtrade.
Exchange volume proxy	Export	Import	Export >> Import $\rightarrow$ Oligopolistic nature of metal markets.
Average weight	2012-2022	2014-2016	For CRMI: average weight for the whole period.
HS nomenclature	HS17	HS12	For CRMI: more recent version of the HS nomenclature.
HS code selection	The shape of the metal in the index series.	Expert judgements	CRMI data selection is better motivated than ETM data.
Sub-indexes	By energy transition sectors	No sub-indexes	CRMI provides sub-indexes.
Robustness	Equal-weighted; Trade-weighted; Trade-weighted with a cap (equi); HHI-weighted; Winsorisation	No robustness checks	CRMI is more robust than ETM.

Notes: The ETM index stands for the Energy Transition Metals Index, which is a sub-index of the Primary Commodity Price Index (PCPI). The latter is implemented and updated by the IMF.

To compare the CRMI with the ETM Index, we must first define the Energy Transition Metals (ETM) index. This index is a subindex of the Primary Commodity Price Index (PCPI), a weighted commodity price index from the IMF. The PCPI, which began in January 1992, is expressed in USD, has a monthly frequency, and is constructed with a base value of 100 for 2016. It covers 68 commodities across four asset classes: energy, agriculture, fertilizers, and metals. The PCPI includes metal prices for both base metals (e.g., aluminum, cobalt, copper, and iron) and precious metals (e.g., gold, silver, palladium, and platinum). Several subindexes are constructed within the PCPI, including the Metals Price Index (PMETA), the Precious Metals Index (PPMETA), and the ETM Index (IMF, 2019).

More specifically, the ETM Index covers sixteen metal prices and began in 2012 (see Table C in the Appendix). The weighting scheme is based on the average global metal import volume from 2014 to 2016, with data sourced from the UN Comtrade database. The product codes are selected from the HS12 6-digit nomenclature and are based on expert judgment. Specifically, two rules are applied for the selection of HS codes: (1) a match between the product description and the commodity group and (2) the selected HS codes focus on raw materials or minor processing, excluding finished products (ibid).

There are several differences between the CRMI and the ETM Index, as highlighted by Table 7. First, the CRMI has broader coverage of metal prices, including 29 metals compared with the 16 covered by the ETM. Notably, some critical and strategic metals essential for the energy transition are missing from the ETM. These include graphite for electric vehicles, iridium for hydrogen production, and gallium and germanium for solar PVs. The absence of these metals is significant, particularly given their strategic importance and the global attention they have attracted due to recent geopolitical tensions involving China. In response to U.S. semiconductor restrictions (Weaver, 2022), China imposed export controls on gallium and germanium in August 2023 (Harper, 2023) and graphite in October 2023 (Benson and Denamiel, 2023).

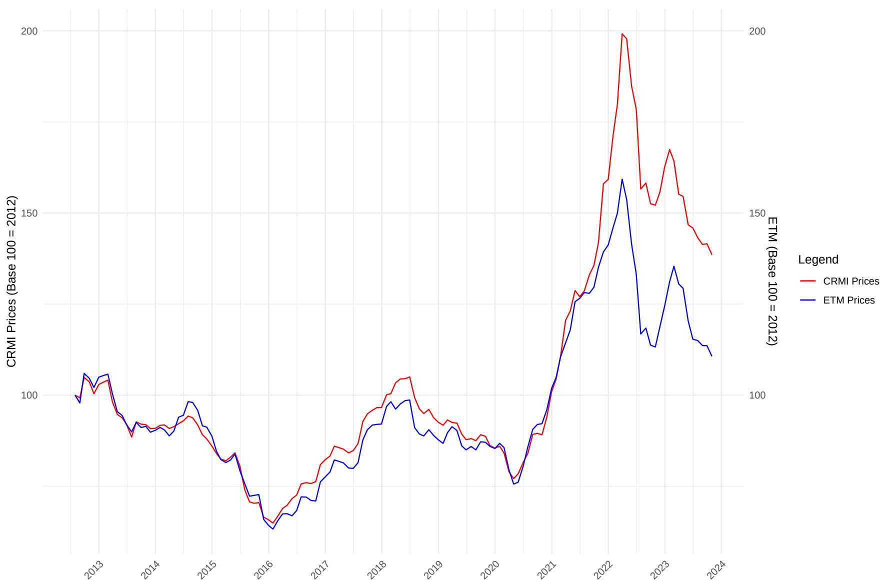
Second, the CRMI is more rigorously motivated in its selection of energy transition metal prices than the ETM Index is. The CRMI's selection is based on the International Energy Agency's (2024) database, providing a sound basis for its metal selection, whereas the ETM's selection appears to be more ad hoc. In addition, the CRMI offers greater granularity, as it is available on a weekly basis compared with the monthly frequency of the ETM. This increased frequency is crucial for a more in-depth assessment of the dynamics of metal prices in financial markets. It also improves the suitability of the index for econometric models, as it provides a sufficient number of observations for the parameters to converge.

Third, regarding the weighting methodology, we find it preferable to use the BACI database, as it has been corrected for several biases (previously highlighted in section 4), allowing us to use export data. Additionally, the HS code selection for the ETM is less rigorous than ours is, and we identified a significant limitation in the ETM weighting methodology: it is performed without a cap. This is problematic given the substantial heterogeneity in exchange volumes between metals. For example, copper constitutes 34% of the ETM Index, whereas rare earths make up only 0.5%. In comparison, the CRMI employs a cap of 20% with a proportional redistribution of weights, resulting in copper and rare earths having more balanced weights (Table D for the CRMI metal weight). Consequently, the ETM Index is heavily influenced by copper prices, rendering the index potentially unstable. Furthermore, the ETM average weighting is based solely on the years 2014 to 2016, whereas for the CRMI, we averaged data from 2012 to 2022.

Finally, the CRMI can be considered more robust than the ETM Index because extensive robustness tests are carried out. We have tested the CRMI using different weighting techniques (e.g., equal weighted, trade weighted, trade weighted with a cap (equi) and HHI weighted) and controlled for extreme value issues using winsorization techniques (Section 7).

In summary, we have demonstrated that the construction of the CRMI addresses several limitations of the ETM Index. Specifically, the CRMI offers a broader perspective on energy transition metals, provides greater granularity, employs a more comprehensive weighting scheme, and includes more extensive robustness tests. However, before moving forward, it is essential to analyze whether significant differences can be observed both graphically and through correlation analysis between the two indices.

Figure 5: Comparing the CRMI and ETM Index



Notes: This figure shows the Critical Raw Materials Index (CRMI) alongside the Energy Transition Metals (ETM) Index, a sub-index of the IMF's Primary Commodity Price Index (PCPI). The data covers the period from July 2012 to October 2023, at a monthly frequency, as the ETM Index is only available on this basis.

As highlighted by Figure 5, the CRMI and ETM indices comove positively throughout the entire period. However, toward the end of the period, a divergence between the two indices becomes apparent, with CRMI prices exceeding those of the ETM. This divergence is primarily due to a significant increase in tin prices from 2020 to 2022, and, to a lesser extent, an increase in gallium prices in 2022 (Figure A in Appendix). Notably, both of these metals are excluded from the ETM Index despite their critical role in the production of solar photovoltaic technologies.

Therefore, this first graphical analysis of the two indices suggests that the CRMI captures different information than the ETM Index does. This suggestion is further confirmed by the correlation coefficient between the two variables. The correlation coefficient is 0.87 and is significant at the 5% level.[2]

In addition, a more recent index worth noting is the IEA Energy Transition Mineral Price Index, introduced in the Global Critical Minerals Outlook 2024 (IEA, 2024b). This index represents a basket price of copper, lithium, nickel, cobalt, graphite, manganese, and neodymium. Its main limitation lies in the narrow selection of metals. Nonetheless, it underscores the pressing need for a more comprehensive index to track the price dynamics of metals critical to the energy transition.

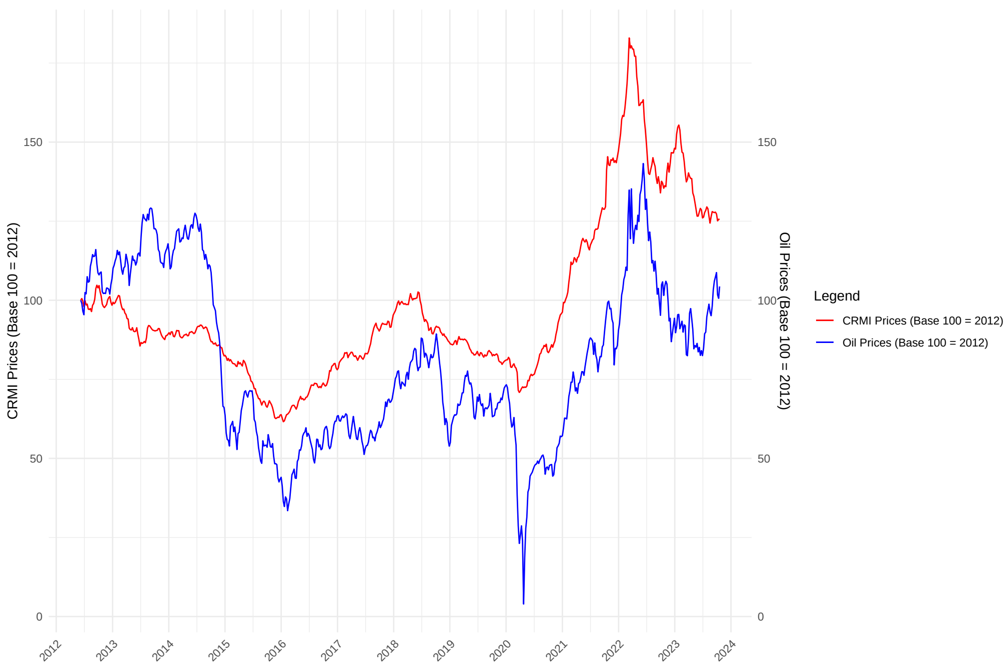
Finally, we compare CRMI prices with oil prices to ensure that our metal price index is not solely influenced by the oil market but also captures information specific to the mining industry. Indeed, oil prices have a significant effect on the costs of the mining sector and therefore on metal prices. The mining industry is highly energy intensive, heavily dependent on fossil fuels and one of the largest emitters of greenhouse gases (Aramendia et al., 2023). In addition, rising oil prices increase shipping costs, as metals are often transported long distances from extraction to refining. Furthermore, fluctuations in oil prices trigger reactions in metal markets. Reboredo and Ugolini (2020) find that REE stocks are positively but weakly correlated with oil prices under normal conditions, but this correlation increases significantly during periods of high market stress. (Song et al., 2021) find similar results during the pandemic crisis.

When examining Figure 6, which plots the CRMI alongside West Texas Intermediate (WTI) oil prices, a positive correlation between the two series is evident. However, there are also notable differences in their dynamics, especially at the beginning of the period. By calculating the correlation coefficient between the CRMI and oil prices, we find it to be approximately 0.18, which is significant at the 5% level.[3] This finding indicates that while the CRMI is significantly and positively correlated with WTI oil prices, it exhibits unique price dynamics and does not merely replicate the behavior of oil prices.

[2]The correlation coefficient was calculated using Pearson's method. In addition, the variables are in logarithm difference, as they are integrated into order one. This conclusion has been reached through unit root tests using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests.

[3]The correlation coefficient was calculated using the Pearson method. Both WTI and CRMI prices are expressed in log differences, as they are both integrated of order one. This integration order was determined using standard unit root tests, specifically the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests.

Figure 6: Comparing the CRMI and oil prices



Notes: This figure represents the plot of the CRMI prices (in red) and oil prices (in blue). The series of oil prices is the West Texas Intermediate prices and has been downloaded from the Federal Reserve Economic Data (FRED). Both series have been computed in base 100 regarding the year 2012.

To conclude the section on comparability, we have shown that the CRMI has significant advantages over other financial products, such as the ETM Index and the IEA Index. In fact, the CRMI addresses several limitations of the ETM and IEA indices, which, to the best of our knowledge, are the closest financial products to ours. The CRMI provides a better overview of critical metals for the energy transition, with greater granularity, transparency and robustness than its counterparts. In addition, a comparison between the CRMI and the oil price index reveals similarities, as they are both commodity price indices, but they also differ in many ways. The CRMI is therefore informative, has added value over other critical metal price indices, and is not driven by fluctuations in the prices of commodities other than critical metals.

7. Robustness tests - Sensitivity analysis

Creating a composite indicator involves subjective decisions such as handling outliers, selecting weight factors and allocating those factors. In the case of the CRMI, these choices could have a dramatic impact on the index. To assess the reliability of our index, a sensitivity analysis examines how changes in assumptions affect the results. In summary, this robustness checks section aims at identifying potential biases and informing discussions about the indicator's limitations.

7.1. *Using an alternative data treatment*

In this subsection, we test the impact of dealing with missing and extreme values. The CRMI construction includes a data imputation process based on the replacement of missing values by their lagged values. Here, we carry out an alternative data imputation, i.e., a moving average data imputation (see Eq. (2) in Subsection 3.1). Table 8 reports the descriptive statistics of the alternative data sample, and Figure 7 illustrates the difference between the original CRMI and the alternative version of the index.

Table 8: Descriptive statistics after alternative data treatment - Missing values

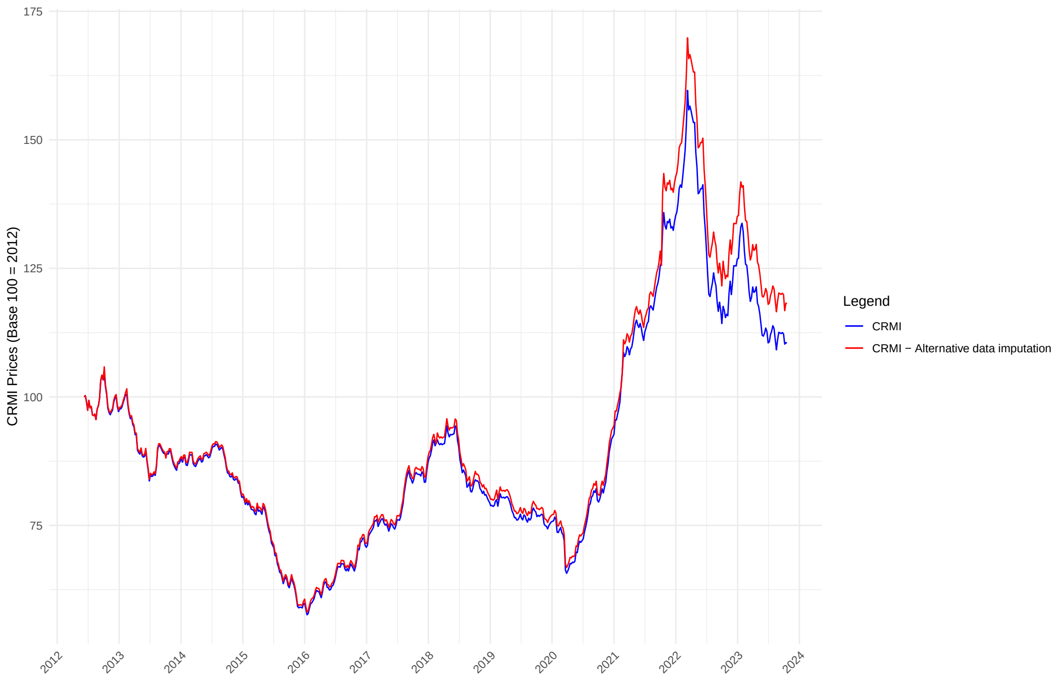
	Obs.	Mean	Median	St. Dev.	Min	Max
Aluminium	593	0.0005	0.0004	0.0241	-0.0862	0.1375
Arsenic	593	-0.0008	0.0000	0.0152	-0.0853	0.1974
Cadmium	593	0.0014	0.0000	0.0233	-0.1304	0.1250
Chromium	593	-0.0004	0.0000	0.0148	-0.0829	0.1303
Cobalt	593	0.0007	0.0000	0.0310	-0.1523	0.1317
Copper	593	0.0004	0.0007	0.0218	-0.0987	0.0914
Dysprosium	593	-0.0015	0.0000	0.0256	-0.1577	0.1593
Gallium	593	0.0006	0.0000	0.0278	-0.1052	0.1268
Germanium	593	0.0005	0.0000	0.0120	-0.0502	0.0872
Indium	593	-0.0008	0.0000	0.0229	-0.0909	0.1174
Iridium	593	0.0029	0.0000	0.0276	-0.0758	0.4089
Lead	593	0.0005	-0.0002	0.0255	-0.0788	0.1097
Lithium	593	0.0027	0.0000	0.0218	-0.1132	0.1564
Manganese	593	-0.0005	0.0000	0.0319	-0.2118	0.1766
Molybdenum	593	0.0013	0.0000	0.0340	-0.1308	0.1297
Neodymium	593	-0.0003	0.0000	0.0295	-0.1187	0.1750
Nickel	593	0.0012	0.0007	0.0478	-0.2563	0.8005
Platinum	593	-0.0004	-0.0003	0.0270	-0.2324	0.0918
Praseodymium	593	-0.0004	0.0000	0.0241	-0.1039	0.1333
Selenium	593	-0.0024	0.0000	0.0341	-0.1837	0.2803
Silicon	593	0.0005	0.0000	0.0352	-0.1232	0.4874
Silver	593	0.0001	-0.0002	0.0316	-0.2499	0.1238
Tellurium	593	-0.0012	0.0000	0.0223	-0.1684	0.1612
Terbium	593	-0.0006	0.0000	0.0304	-0.1294	0.1509
Tin	593	0.0009	0.0009	0.0301	-0.1371	0.1435
Vanadium	593	0.0008	0.0000	0.0339	-0.1379	0.1498
Yttrium	593	-0.0047	0.0000	0.0309	-0.2041	0.1391
Zinc	593	0.0008	0.0026	0.0280	-0.0970	0.1376
Graphite	593	-0.0010	0.0000	0.0116	-0.1242	0.0596

Notes: This table reports descriptive statistics of critical materials returns after alternative data imputation (i.e., moving average imputation).

The results reported in Table 8 indicate that the moving average imputation of data has a weak effect on the descriptive statistics of critical raw returns. The results are consistent with the fact that moving average imputation replaces missing values in a dataset from several lagged values instead of just the latter one.

Figure 7 illustrates the sensitivity of the index to the data treatment. The comparison between the original index and the alternative index indicates only a few differences. Hence, the sensitivity of the CRMI to this alternative data treatment appears to be not significant.

Figure 7: Sensitivity analysis - Alternative data treatment - Missing values



Notes: This figure illustrates the sensitivity of a different data treatment (i.e., moving average imputation).

While the CRMI construction does not imply any specific treatment for extreme values, here, we perform a winsorization of the data (see Eq. (3) in Subsection 3.1). Table 9 reports the descriptive statistics of the alternative data sample, and Figure 8 illustrates the difference between the winsorized and nonwinsorized indices. The results reported in Table 9 indicate that winsorization has an effect not only on the minimum and maximum values but also on the mean and standard deviation of critical raw returns. However, the median value of the returns is not affected. The results are consistent with the fact that winsorization replaces outliers in a dataset with predetermined percentile values.

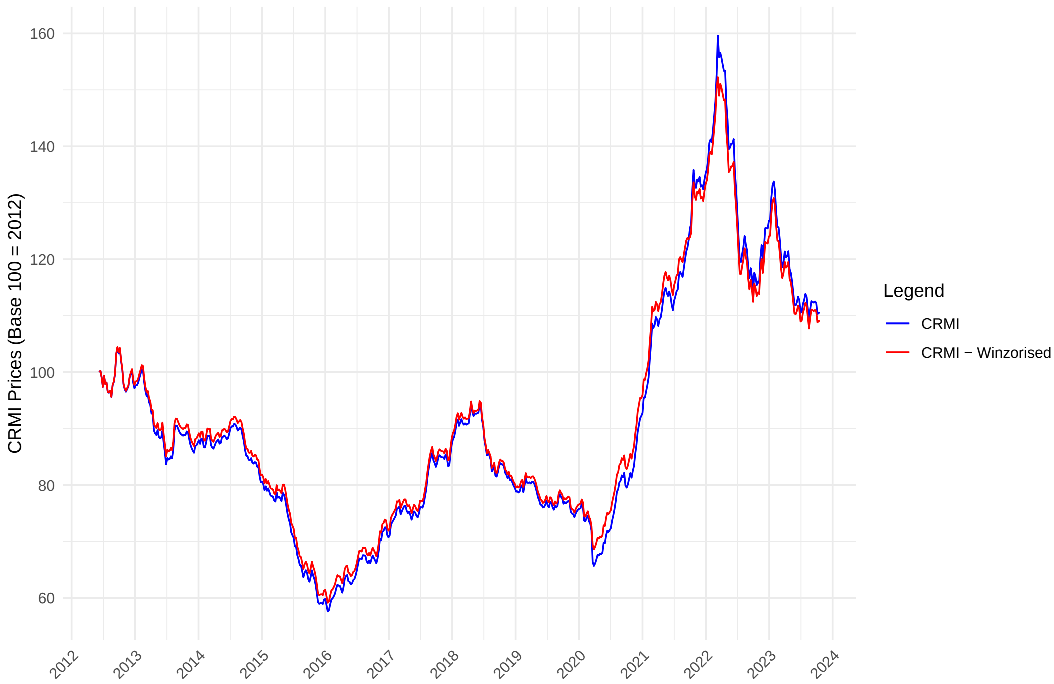
Figure 8 illustrates the sensitivity of the index to the data treatment. The comparison between the original index and the index built from a winsorized data sample indicates only a few differences. Hence, the sensitivity of the CRMI to this alternative data treatment appears to be not significant.

Table 9: Descriptive statistics after alternative data treatment - Extreme values

	Obs.	Mean	Median	St. Dev.	Min	Max
Aluminium	593	0.0004	0.0004	0.0236	-0.0739	0.0907
Arsenic	593	-0.0011	0.0000	0.0119	-0.0739	0.0907
Cadmium	593	0.0014	0.0000	0.0213	-0.0739	0.0907
Chromium	593	-0.0005	0.0000	0.0139	-0.0739	0.0907
Cobalt	593	0.0010	0.0000	0.0283	-0.0739	0.0907
Copper	593	0.0004	0.0007	0.0216	-0.0739	0.0907
Dysprosium	593	-0.0016	0.0000	0.0230	-0.0739	0.0907
Gallium	593	0.0004	0.0000	0.0261	-0.0739	0.0907
Germanium	593	0.0005	0.0000	0.0120	-0.0502	0.0872
Indium	593	-0.0009	0.0000	0.0224	-0.0739	0.0907
Iridium	593	0.0019	0.0000	0.0195	-0.0739	0.0907
Lead	593	0.0005	-0.0002	0.0253	-0.0739	0.0907
Lithium	593	0.0024	0.0000	0.0187	-0.0739	0.0907
Manganese	593	-0.0003	0.0000	0.0255	-0.0739	0.0907
Molybdenum	593	0.0014	0.0000	0.0309	-0.0739	0.0907
Neodymium	593	-0.0006	0.0000	0.0269	-0.0739	0.0907
Nickel	593	0.0004	0.0007	0.0327	-0.0739	0.0907
Platinum	593	-0.0001	-0.0003	0.0254	-0.0739	0.0907
Praseodymium	593	-0.0005	0.0000	0.0226	-0.0739	0.0907
Selenium	593	-0.0028	0.0000	0.0278	-0.0739	0.0907
Silicon	593	-0.0008	0.0000	0.0192	-0.0739	0.0907
Silver	593	0.0005	-0.0002	0.0286	-0.0739	0.0907
Tellurium	593	-0.0010	0.0000	0.0183	-0.0739	0.0907
Terbium	593	-0.0004	0.0000	0.0281	-0.0739	0.0907
Tin	593	0.0010	0.0009	0.0274	-0.0739	0.0907
Vanadium	593	0.0013	0.0000	0.0305	-0.0739	0.0907
Yttrium	593	-0.0045	0.0000	0.0256	-0.0739	0.0907
Zinc	593	0.0008	0.0026	0.0274	-0.0739	0.0907
Graphite	593	-0.0009	0.0000	0.0108	-0.0739	0.0596

Notes: This table reports descriptive statistics of critical materials returns after data winsorization.

Figure 8: Sensitivity analysis - Alternative data treatment - Extreme values



Notes: This figure illustrates the sensitivity of a different data treatment (i.e., winsorization) on the index.

7.2. Using alternative weights

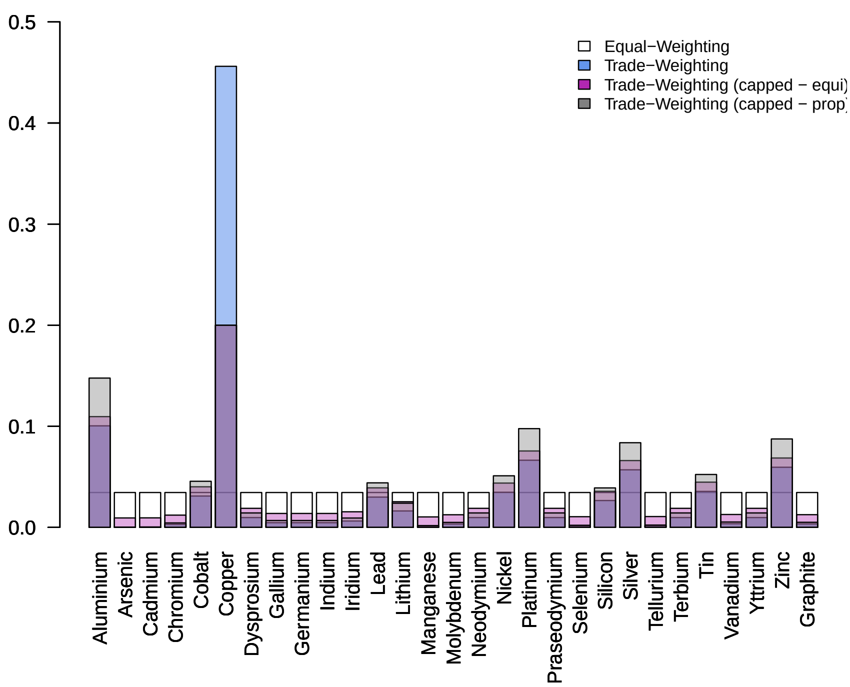
In this subsection, we assess the sensitivity of the CRMI to different weights. Specifically, we test (i) the impact of using a different weighting scheme (e.g., equal weighting) and (ii) the impact of using an alternative weighting factor (i.e., the market concentration).

As described in Subsection 3.2, we first investigate the sensitivity of the index to different weighting schemes. Figure 9 illustrates the different weighting schemes: equal weighting, trade weighting and trade weighting (capped). The comparison between the distributions of weights indicates that the most significant difference lies between the equal weighting scheme and the other weighting schemes, where five critical raw materials are weighted very differently . Then, the trade weighting scheme exhibits a single observable difference from the two other capped weighting schemes: copper is the only weight capped to 20%. Figure 10 illustrates the sensitivity of the CRMI to different weighting schemes. Logically, it appears that trade weighted indices are very similar, whereas the equally weighted index exhibits the same features as the other indices, apart from the level of this index.

We then experiment with another change in the CRMI construction: we use weights related to the Herfindahl-Hirschman Index (HHI) of each critical raw material instead of their respective trade volumes. The economic rationale is that the HHI reflects the supply risk aspect of criticality (Bucciarelli et al., 2024). Figure 11 illustrates the sensitivity of the CRMI to a different weight factor. Instead of relying on the trade volume, which is a common way to construct a commodity index, using the HHI of each critical raw enables us to construct an index weighted differently, depending on the criticality of these raw materials (for the method, see Thomas et al. (2022)). The resulting HHI weighted index is an alternative to the trade weighted index, so the comparison between those two indices reflects the sensitivity of the CRMI to different weight factors.

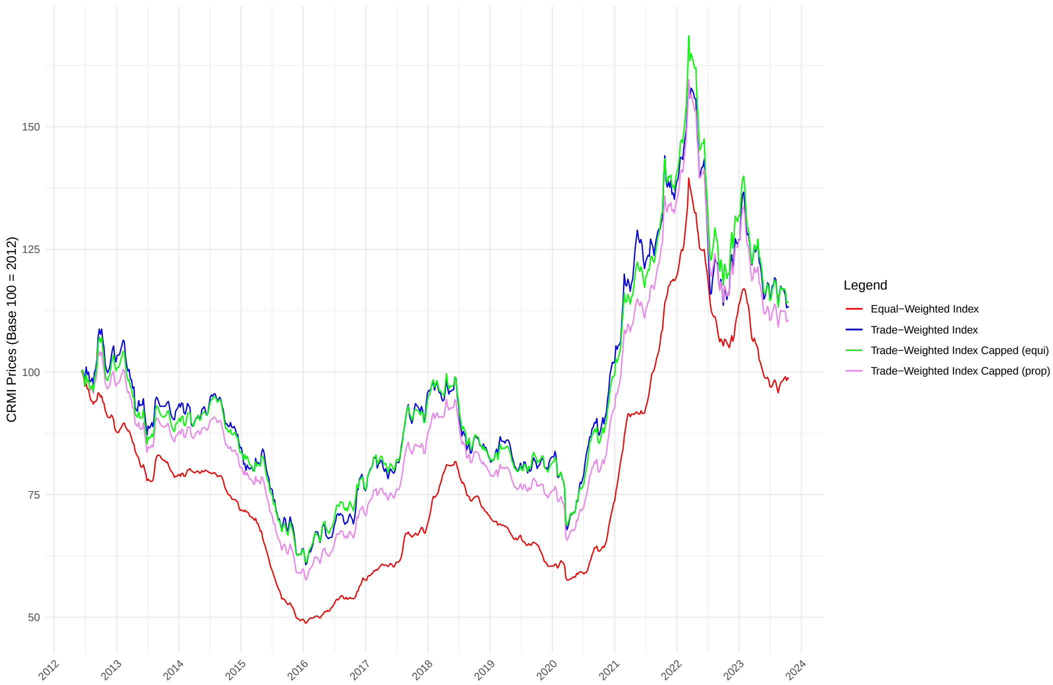
Comparing these two indices in Figure 11, which differ only in the definition of the weights allocated to each critical resource, enables us to assess the sensitivity of the index to the choice of weight factors. This finding indicates that the index is robust to the definition of the weighting factors.

Figure 9: Weighting critical metals



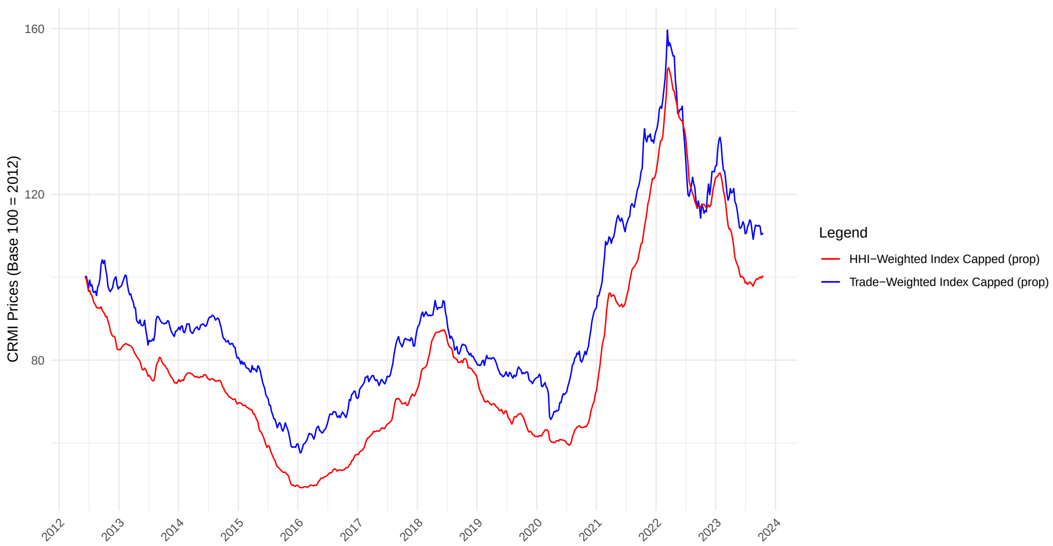
Notes: This figure illustrates the different weighting schemes possible when constructing the index.

Figure 10: Sensitivity of different weighting schemes



Notes: This figure illustrates the sensitivity of different weighting schemes on the index.

Figure 11: Sensitivity of different weighting factors



Notes: This figure illustrates the sensitivity of different weighting factors on the index.

8. Conclusion

We propose and implement a critical raw materials index (CRMI) that is designed to be representative of the critical raw materials market for energy transition. Specifically, the CRMI is a fixed-weight price index aggregating the prices of critical raw materials from their respective trade volumes. This composite indicator tracks a basket of selected critical raw materials to capture the price dynamics of the raw materials essential for energy transition sectors. A detailed set of validation exercises confirms that the CRMI (i) accurately captures the timing and intensity of economic and geopolitical events over time and (ii) shares similarities with the IMF's ETM Index, although the CRMI has comparative advantages in terms of representativeness and usability.

The CRMI provides policymakers with a crucial tool for understanding and addressing the intricate dynamics of the mining market. By tracking the supply, demand, and pricing trends of these critical metals, policymakers can gain valuable insights into the potential bottlenecks and disruptions that could hinder the transition to a net-zero economy. This index enables informed decision-making regarding investments in mining, processing, and recycling infrastructure, as well as the development of effective policies to ensure a secure and sustainable supply of critical metals.

In summary, our new index provides policymakers with a valuable tool for monitoring the price dynamics of raw materials essential to the energy transition. This finding is in line with the recommendations of the Draghi Report (2024) on EU competitiveness, which stresses the importance of increasing transparency in the markets for critical minerals. The development of reliable references on metal prices, as advocated in the report, is crucial for guiding investment decisions.

Finally, our findings pave the way for new research opportunities. The availability of a price index representative of the prices of all critical materials at a weekly frequency will help researchers carry out empirical studies in temporal and cross-sectional dimensions. Among the research topics made possible, research into the impact of supply and demand shocks on this market could be of interest to both academics and policymakers.

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Appendix

A. Definition

Table A: Comparison of clean energy critical metals with the EU and US lists

Metal	Energy transition sectors	EU	USA	TOTAL
Aluminium	Electricity Networks	1	1	1
Arsenic	Solar PV	1	1	1
Boron*	Wind	1	0	0
Cadmium	Solar PV	0	0	1
Chromium	Wind	0	1	1
Cobalt	Electric Vehicles; Grid battery storage; Hydrogen	1	1	1
Copper	Electric Vehicles; Electricity Networks; Grid battery storage; Hydrogen; Solar PV; Wind	1	0	1
Dysprosium (REE)	Electric Vehicles; Wind	1	1	1
Gallium	Solar PV	1	1	1
Germanium	Solar PV	1	1	1
Graphite	Electric Vehicles	1	1	1
Indium	Solar PV	0	1	1
Iridium (PGM)	Hydrogen	1	1	1
Lead	Solar PV	0	0	1
Lithium	Electric Vehicles; Grid battery storage	1	1	1
Manganese	Electric Vehicles; Grid battery storage; Wind	1	1	1
Molybdenum	Solar PV; Wind	0	0	1
Neodymium (REE)	Electric Vehicles; Wind	1	1	1
Nickel	Electric Vehicles; Grid battery storage; Hydrogen; Solar PV; Wind	1	1	1
Platinum (PGM)	Hydrogen	1	1	1
Praseodymium (REE)	Electric Vehicles; Wind	1	1	1
Selenium	Solar PV	0	0	1
Silicon	Electric Vehicles; Grid battery storage; Solar PV	1	0	1
Silver	Solar PV	0	0	1
Tellurium	Solar PV	0	1	1
Terbium (REE)	Electric Vehicles; Wind	1	1	1
Tin	Solar PV	0	1	1
Vanadium	Grid battery storage	1	1	1
Yttrium	Hydrogen	1	1	1
Zinc	Solar PV; Wind	0	1	1
Zirconium**	Hydrogen	0	1	0
TOTAL		*20*	*23*	29

Notes: The IEA (2024) provides the list of critical metals for the energy transition. The final report of the European Commission (2023) provides a detailed overview of the critical metals classified for the European Union. The US Geological Survey (2022) provides a list of critical metals for the United States. Please note that a value of '1' indicates that the metal is included in the respective list, while a value of '0' indicates that the metal is not on the list. REE stands for rare earth elements, PGM for platinum group metals and PV for photovoltaics. Finally, * indicates that we were unable to find the data, while ** indicates that the quality of the data was insufficient to be included in our index.

Table B: Screened Metal Series

Name	Series	Rules	Currency	Unit	Frequency	Provider	Database	Start date
Aluminum	**LME-Aluminum 99.7% Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**31/07/1957**
Arsenic	**China Arsenic Metal 99% FOB**	**1**	**USD**	**t**	**D**	**NA**	**Bloomberg**	**02/07/2004**
	Arsenic CIF NWE U$/LB		USD	lb	D	NA	Datastream	08/10/1993
	Arsenic Metal =99.5% Domestic		CNY	t	D	SMM	Datastream	01/06/2012
	Minor Metals Arsenic 99.5 - %		CNY	t	D	SHMET	Datastream	04/01/2011
Cadmium	**Europe Cadmium Ingot 99.99% In warehouse Rotterdam**	**1**	**USD**	**lb**	**D**	**Asian Metal**	**Bloomberg**	**01/02/2006**
	Cadmium 99.95% CIF NWE U$/LB		USD	lb	D	NA	Datastream	07/10/1994
	Cadmium 99.99% CIF NWE U$/LB		USD	lb	D	NA	Datastream	07/10/1994
	#0 Cadmium Ingot & Bar=99.995 Dom.		CNY	t	D	SMM	Datastream	01/06/2012
Chromium	**China Chromium Metal 99% FOB**	**1**	**USD**	**t**	**D**	**Asian Metal**	**Bloomberg**	**12/01/2001**
	#1 Chromium =99.2%, Coarse Particle		CNY	t	D	SMM	Datastream	01/06/2012
	Mtl Electrolytic Chromium 0.9997		CNY	t	D	SHMET	Datastream	04/01/2011
Cobalt	**LME-Cobalt Cash**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**22/02/2010**
Copper	**LME-Copper Grade A Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**30/01/1957**
Dysprosium	**China Dysprosium Oxide 99% FOB**	**1;2**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**20/04/2001**
	Dysprosium Oxid Dy2O 3/TREO 99.5-99.9		CNY	kg	D	SMM	Datastream	01/06/2012
	Dysprosium-Iron Alloy Dy80 Dom.		CNY	t	D	SMM	Datastream	01/06/2012
	Dysprosium Metal Dy/ TREM=99% Dom.		CNY	kg	D	SMM	Datastream	01/06/2012
	Dysprosium Metal 99% FOB China US/kg		USD	kg	D	Asian Metal	Datastream	18/04/2003
Gallium	**China Gallium Metal 99.99% FOB**	**1**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**12/01/2001**
	Gallium =99.99% Dom.		CNY	kg	D	SMM	Datastream	01/06/2012
	Gallium Ingots CIF NWE U$/KG		USD	kg	D	Refinitv	Datastream	08/03/2002
	Minor Metals Gallium 99.99 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
Germanium	**China Germanium Metal 99.99% FOB**	**1;2**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**09/04/2004**
	Germanium 50ohm CIF NWE U$/KG		USD	kg	D	NA	Datastream	07/07/1995
	Germanium Dioxide CIF NWE U$/KG		USD	kg	D	NA	Datastream	08/06/1995

Name	Series	Rules	Currency	Unit	Frequency	Provider	Database	Start date
	China Germanium Dioxide 99.99% FOB		USD	kg	D	Asian Metal	Bloomberg	12/01/2001
	Germanium Ingot 50O/ Cm Dom.		CNY	kg	D	SMM	Datastream	01/06/2012
	Minor Metals Germanm 50 ohm/cm		CNY	kg	D	SHMET	Datastream	04/01/2011
Graphite	**Graph spherical 99.9 FOB China**	**1;2**	**USD**	**t**	**W**	**Fastmarkets MB**	**Datastream**	**30/03/2012**
	Grphtflk94C-100 mesh fob CN $/ton		USD	t	W	Fastmarkets MB	Datastream	16/08/2018
	China Flake Graphite -194 FOB USD/mt		USD	t	D	Asian Metal	Bloomberg	02/09/2015
Indium	**China Indium Ingot 99.99% FOB**	**1**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**12/01/2001**
	Indium =99.99% Domestic		CNY	kg	D	SMM	Datastream	01/06/2012
	Indium CIF NWE U$/KG		USD	kg	D	NA	Datastream	08/10/1993
	Minor Metals Indium 99.99 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
Iridium	**JM Iridium London U$/Troy Oz**	**1**	**USD**	**t oz**	**D**	**JM**	**Datastream**	**01/07/1992**
	Precious Metals Iridium 99.95 - %		CNY	gm	D	SHMET	Datastream	04/01/2011
Lead	**LME-Lead Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**05/07/1993**
	Lead-Antimony Alloy		CNY	t	D	SMM	Datastream	01/06/2012
	#1 Lead Ingot Pb99.994 Dom.		CNY	t	D	SMM	Datastream	01/06/2012
Lithium	**Lithium Metal =99%, Battery Grade**	**2**	**CNY**	**t**	**D**	**SMM**	**Datastream**	**01/06/2012**
	China Lithium Hydroxide Monohydrate 56.5% FOB		USD	kg	D	Asian Metal	Bloomberg	09/01/2018
	LME Lithium Hydroxide CIF (Fastmarkets MB)		USD	kg	D	Asian Metal	Bloomberg	20/07/2021
Manganese	**SMM Electrolytic Manganese Metal Spot Price Daily (FOB)**	**1**	**USD**	**t**	**D**	**SMM**	**Reuters**	**01/06/2012**
	Manganese Electro CIF NWE US/MT		USD	t	D	NA	Datastream	08/10/1993
	Manganese Ferro CIF NWE US/MT		USD	t	D	NA	Datastream	06/06/2003
Molybdenum	**Europe Molybdenum Oxide 57% In warehouse Rotterdam**	**1**	**USD**	**lb**	**D**	**Asian Metal**	**Bloomberg**	**26/10/2005**
	FerAly Molybdenum Iron mo60 SP		CNY	t	D	SHMET	Datastream	04/01/2011
	Minor Metals Molybdenum 99 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
	Mtlc Cmpd Industrial Molybdnm Oxd51 - %		CNY	t	D	SHMET	Datastream	04/01/2011
Neodymium	**China Neodymium Oxide 99% FOB**	**1;2**	**USD**	**t**	**D**	**Asian Metal**	**Bloomberg**	**20/04/2001**
	Neodymium Metal ND / Trem 99.0-99.99% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
	Neodymium Metal 99% FOB China US/kg		USD		D	Asian Metal	Datastream	18/04/2003

Name	Series	Rules	Currency	Unit	Frequency	Provider	Database	Start date
	Neodymium Oxide ND2O3 / Treo 99.0-99.9% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
Nickel	**LME-Nickel Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**20/07/1993**
Platinum	**JM Platinum London U United States Dollar Per t oz**	**1**	**USD**	**t oz**	**D**	**JM**	**Datastream**	**01/07/1992**
	Precious Metals Platinum 99.95 - %		CNY	gm	D	SHMET	Datastream	12/07/2007
Praseodymium	**China Praseodymium Oxide 99% FOB**	**1;2**	**USD**	**t**	**D**	**Asian Metal**	**Bloomberg**	**04/02/2005**
	Praseodymium Metal Praseodymium / Trem 96.0-99.0% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
	Praseodymium Metal 99% Minimum Free on Board China United States Dollar Per Kilogram		USD	kg	D	Asian Metal	Datastream	18/04/2003
	Praseodymium Oxide PR6O11 / Treo 99.0-99.9% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
	Praseodymium-Neodymium Alloy Praseodymium / Trem 20-25% ND / Trem 75-80% Trem = 98.5% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
Selenium	**Europe Selenium Powder 99.9% In warehouse Rotterdam**	**1**	**USD**	**lb**	**D**	**Asian Metal**	**Bloomberg**	**21/12/2005**
	Minor Metals Selenium 99.90 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
	Minor Metals Selenium 99.99 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
	Selenium CIF NWE U$/LB		USD	lb	D	Refinitv	Datastream	08/10/1993
	Selenium Dioxide =98% Dom.		CNY	kg	D	SMM	Datastream	01/06/2012
	Selenium Ingot =99.9 - %		CNY	kg	D	SMM	Datastream	01/06/2012
Silicon	**China Silicon Metal 2-2-02 FOB**	**1;4**	**USD**	**t**	**D**	**Asian Metal**	**Bloomberg**	**20/10/2011**
	Minor Metals Silicon 2202#		CNY	t	D	SHMET	Datastream	04/01/2011
	Silicon 3-3-0-3 Free on Board China USD / Metric Ton		USD	t	D	Asian Metal	Datastream	17/10/2011
	Minor Metals Silicon 3303#		CNY	t	D	SHMET	Datastream	04/01/2011
	Silicon 4-4-1 Free on Board China United States Dollar Per Metric Ton		USD	t	D	Asian Metal	Datastream	07/04/2004
	Minor Metals Silicon 441#		CNY	t	D	SHMET	Datastream	04/01/2011
	Silicon 5-5-3 Free on Board China United States Dollar Per Metric Ton		USD	t	D	Asian Metal	Datastream	18/04/2003
	Minor Metals Silicon 553#		CNY	t	D	SHMET	Datastream	04/01/2011
	Silicon Lumps CIF NWE U$/MT		USD	t	D	Refinitv	Datastream	08/10/1993

Name	Series	Rules	Currency	Unit	Frequency	Provider	Database	Start date
Silver	**LBMA Silver Price USD/t oz DELAY**	**1;3**	**USD**	**t oz**	**D**	**ICE**	**Datastream**	**02/01/1968**
	Precious Metals Silver 1# 99.99 - %		CNY	kg	D	SHMET	Datastream	12/07/2007
	Precious Metals Silver 2# 99.95 - %		CNY	kg	D	SHMET	Datastream	12/07/2007
	Precious Metals Silver 3# 99.9 - %		CNY	kg	D	SHMET	Datastream	12/07/2007
	Silver, Handy&Harman (NY) U$/Troy OZ		USD	t oz	D	Handy&Harman	Datastream	02/01/1979
Tellurium	**Europe Tellurium Metal 99.99% In warehouse Rotterdam**	**1**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**16/05/2008**
	Tellurium =99.99% Domestic		CNY	kg	D	SMM	Datastream	01/06/2012
	Europe Tellurium Metal 99.9% In warehouse Rotterdam		USD	kg	D	Asian Metal	Bloomberg	23/11/2012
	Minor Metals Tellurium 99.99 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
Terbium	**China Terbium Oxide 99.9% FOB**	**1;2**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**04/02/2005**
	Terbium Metal TB / Trem = 99.9% Domestic RMB / kg		CNY	kg	D	SMM	Datastream	01/06/2012
	Terbium Metal 99% Minimum Free on Board China United States Dollar Per Kilogram		USD	kg	D	Asian Metal	Datastream	18/04/2003
	Terbium Oxide TB4O7 / Treo 99.95-99.99% Domestic RMB / kg		CNY	kg	D	SMM	Datastream	01/06/2012
Tin	**LME-Tin 99.85% Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**31/01/1957**
	#1 Tin Ingot Sn99.90 Domestic		CNY	t	D	SMM	Datastream	01/06/2012
	Mtl Pwdr Tin 200mesh 300mesh		CNY	t	D	SHMET	Datastream	04/01/2011
Vanadium	**China Vanadium Pentoxide Flake 98%min In warehouse Rotterdam USD/lb V2O5**	**1**	**USD**	**lb**	**D**	**Asian Metal**	**Bloomberg**	**30/11/2005**
	FerAly Vanadium Iron FeV50 SP		CNY	t	D	SHMET	Datastream	04/01/2011
	Vanadium Fe 80 CIF NWE U$/KG		USD	kg	D	Refinitv	Datastream	08/10/1993
	Minor Metals Vanadium 99.50 - %		CNY	kg	D	SHMET	Datastream	04/01/2011
	Vanadium Pentoxide CIF NWE		USD	lb	D	Refinitv	Datastream	08/11/1994
Yttrium	**China Yttrium Oxide 99.999%min FOB USD/kg**	**1;2**	**USD**	**kg**	**D**	**Asian Metal**	**Bloomberg**	**27/08/2010**
	Yttrium Metal Y/TREM 99.9-99.95 Dom.		CNY	kg	D	SMM	Datastream	01/06/2012
	Yttrium Metal 99% Minimum Free on Board China United States Dollar Per Kilogram		USD	kg	D	Asian Metal	Datastream	18/04/2003
	Yttrium Oxide Y2O3/T REO 99.995-99.99		CNY	t	D	SMM	Datastream	01/06/2012

Name	Series	Rules	Currency	Unit	Frequency	Provider	Database	Start date
Zinc	**LME-SHG Zinc 99.995% Cash U$/MT**	**1**	**USD**	**t**	**D**	**LME**	**Datastream**	**31/01/1957**
	Zinc Alloy Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
	#1 Zinc Ingot Zn99.99		CNY	t	D	SMM	Datastream	01/06/2012
	Zinc Oxide ZNO = 99.7% Domestic Yuan/Metric Ton		CNY	t	D	SMM	Datastream	01/06/2012
	Mtlc Cmpd Zinc Oxide 99.7		CNY	t	D	SHMET	Datastream	04/01/2011

Notes: This table shows all the metal series screened, with those selected for the construction of our index highlighted in bold. Only series with spot prices are shown, as many metals are traded over the counter and do not have hedging instruments. However, it is worth noting that metals traded on the London Metal Exchange (LME), such as copper and cobalt, also offer futures contracts for three or fifteen months. The selection method for metal prices is based on several criteria. (1): The series is traded on a global exchange; if not, it is a domestic export price series, i.e., free on board (FOB). (2): The series has a higher trading volume than its counterpart and/or a longer historical coverage. (3): The choice of series was based on the provider. (4): The choice was driven by the form of the metal being traded. Let us take a few examples. In the case of dysprosium, this series was selected because it is an FOB price and has a higher trading volume than its counterparts. The literature indicates that rare earth oxides are the most traded form on the market Proelss et al. (2018). For silicon, this series was chosen because of its FOB status and its form, specifically #2202. The silicon used in photovoltaics requires a high purity level (99.99% - 9N). Although we lack a price series for this exact purity, we selected silicon #2202, which has a purity of 99.58% (SCRREEN, Silicon, 2023). The only exception to our selection criteria is lithium. We do not have an FOB price series, and the series traded by the LME started only in 2021. We therefore keep the series in CNY. When series are expressed in USD, they are global exchange series or FOB/CIF series. When series are expressed in CNY, they represent Chinese domestic series. Finally, in the table, in the column on units, 't' stands for tons, 'kg' for kilograms, 'gm' for grams, 'lb' for pounds, and 't oz' for troy ounces. In the frequency column, 'D' stands for daily prices, and 'W' stands for weekly prices.

B. Comparability

Table C: Energy Transition Metals (ETM) Index

Metal	Weight	Series	Unit	Source
Aluminum	15.9%	Aluminum, 99.5% minimum purity, LME spot price, CIF UK ports, USD/mt	USD/mt	LME
Chromium	3.2%	Chromium, #1 Chromium = 99.2%, 99A, Coarse Particle, Fine Particle, USD/mt	USD/mt	SMM
Cobalt	0.6%	Cobalt, minimum 99.80% purity, LME spot price, USD/mt	USD/mt	LME
Copper	34.3%	Copper, grade A cathode, LME spot price, CIF European ports, USD/mt	USD/mt	LME
Lead	3.8%	Lead, 99.97% pure, LME spot price, CIF European Ports, USD/mt	USD/mt	LME
Lithium	0.3%	Lithium, 99% pure, industrial grade, battery grade, USD/mt	USD/mt	SMM
Manganese	3.7%	Manganese Electro CIF North West Europe, USD/mt	USD/mt	Refinitiv
Molybdenum	5.3%	Molybdenum MO3, Insurance and Freight North West Europe, USD/mt	USD/mt	Refinitiv
Nickel	6.7%	Nickel, melting grade, LME spot price, CIF European ports, USD/mt	USD/mt	LME
Palladium	3.1%	Palladium, LME spot price, USD/t oz	USD/t oz	LME
Platinum	4.4%	Platinum, LME spot price, USD/t oz	USD/t oz	LME
REE	0.5%	Rare earth carbonate REO 42-45% purity, USD/mt	USD/mt	SMM
Silicon	5.1%	Silicon lumps, CIF North West Europe, USD/mt	USD/mt	Refinitiv
Silver	7.0%	Silver, London Bullion Market Association, USD/t oz	USD/t oz	ICE
Vanadium	0.2%	Vanadium pentoxide, CIF North West Europe, USD/mt	USD/mt	Refinitiv
Zinc	6.1%	Zinc, minimum special high-grade zinc of 99.995% purity, USD/mt	USD/mt	LME

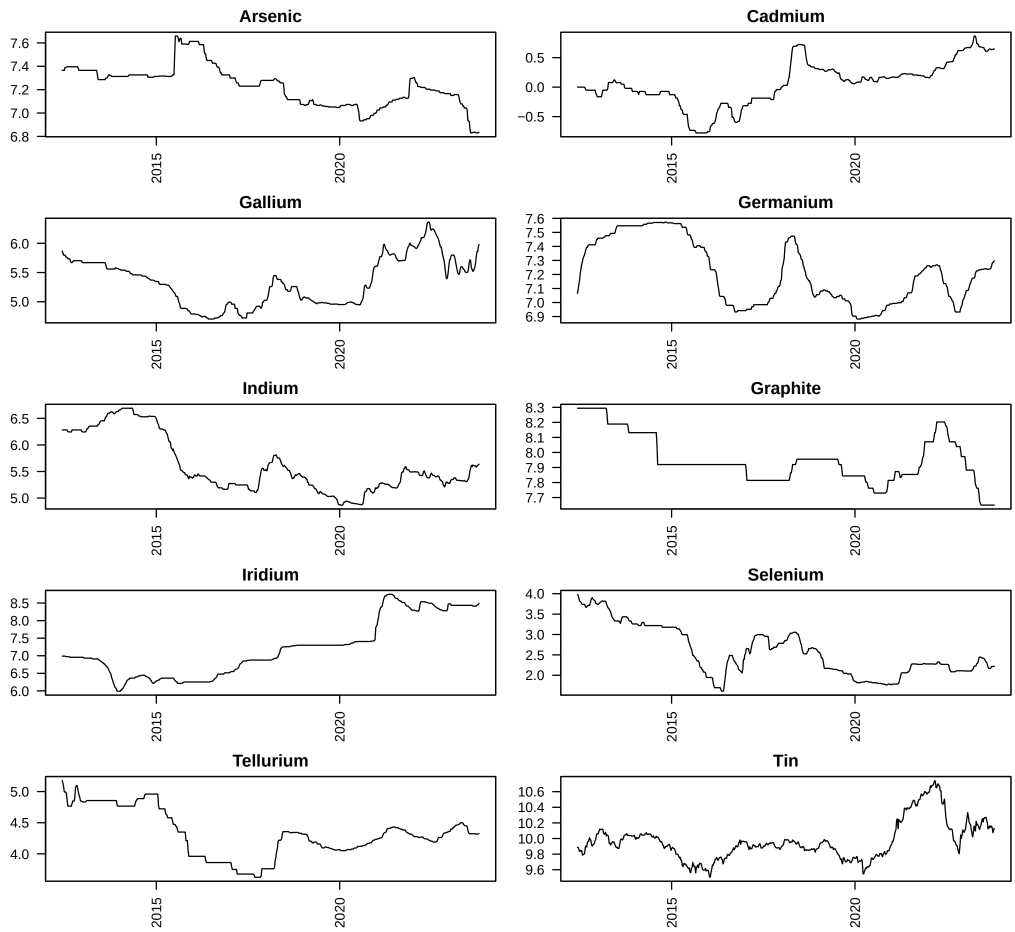
Notes: The Energy Transition Metals (ETM) Index is a sub-index of the Primary Commodity Price Index (PCPI) and is implemented and updated by the IMF. REE stands for Rare Earth Elements and mt, t oz for metric tonnes and troy ounces respectively.

Table D: Critical Raw Material Index (CRMI) - Based on different weighting methodologies

Metal	(1)	(2)	(3)	(4)	(5)
Aluminium	0.0345	0.1004	0.1096	0.1477	0.00723
Arsenic	0.0345	0.0002	0.0093	0.0003	0.11608
Cadmium	0.0345	0.0003	0.0094	0.0004	0.04737
Chromium	0.0345	0.0030	0.0121	0.0044	0.04219
Cobalt	0.0345	0.0310	0.0402	0.0456	0.19339
Copper	0.0345	0.4561	0.2000	0.2000	0.02376
Dysprosium	0.0345	0.0097	0.0188	0.0143	0.06547
Gallium	0.0345	0.0046	0.0138	0.0068	0.02777
Germanium	0.0345	0.0046	0.0138	0.0068	0.02777
Indium	0.0345	0.0046	0.0138	0.0068	0.02777
Iridium	0.0345	0.0063	0.0154	0.0092	0.07954
Lead	0.0345	0.0299	0.0391	0.0440	0.01452
Lithium	0.0345	0.0162	0.0254	0.0239	0.11442
Manganese	0.0345	0.0012	0.0104	0.0018	0.01533
Molybdenum	0.0345	0.0033	0.0125	0.0049	0.04920
Neodymium	0.0345	0.0097	0.0188	0.0143	0.06547
Nickel	0.0345	0.0347	0.0438	0.0510	0.02387
Platinum	0.0345	0.0664	0.0756	0.0977	0.03126
Praseodymium	0.0345	0.0097	0.0188	0.0143	0.06547
Selenium	0.0345	0.0014	0.0106	0.0021	0.03770
Silicon	0.0345	0.0265	0.0357	0.0390	0.03121
Silver	0.0345	0.0569	0.0661	0.0838	0.02391
Tellurium	0.0345	0.0016	0.0107	0.0023	0.10502
Terbium	0.0345	0.0097	0.0188	0.0143	0.06547
Tin	0.0345	0.0356	0.0447	0.0523	0.02548
Vanadium	0.0345	0.0036	0.0128	0.0053	0.07331
Yttrium	0.0345	0.0097	0.0188	0.0143	0.06547
Zinc	0.0345	0.0595	0.0686	0.0875	0.01843
Graphite	0.0345	0.0034	0.0126	0.0050	0.05435

Notes: This table displays the metals and their respective weights in the Critical Raw Materials Index (CRMI) according to various weighting methodologies: (1) equal weighting, (2) trade weighting, (3) trade weighting with cap and equal redistribution, (4) trade weighting with cap and proportional redistribution, and (5) HHI weighting.

Figure A: Comparison of the metal prices: CRMI-exclusive metals vs. ETM (logarithmic scale)



Notes: This figure illustrates the price series of metals that are included in the Critical Raw Materials Index (CRMI) but are not part of the Energy Transition Metals (ETM) Index. The ETM Index, a sub-index of the Primary Commodity Price Index (PCPI), is implemented and updated by the IMF. Prices are presented on a logarithmic scale to better capture trends and variations over time.