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Minerals' criticality and countries' mining competitiveness: Two faces of the same coin☆

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ABSTRACT

This article introduces a novel theoretical and empirical framework for estimating the criticality of key minerals that are intensively used in the energy transition and the mining competitiveness of countries producing them, using economic complexity techniques.

The theoretical framework proposes that the most competitive countries are those exporting a broad range of mineral goods, including the most critical ones. Meanwhile, the most critical minerals are the least ubiquitous and are exported by the most competitive countries. The empirical framework relies on an endogenous system of equations in which countries' mining competitiveness and mineral criticality are simultaneously co-determined. The equation system is solved using the Fitness-Criticality algorithm (FCa), an adaptation of the Economic Fitness-Complexity algorithm.

The results show that South Africa, Russia, the United States, and China are the most competitive mining countries. Meanwhile, the platinum group metals, silicon, rare earths, and lithium are the most critical minerals. These results are consistent with other methodologies employed by different experts that separately estimate both dimensions and derive rankings of countries and minerals, but are obtained with a methodology that offers substantial advantages.

1. Introduction

There is wide consensus on the increasing demand for minerals as a direct consequence of the current energy transition. For instance, the International Energy Agency (IEA) estimated that meeting the Paris Agreement to limit the global temperature increase to "well below 2 °C″ would require a fourfold surge in the demand for minerals used in clean energy technologies by 2040 (International Energy Agency, 2021a).

The fundamentals of rising demand for minerals are the higher consumption intensity of minerals by the emerging technologies compared to the incumbent technologies, and the magnitude of the energy transition underway, i.e., the clean energy technology paradigm is more intensive in mineral use than the fossil fuel paradigm. Moreover, low-carbon technologies require not only significantly larger quantities of minerals but also a broader range of them (Bazilian, 2018). For example, a wind power plant requires nine times more minerals than a gas plant, and an electric car needs six times more minerals than a traditional gasoline-powered car. Similarly, a wind plant and an electric car use seven different types of minerals, while a gas plant and a conventional car use only two (International Energy Agency, 2021b). Consequently, the supply chains of clean energy technologies are more complex than those of fossil fuel technologies, and therefore, the risk of disruption becomes a central issue. In this regard, minerals intensively employed by new technologies become critical for countries involved in the energy transition (Islam et al., 2023).

There is no single definition of mineral criticality, nor is there a standard methodology to estimate it, and hence, there is no unique list of critical minerals (Schrijvers et al., 2020; McNulty and Jowitt, 2021). This depends on the stakeholder perspective (company, country, region, or technology), the goals and scope of the evaluation, the complexities of

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estimating a non-binary multi-dimensional feature, and the time of analysis, among other factors (Graedel et al., 2014). However, the underlying idea behind raw materials' criticality has remained almost unchanged for decades. Indeed, Buijs et al. (2012) show that criticality analyses performed in the 70s and 80s were based on the same variables and parameters employed today, which are measures of the risks of supply shortages and economic importance/vulnerability. Additionally, this study illustrates that results from that time differ from results today, even when using the same methodology, which indicates the dynamic nature of criticality. Therefore, assessing the criticality of minerals requires a complex, dynamic, and tailored analysis with a large set of information from both the demand and supply sides.

Within this context, the present paper introduces a novel theoretical framework that relates mineral criticality to countries' mining competitiveness, and an empirical method based on economic complexity techniques to simultaneously estimate both dimensions. This method has the following advantages over other methodologies: i) it is efficient as it does not require a large set of variables to be calculated; ii) it is neutral as it does not employ arbitrary parameters to calibrate the final indexes, allowing for straightforward replicability; and iii) it can be periodically computed without the need to convene an assessment group.

The proposed framework is built on three cornerstones: mineral criticality is assessed from the perspective of the new clean technologies, there is an endogenous relationship between mineral criticality and countries' mining competitiveness, and economic complexity techniques are used to empirically estimate this endogenous relationship.

In sum, we define criticality from the perspective of the new technologies driving the ongoing energy transition. Therefore, the stakeholders are the technologies, such as solar panels, wind turbines, or electrolyzers. This approach differs from the more common assessment, where mineral criticality is evaluated from the perspective of countries and regions. In this context, we assume that these technologies are the foundation for achieving global climate goals, and thus, the minerals used in their production are critical minerals for the world.

Next, we propose a non-linear endogenous relationship between the criticality of those key minerals intensively used by the new clean technologies and the mining competitiveness of the countries producing them. On one hand, mining competitiveness is defined as the weighted sum of the mineral varieties a country exports, where the criticality level of the minerals provides the weights, i.e., a country is more competitive if it exports a broader range of minerals, including the most critical ones. On the other hand, mineral criticality is defined as an inverse function of the weighted mineral ubiquity, where the weights correspond to the (inverse) competitiveness level of the exporting countries. In this regard, the criticality level accounts for how scarce the mineral is, the industrial organization of the mineral market, and the competitiveness of the exports.

Finally, we employ economic complexity techniques to estimate the simultaneous equation system that emerges from the relationship between minerals' criticality and countries' mining competitiveness. Specifically, we apply the Economic Fitness-Complexity (Tacchella et al., 2012) to a sub-sample of the world's bipartite network of products and countries, where products are raw and low-processed mineral goods, and the countries are mineral-producing economies. We base this on the Economic Fitness-Complexity (EFC) algorithm because it captures the diversity of exported minerals, and its non-linearity accounts for the geological relationship between major minerals and co-products. The execution of the EFC on our sub-sample of mineral goods and mining countries, along with some methodological adaptations,[1] gives rise to our Fitness-Criticality Algorithm (FCa), which delivers two vectors: the Mining Fitness Index (MFI), accounting for countries' mining competitiveness, and the Criticality Minerals Index (CMI), accounting for the extent of minerals' criticality.

The Fitness-Criticality Algorithm (FCa) is computed yearly for the period 1996–2018. The primary input for its computation is the bipartite specialization networks of mineral goods and mining countries, represented through 23 non-binary matrices of Revealed Comparative Advantages (RCAs). The results of the algorithm show that the top 10 most competitive countries for the period 1996–2018 were: 1) South Africa, 2) Russia, 3) the United States, 4) China, 5) Australia, 6) Norway, 7) Canada, 8) Chile, 9) Brazil, and 10) Finland. Meanwhile, the top 10 most critical minerals for the period 1996–2018 were: 1) ruthenium (Ru1), 2) rhodium (Rh1), 3) rare earths (REE), 4) palladium (Pd1), 5) silicon (Si1), 6) lithium (Li2), 7) platinum (Pt1), 8) lithium (Li3), 9) nickel (Ni4), and 10) molybdenum (Mo3).[2]

To the best of our knowledge, no study has proposed a theoretical framework relating mining competitiveness and mineral criticality, nor are there empirical studies testing the relationship between these variables. This represents a major contribution of this paper, along with a clear and standardized methodology to evaluate both dimensions. We are also aware that our framework is supply-based, and there is an open avenue to refine this model with demand-side information.

The paper is structured as follows. Section II reviews the literature on mining competitiveness, mineral criticality, and economic complexity. Section III introduces the theoretical framework relating mining competitiveness and mineral criticality. Section IV presents the empirical framework, including a detailed introduction to the Fitness-Criticality Algorithm (FCa). Section V shows the results of the Fitness-Criticality Algorithm (FCa), represented by the Mining Fitness Index (MFI) and the Criticality Mineral Index (CMI). Section VI provides a robustness check of the results. Finally, Section VII presents the concluding remarks.

2. Literature review

This section summarizes the literature on mining competitiveness, critical minerals and economic complexity, which provides the theoretical grounds for our theoretical and empirical framework.

2.1. Mining competitiveness

The traditional literature on mining competitiveness states that countries' competitiveness is a function of high-quality, low-cost mineral deposits (Tilton, 1992). This view is closely related to the neoclassical international trade theory, in which comparative advantages are defined by countries' factor endowments (Heckscher, 1919; Ohlin, 1933). Therefore, market and export share gaps between countries would exclusively result from mineral endowments. Later, the literature developed along alternative lines, stating that mineral endowments are necessary but not sufficient conditions to ensure competitiveness. Other variables, such as the institutional framework, infrastructure, tax burdens, energy costs, and regulatory framework, emerged as crucial factors in determining countries' competitiveness (Otto et al., 2006). Indeed, while mineral reserves largely determine current production for some minerals, as we move downstream along the supply chain, the role of reserves weakens, and other factors become more significant (Tilton, 1983; Tilton, 1992; Tilton and Guzmán, 2016).

The straightforward approach to measuring countries' mining competitiveness is through their market share in international minerals markets. This is because minerals markets are assumed to be perfectly competitive, where market shares are a direct function of production costs. However, given the nature of the mining sector, some important considerations arise when using market share as a competitiveness indicator.

First, market shares in the mining industry exhibit high path

[1] The specific adaptations are presented in Section IV.

[2] The specific products for each mineral are presented in Annex A.

dependence due to the long life of mining operations and high sunk capital costs: current mineral production is the result of investments made decades ago. This implies that mining competitiveness, as measured by market shares, may reflect past competitive conditions. For current conditions to affect market share, the average variable cost must exceed the mineral price, which would signal the exit point for firms. Otherwise, mining companies will continue producing. Therefore, even if there are major changes in the competitiveness conditions of a mining country, market share may not reflect these changes in the short term (Tilton, 1983).

Second, market shares not only reflect natural competitiveness factors (endowment, labor, capital, and technology) but also consider policy distortions introduced by regulations and public policies. Consequently, countries with clear comparative advantages (large mineral endowments) are not necessarily competitive in mineral extraction if governments impose overly strict regulations, such as excessive royalties or permit compliance (Tilton, 1992).

For all the reasons mentioned above, the empirical literature on mining competitiveness has opted to measure competitiveness in terms of a country's ability to attract mining investments, i.e., through foreign direct investment (FDI) in exploration (Otto et al., 2006). It is argued that past reserves explain a large portion of current production, so future production and market shares will depend on new reserves, which are a function of today's investments in exploration. Furthermore, because investments are highly sensitive to the investment climate, they should automatically capture variations in the variables that influence competitiveness (Jara et al., 2008; Jara, 2017; Castillo and Roa, 2021; Vasquez and Prialé, 2021).

Jara (2017) and Vasquez and Prialé (2021) model competitiveness to attract FDI to the mining sector as a function of mineral endowments and the investment climate, using slightly different variables and econometric methods. In these models, FDI allocated to exploration is taken as a proxy for mining competitiveness by country (dependent variable), while the land area of countries or market share is used as a proxy for the geological endowment of countries (independent variable). The Index of Economic Freedom[3] and the Governance Index from the World Bank are used as proxies for the mining investment climate (independent variable). In their estimations, Jara (2017) employs a second-order Taylor expansion and ordinary least squares on cross-sectional data, while Vasquez and Prialé (2021) use a multiplicative functional form and pseudo-maximum likelihood on cross-sectional data. Both studies find evidence supporting the view that investment climate variables statistically significantly explain mining competitiveness.

In turn, Castillo and Roa (2021) focus on explaining and estimating the determinants of mineral endowments. This approach challenges the exogeneity of mineral endowments and proposes that geological maturity is a positive function of information spillovers and a negative function of the depletion of exploration opportunities. They test this hypothesis in the copper and gold industries. In the case of copper, the results suggest that the spillover and depletion effects cancel each other out, while in the case of gold, the spillover effect dominates the depletion effect.

In sum, although all these empirical approaches are very compelling, they do not directly estimate mining competitiveness due to the lack of a variable reflecting current productive competitiveness. Therefore, one of the main empirical contributions of our paper is the provision of a new variable that accounts for current productive competitiveness.

2.2. Critical minerals

Historically, the concept of critical minerals dates back to 1939 with the "Strategic and Critical Materials Stock Piling Act in the United States," established in the context of WWII (U.S Congress, 1939). In the 70s and 80s, this topic gained popularity again due to national security concerns in the United States and Europe during the Cold War (Buijs et al., 2012). Since then, mineral criticality has re-emerged as a relevant topic due to several factors: the supercycle of commodity prices triggered by Chinese demand in the early 2000s, the current energy-digital transition stressing mineral markets in both the short and long run, and the trade war between the U.S. and China, which has influenced supply chains of critical raw materials. These developments confirm that the concept of mineral criticality changes according to global socioeconomic evolution. Indeed, Buijs et al. (2012) shows that criticality analyses performed in the 70s and 80s produced a list of critical minerals very different from today's, despite considering the same dimensions. This confirms the dynamic nature of criticality as a function of the prevailing socioeconomic system.

However, the list of critical minerals varies significantly due to the lack of a common definition and standardized framework. All assessments consider one, two, or three of the following dimensions: supply risk, environmental implications, and vulnerabilities to supply restrictions. They also adopt different assessment perspectives, such as the corporate, national, or technological levels, and may target economic and strategic importance or the potential impact of supply disruptions. Additionally, the assessments may reflect short-, medium-, and long-term considerations. Therefore, the list of critical minerals is bound to vary due to the different considerations made by researchers (Graedel et al., 2014; Helbig et al., 2016; McNulty and Jowitt, 2021; Schrijvers et al., 2020).

Furthermore, the lack of a harmonized methodology, data availability, and the ad-hoc assumptions used in each case make it very difficult to compare different assessments (Buijs et al., 2012; Helbig et al., 2016). Therefore, although it is not possible to converge on a single and universal criticality assessment, there is ample room to improve and standardize measures to ensure meaningful and consistent assessments (Graedel et al., 2014).

The innovation literature has recently studied the association between countries' natural resources and the supply of materials in the evolution of technological paradigms. These studies have identified critical materials based on their intensity in technological innovations related to the information and communication technologies (ICT) paradigm and have found an association between technological dynamics and the demand for critical materials over time (Diemer et al., 2022; Li et al., 2024). The intensive use of critical raw materials is also found in green technologies, especially the more mature ones, such as metal processing innovations (De Cunzo et al., 2023).

In sum, two cornerstones can depict the state of the art in critical minerals assessment: a general flexible definition and a broad framework. The definition proposed by Schrijvers et al. (2020) accurately illustrates the development of the literature in this area. The authors define raw material criticality as "the field of study that evaluates the economic and technical dependency on a certain material, as well as the probability of supply disruptions, for a defined stakeholder group within a certain time frame" (p.2).

The long-standing tradition of evaluating criticality based on risks of supply disruptions and a mineral's economic importance or economic vulnerability remains (Buijs et al., 2012; Graedel et al., 2014; Schrijvers et al., 2020). Among the main indicators used to measure disruption supply risk are the net import reliance ratio, global supply concentration, reserves, by-product dependency, recyclability, political stability, regulations, and governance of the mineral (disruption risks). Meanwhile, the total material required, value added of end-use sectors, demand growth, trade restrictions, price volatility, and substitutability are used to measure the minerals' economic importance/vulnerability (Buijs et al., 2012; Graedel et al., 2014; Schrijvers et al., 2020).

[3] Published by the Heritage Foundation and Wall Street Journal.

2.3. Economic complexity

The foundations of the economic complexity indexes literature[4] emerged in the early 2000s with the idea that what countries produce/export matters in terms of economic development (Hausmann and Rodrik, 2003; Hausmann et al., 2007). This theoretical literature found its empirical toolkit in network economics and complex systems to infer countries' capabilities based on what they produce, allowing for the estimation of the complexity of countries (Fitness) and products (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Tacchella et al., 2012).

The seminal paper on economic complexity provides an intuition of what complexity is by using the analogy of Lego blocks (Hidalgo and Hausmann, 2009). Simply put, the authors propose that if we can infer the diversity and exclusivity of the Lego pieces in a child's bucket, we can infer the diversity and exclusivity of countries' capabilities by looking at their production/export baskets. Income differences between countries, therefore, can be explained because, even in a globalized world with perfect factor mobility, there are some sticky factors they call domestic capabilities. Similarly, Tacchella et al. (2012) refer to economic complexity (Fitness) as an approach capable of capturing the underlying link between countries' export baskets and their industrial competitiveness.

On the empirical side, economic complexity is developed from a bipartite specialization network of products (exports, patents, etc.) and locations (regions, countries, etc.).[5] The projection of this network onto the product dimension creates the product space and proposes that products are related according to the set of knowledge employed to produce them. The conceptual idea suggests that more complex products are located at the center of the space, while less complex products are in the periphery, reflecting the degree to which products are connected by the various types of knowledge used in their production (Hidalgo et al., 2007).

In practice, there are two main alternative methods to estimate complexity, both starting from a common observation: underdeveloped countries can export a limited set of goods, while developed countries can export a large diversity of goods. Therefore, if an underdeveloped country exports a good, it can be inferred that the good requires low capabilities or has a low level of sophistication. This observation is known as the nestedness property (Bustos et al., 2012).

On one hand, Hidalgo and Hausmann (2009) propose the Reflection Method, which essentially solves an eigenvector equation system for an ad-hoc matrix. In this method, the complexity of a country is the average complexity of its exported products, while the complexity of a product is the average complexity of the countries producing it. On the other hand, Tacchella et al. (2012) argue that the nestedness property indicates a non-linear relationship between countries' complexity and products' complexity; thus, product complexity cannot be defined as the average of the countries' complexity producing it. Consequently, they propose an alternative non-linear model called Economic Fitness Complexity, which captures the fact that only the most diversified countries (high fitness) can export the most complex goods.

It should be noted that this theoretical-methodological approach has recently been used in the analysis of sustainable development (Stojkoski et al., 2023) and environmental competitiveness (Barbieri et al., 2023). Caldarola et al. (2024) identify two main applications of economic complexity in the green transition. The first explores the association between productive structure complexity and variables linked to sustainability, such as CO2 emissions. The second, more influenced by evolutionary economics, studies the productive and technological bases of different economies by analyzing their specialization in green products or technologies and the relatedness between green and non-green goods and technologies.

3. Theoretical framework

In this section, we present the economic foundations that shape the Fitness-Criticality Algorithm (FCa). To the best of our knowledge, there is no previous theory or empirical method that combines mining competitiveness and mineral criticality. The FCa is built on an endogenous relationship between the mining competitiveness of countries and the criticality level of minerals, where the diversity of minerals produced by countries and the ubiquity of minerals in world markets are the two exogenous inputs feeding the algorithm.

In summary, the idea underlying our theoretical framework is that countries' mining competitiveness is a function of the diversity of extracted minerals and their degree of criticality. In turn, the criticality of minerals depends on their relative scarcity and market concentration, which is approximated by the inverse of mineral ubiquity and the competitiveness of producer countries. Thus, countries' mining competitiveness and minerals' criticality are simultaneously determined. Fig. 1 illustrates this relationship, whose economic logic will be explained in subsections 3.1 and 3.2.

3.1. Country mining competitiveness

As the literature review illustrated, measuring mining competitiveness is a challenging task. On the one hand, market shares incorporate high path dependency given the long lives of mines, and therefore they do not reflect competitiveness in real-time. On the other hand, FDI allocated to exploration reveals the competitive expectations of a country and, at best, forecasts its future competitiveness.

In our approach, we define countries' mining competitiveness based on the specialization of countries exporting minerals, which is approximated by the revealed comparative advantage (RCA) of each country in each critical mineral. Specifically, competitiveness is a direct function of

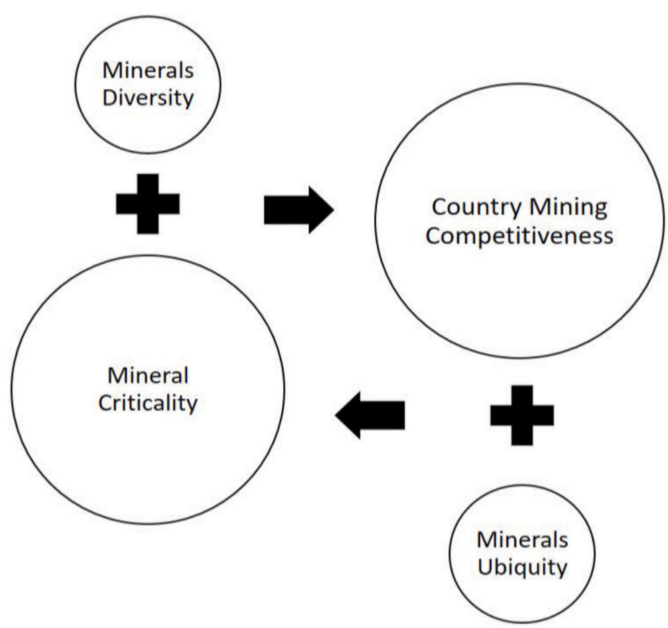

Fig. 1. Conceptual relationship between Mineral Criticality and Countries' Mining Competitiveness.
Source: Authors' elaboration.

[4] The two most famous are the Economic/Product Complexity Index (Hidalgo and Hausmann, 2009) and the Economic Fitness-Complexity (Tacchella et al., 2012).

[5] Recently, Pugliese et al. (2019) extend the bipartite networks to a multi-layered network to study the dynamics of national systems of innovation considering productive specialization (products), scientific specialization (publications) and technological specialization (patents).

the specialization diversity level of countries exporting minerals and the criticality level of these minerals. In this sense, a country will be more competitive if it specializes in exporting a wider range of minerals, especially the most critical ones. From this definition, three relevant dimensions emerge.

First, our definition replaces market share and FDI exploration share with the specialization level in minerals' exports. Therefore, competitiveness is a relative measure, normalized according to the size of the economy, to allow for cross-country comparisons. This approach also reduces the temporality bias that arises from the stickiness of market share in relation to production costs. This is because the specialization level is a measure relative to other economic sectors. According to firm theory, if production costs in the mining sector increase, margin reductions will induce a shift towards increasing exports of other sectors. Thus, even though the quantity of exported minerals remains constant, their export share in the country's basket diminishes. In the long run, the country's specialization in a specific mineral should reflect the production costs of that mineral.

Second, our definition expands the scope of competitiveness to include the diversity of exported minerals as a determinant of competitiveness. This is because more diversified countries are more resilient to mineral substitution triggered by technological change, where diversification acts like an insurance instrument (Markowitz, 1991). The demand substitution risk has two sources. First, the substitution of one mineral for another in the production of a given technology. Second, the substitution of the entire technology, along with all the minerals used in the obsolete technology. The former is part of the essence of technological progress, where emerging technologies seek to reduce costs. A clear example of this risk is the current technological race in Li-ion batteries, wherein different sub-technologies are competing to lead the market, differing in their proportions of various minerals. For instance, the NMC battery uses 33.3% nickel, 33.3% manganese, and 33.3% cobalt, while the NMC811 battery uses 80% nickel, 10% manganese, and 10% cobalt (Hund et al., 2020). The latter risk is identified in less mature technologies, such as energy storage systems, where the technological race is still in its early stages, and there is no dominant technology yet. For example, new prototypes of energy storage technologies are replacing lithium–cobalt batteries with salt batteries employing non-critical or less critical minerals, such as sodium, nickel, and chloride (Armand et al., 2023).

Third, our definition states that each mineral contributes to competitiveness to a different extent, depending on its own criticality level. Thus, ceteris paribus, countries specializing in more critical minerals have higher competitiveness than countries specializing in less critical minerals. The economic fundamentals underlying this relationship lie in the source of minerals' criticality, which stems from their scarcity and market concentration, revealing the market power of countries to influence market prices and rents. Silicon and Rare Earths are pertinent examples, where imperfect markets prevail, and prices are determined by undisclosed contracts between a small number of economic actors. Indeed, many minerals' markets are imperfectly competitive.

Therefore, we formally define country mining competitiveness as follows:

$$MC_c = \sum_{m=1}^{M} x_{m,c} \bullet C_m \tag{1}$$

Where MC_c is the mining competitiveness of country c, $x_{m,c}$ is the specialization level of country c in producing mineral m and C_m is the criticality level of mineral m. Thereby, the mining competitiveness is a direct function of the diversity of the minerals that country c specializes in (sum across all specialization varieties) and the criticality level of each produced mineral.

3.2. Mineral criticality

Although changing preferences and a rise in demand exert pressure on mineral markets, it is the incapacity of the supply to satisfy demand in the medium and long term that triggers mineral criticality (Hayes and McCullough, 2018). A supply disruption can be caused by physical shortages or market conditions, such as persistent mineral price hikes, which prevent the production of optimal mineral quantities. In this regard, it is important to understand whether shortages are caused by transitory or permanent shocks (Buijs et al., 2012).

In a traditional market, differentiating supply shortages based on physical or market causes makes no sense since both triggers are endogenous (the price is the mechanism by which physical quantities are adjusted). For instance, a physical market shortage would increase the product price, which in turn would incentivize new suppliers to enter the market (with higher marginal costs), thus overcoming the shortage. On the other hand, if price excessively climbs due to a supply chain disruption incumbents and entrants are incentivized to innovate to reduce production costs and thereby capture a larger share of the market (under perfect or monopolistic competition). The same result can be reached in an oligopolistic mineral market where countries compete on price (Bertrand competition).

However, mining markets have some particularities that differentiate them from traditional markets. First, mineral supply is inelastic to price changes in the short and medium term due to the long time required to develop a new project. Once the exploration process succeeds, which can take decades, developing a project, building the mine, and starting production can easily take ten years.[6] Therefore, quantities react slowly to price movements in the short and medium term. Second, several critical minerals are produced in small quantities as co-products of major minerals such as copper, nickel, or iron. Thus, the economic viability of extracting co-products depends on the joint profit maximization of different minerals, which is not always profitable or technologically feasible. For instance, the quality of the major mineral ore might not be high enough to justify extraction, making the project profitable only by considering the co-product credit. Moreover, co-products exhibit higher price volatility due to their non-competitive price formation. Another issue is the availability of adequate technology to recover (extract) by-products, as companies focused on major minerals often do not incorporate the necessary technology, causing these minerals to end up in tailings. Similarly, co-products can only be recovered during the metallurgical process if the smelter has the necessary technology; otherwise, they end up as waste.

Another microeconomic peculiarity of mineral markets that affects mineral criticality is the relationship between short- and long-term average cost curves (Envelope Theorem). The long-term average cost curve does not necessarily envelop the short-term curves as textbook microeconomic theory suggests (Perloff, 2004). This is because, in the mining sector, the long term still presents rigidities due to mineral endowments and mine production scales, which push marginal costs up as mineral depletion advances, as ore quality decreases and distances in the mine increase. Although these geological drivers of marginal costs are countered by technological progress that reduces extraction costs, particularly for new projects, the effect is rarely complete, and the net result can be a higher marginal cost in the long term. The case of copper in Chile provides a good example, as production costs have increased over the past two decades due to diminishing ore quality. Of course, this is also due to the maturity level of the industry and the decreasing economies of scale in new operations relative to older ones.

Therefore, mineral criticality is shaped by several peculiarities of mining markets. In this context, we define mineral criticality not as a dichotomous variable, but as a continuous variable that reflects the

[6] Brine lithium projects take a shorter time depending on the regulatory framework of the host country.

relative scarcity and market concentration of a mineral in the long term, as well as its supply chain disruption risks. Specifically, mineral criticality is measured through mineral ubiquity, which accounts for the number of countries specializing in exporting the mineral, and the competitiveness of producer countries, confirming the fact that the most competitive countries are the only ones capable of exporting the most critical minerals. This empirical fact is known as the *nestedness* property (see Subsection 4.3) and is modeled through the non-linearity of the algorithm, as well as in the original Economic Fitness-Complexity algorithm.

A ubiquitous mineral means that several countries possess the endowment, institutions, and technology to efficiently produce and export it. Consequently, a more ubiquitous mineral is less critical since the probability of disruptions or shortages is lower (i.e., there are more substitution options). From a geological perspective, the ubiquity of several minerals is due to their status as co-products of major minerals, meaning they are present in very low quantities alongside major mineral deposits. As a result, estimating their reserves is a difficult task (McNulty and Jowitt, 2021). For each co-product extracted, a couple of other minerals are mined, meaning that countries producing these scarce co-products tend to produce (and export) a larger variety of minerals. Therefore, given that we define mining competitiveness as an increasing function of mineral diversity, more competitive countries are also those capable of exporting the most critical minerals.

Now, ore endowment can be considered a semi-exogenous variable since the amount and distribution of minerals in the earth are exogenous, but discovering ore veins is endogenous to investment in exploration (Castillo and Roa, 2021). Therefore, mineral ubiquity is driven by the random distribution of ores around the world, plus the effort countries put into discovering new deposits, which is strongly dependent on countries' institutions and governance conditions. If we include institutional quality and governance in a definition of local capabilities, the non-linearity of the model can be partially explained by local capabilities.

Formally, we define mineral criticality as:

$$C_m = \frac{1}{\sum_{c=1}^{C} x_{m,c}\left({}^{1}/_{MC_c}\right)} \tag{2}$$

Where C_m is the criticality level of mineral m, $x_{m,c}$ is the specialization level of country c in producing mineral m and MC_c is the mining competitiveness of country c. In this regard, the mineral criticality inversely depends on its ubiquity, which is given by sum of mineral specialization across countries. In turn, the mineral ubiquity is weighted by the mining competitiveness level of the exporter country, with which minerals produced by more competitive countries are less ubiquitous than minerals produced by less competitive countries.

4. Empirical framework

We simultaneously estimate the criticality of key minerals intensively used by new clean technologies and the mining competitiveness of the countries producing them using economic complexity techniques. We chose this method due to the endogenous nature of the relationship between competitiveness and criticality, as outlined in our theoretical framework. In this way, characteristics at the country level shape a product-based variable, and vice versa.

We apply the Fitness-Complexity algorithm introduced by Tacchella et al. (2012) over a sub-sample of the bipartite network of products and countries, allowing us to infer features of minerals and countries based on their intrinsic co-simultaneity. We call this algorithm the Fitness-Criticality Algorithm (FCa) since our theoretical formulation relates the fitness (competitiveness) of countries to the criticality of minerals. The features of minerals and countries delivered by the algorithm give rise to the Critical Mineral Index (CMI) and the Mining Fitness Index (MFI), respectively.

Subsection 4.1 describes the sequential steps followed to configure and run the Fitness-Criticality Algorithm, and subsection 4.2 introduces and explains the mechanics of the algorithm itself.

4.1. Methodology steps

The first step consisted of selecting the most relevant technologies brought about by the energy transition and then identifying the minerals most intensively used by these technologies. This process relied on an extensive literature review, which included the analysis of scenarios conducted by the International Energy Agency and the World Bank in recent years (Hund et al., 2020; International Energy Agency, 2021b).

As a result of this analysis, we identified 10 key technologies, and 20 critical minerals consumed by them (Table 1).

The second step was to identify all traded products containing these minerals. For this purpose, we performed a text analysis of the product code descriptions from the United Nations COMTRADE database (disaggregated to six digits). We searched for our mineral keyword list (without any specific truncation or proximity operators) (See Table 1), followed by keywords such as mineral, ores, concentrates, natural, unroasted, flakes, powder, oxides, hydroxides, cathodes, anodes, raw, unalloyed, mattes, and carbonates, as we are interested in minerals belonging to extractive industries and low-processed goods. As a result, we arrived at a list of products ranging from ores/concentrates to goods from the first metallurgical/chemical stages (anodes, cathodes, oxides, hydroxides, etc.).

Thus, our sample consisted of 42 mineral products distributed as follows: iron products (6); aluminum/bauxite products (4); copper products (4); nickel products (4); molybdenum products (3); lithium products (3); zinc products (3); graphite products (2); silicon products (2); chromium products (1); silver products (1); rare earths product (1); cobalt product (1); niobium, tantalum & vanadium products (1); manganese product (1); lead product (1); ruthenium, osmium and iridium product (1); rhodium product (1); palladium product (1); and platinum product (1).[7]

The third step consisted of differentiating mineral producers from mineral exporter countries, as the COMTRADE database accounts for gross exports, which means it includes products re-exported by countries. To address this, we cross-referenced the export data with production data from the United States Geological Survey (USGS) and removed all countries with null or minimal levels of mineral production during the studied period. If a country was a top producer of at least one of the selected minerals, it was included in the sample. In this way, we obtained a sub-sample of 48 countries.

The fourth step was to estimate the specialization level of countries in producing each mineral for each year. To do this, we calculated the Revealed Comparative Advantage (RCA) for each country-mineral pair across the entire bipartite matrix (5040 products and 147 countries). The RCA_{ij} reflects the specialization level of country i in mineral j over the full range of exported products, and it is computed as follows:

$$RCA_{ij} = \frac{X_{ij} \Big/ \sum_j X_{ij}}{\sum_j X_{ij} \Big/ \sum_j \sum_j X_{ij}}$$

Where X_{ij} represents the exports of sector j by country i. Hence, RCA_{ij} is a relative measure of the weight of sector j in the export basket of country i regarding the weight of sector j in the export basket of the world.

The fifth step was to build up the country-mineral bipartite network by using the RCAs previously calculated. The network is represented as a

[7] See the Annex A for further information regarding the products selected.

Table 1
Critical minerals list and clean technologies.

Minerals/Technologies	Solar PV	CSP	Wind	Geothermal	Hydro	Nuclear	Electricity Networks	Energy Storage	Hydrogen	Bio-energy
Aluminum	X	X	X		X	X	X	X	X	X
Chromium		X	X	X	X	X				
Cobalt								X		
Copper	X	X	X	X	X	X	X	X		X
Graphite								X		
Iron Ore			X					X		
Lead	X		X		X	X				
Lithium								X		
Manganese			X	X	X			X		
Molybdenum	X		X	X	X	X				
Nickel	X	X	X	X	X	X		X	X	
Niobium, tantalum and vanadium						X		X		
Palladium									X	
Platinum									X	
Rare Earths			X					X	X	
Rhodium									X	
Ruthenium, osmium and iridium									X	
Silicon	X									
Silver	X	X				X				
Zinc	X	X	X		X	X		X		

Note: CSP-Concentrated solar power.
Source: Author's elaboration based on Hund et al. (2020) and International Energy Agency (2021a).

specialization matrix composed of all RCAs for our country-mineral subsample. Thereby we obtained a specialization matrix with 48 countries x 42 minerals, per each year, i.e., 23 matrices (from 1996 to 2018).

4.2. *Fitness-Criticality Algorithm (FCa)*

The Fitness-Criticality Algorithm (FCa) is an adaptation of the non-linear Economic Fitness-Complexity (EFC) algorithm proposed by Tacchella et al. (2012). The two main differences are: i) RCAs are calculated based on the total export basket, but the FCa is run only over the sub-sample of critical minerals and mining producer countries. This differs from the sectoral approach followed by the EFC literature (Caldarola et al., 2023), which calculates sector indicators based on the algorithm's computation on the full bipartite network of products and countries, and then sums the complexity of the specific goods of interest. ii) RCAs are employed in a non-binary format, instead of the common practice of binarizing them.

The first methodological difference is based on the idea that specializing in mining goods is a function of the specialization level in the rest of the economy. However, mineral criticality and countries' mining fitness are not functions of the complexity of the rest of the goods or the fitness of non-mining countries. In other words, the extent of a country's specialization in critical minerals will move according to changes in its specialization in other economic sectors, but its mining fitness will depend only on the diversity and criticality of exported minerals. Otherwise, if we considered all products and countries (as in the original Economic Fitness-Complexity approach), we would be implying that the criticality of lithium hydroxide is affected by the capacity of the United States to export a large variety of goods, particularly complex goods such as pharmaceuticals or electronics.

The second methodological difference reflects our judgment that the level of specialization matters in terms of countries' fitness and minerals' criticality. For instance, if many countries have RCAs <1 for a particular mineral good and only a few have RCAs >1, it will indicate that a few countries are specialized in exporting it, but the mineral is not scarce. Conversely, if only a few countries have RCAs >1 and the rest have RCA $= 0$, it would indicate that few countries are specialized in exporting it, and the mineral is physically scarce. Therefore, we use normalized and continuous RCA matrices in the range [0, 1], as proposed by Tacchella (2020).

We adhere to the EFC algorithm instead of the one proposed by Hidalgo and Hausmann (2009) because the former preserves the information on export diversification and captures the non-linear relationship between countries and minerals expressed in the triangular matrix (*nestedness* property[8]).

The FCa provides two vectors as the final output: the Mining Fitness Index (MFI), which accounts for the competitiveness of countries in exporting critical minerals, and the Criticality Minerals Index (CMI), which accounts for the criticality level of minerals intensively used in new clean technologies. Specifically, the MFI is the result of an iterative process in which the export specializations of countries are weighted by the criticality of minerals.[9] In turn, the CMI is the result of an iterative process in which the inverse of the minerals' ubiquities is weighted by the inverse of the MFI, which defines the non-linear relationship between both dimensions.[10]

4.3. *Nested network of countries – minerals*

The *nestedness* property refers to "a hierarchical organization where the set of neighbors of a node is a subset (superset) of the neighbors of lower (larger) degree" (Mariani et al., 2019). In economic systems, the *nestedness* property has been observed through the triangularity of trade specialization matrices (Tacchella et al., 2012; Bustos et al., 2012; Cristelli et al., 2015), which reflects that countries with higher fitness are those capable of exporting the most complex goods, and hence, the most complex goods are exported by the most fit countries.

In our case, the *nestedness* property is visualized when the adjacency matrix for our minerals–countries network is sorted in ascending order by product complexity (rows) and then in descending order by countries' fitness (columns). Fig. 2 shows that our sorted adjacency matrix for the year 2018 exhibits a triangular shape, thus supporting the *nestedness* property. Simply put, in our case, this reflects that the most competitive mining countries are those capable of exporting the most critical minerals, and consequently, the most critical minerals are exported by the most competitive countries in the mining sector.

Our Fitness-Criticality (FCa) algorithm offers an alternative perspective on the fundamentals underlying the adjacency matrix compared to the viewpoint adopted by standard economic complexity literature. In the traditional approach, the most competitive countries

[8] We delve into this point later.
[9] At the iteration n-1.
[10] At the iteration n-1.

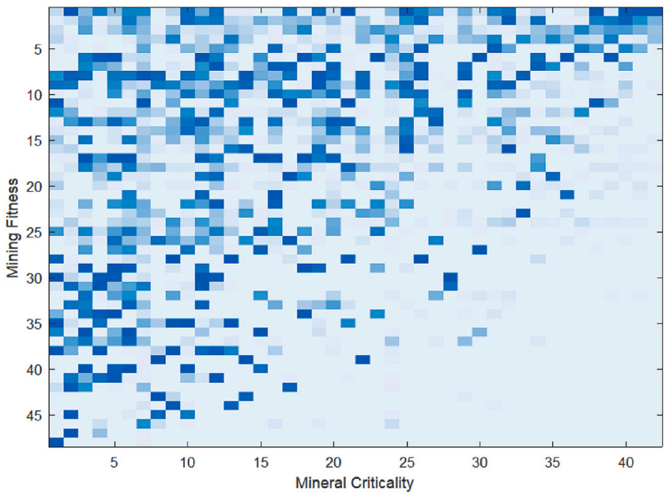

Fig. 2. Triangular adjacency matrix (2018).
Source: Author's elaboration.

(high fitness) can produce the most complex goods because they possess a larger and more exclusive set of capabilities. We argue that for this specific sector, the geological endowment distribution shapes the positive relationship between countries' fitness and minerals' criticality. This is due to the geological pattern followed by critical minerals, where the less ubiquitous minerals are present in minimal concentrations within deposits of major minerals, and hence, they are mined as by-products. As a result, these minerals are produced in tandem with major minerals, meaning that countries producing these minerals tend to have a more diverse mineral export basket. Consequently, the most critical minerals are produced by the highest fitness countries, while countries with lower fitness can produce only the less critical minerals.

4.4. The functional form

Formally, the Fitness Criticality algorithm (FCa) is defined by the following system of equations:

$$\widehat{MFI}_c^{(n)} = \sum_m M_{cm} CMI_m^{(n-1)} \tag{13}$$

$$\widehat{CMI}_m^{(n)} = \frac{1}{\sum_c M_{cm}\left(1/MFI_c^{(n-1)}\right)} \tag{14}$$

$$MFI_c^{(n)} = \frac{\widehat{MFI}_c^{(n)}}{\left\{\widehat{MFI}_c^{(n)}\right\}_c} \tag{15}$$

$$CMI_m^{(n)} = \frac{\widehat{CMI}_m^{(n)}}{\left\{\widehat{CMI}_m^{(n)}\right\}_m} \tag{16}$$

Where MFI_c is the fitness of country c, M_{cm} is the country-mineral RCA matrix (specialization matrix) and CMI_m is the criticality level of the mineral m. Thereby, Equation (13) computes the mining fitness as the weighted sum of specializations in exporting critical minerals (diversity), wherein weights are given by the criticality level of each exported mineral one iteration back. In turn, Equation (14) computes the minerals' criticality as the weighted sum of minerals' ubiquity inverse, wherein weights are given by the inverse mining fitness of the exporter country one iteration back. Finally, equations (15) and (16) state the fitness and criticality values of order n, in which each vector is normalized by its average value.

The equation system clearly expresses the iterative dependency between minerals criticality and mining fitness (competitiveness), which is numerically solved by the fixed point in which the differences between MFI_n - MFI_{n-1} and CMI_n - CMI_{n-1} is equal to ε (Nomaler and Verspagen, 2022). Further details on the convergence process of the EFC are presented in Pugliese et al. (2016).

The interpretation of the Mining Fitness and the Criticality Minerals indexes is as follows. On the country fitness (competitiveness) side, a diversified portfolio of critical minerals reduces demand substitution risks related to the inherent uncertainty of ongoing technological races and balances the risk associated with the technological concentration of minerals (Markowitz, 1991). Meanwhile, exporting the most critical minerals increases the benefits (rents) captured by mining countries since these minerals are produced under monopolistic competition. Therefore, competitiveness accounts for the expected benefits of a country, considering the demand risks.

On the minerals' criticality side, a less ubiquitous mineral implies that few countries can competitively export it. Therefore, the disruption risk in the supply chain of these minerals is higher, and hence their criticality is also high. However, the characteristics of the mineral-exporting country are also relevant for determining the criticality level of a mineral, as a higher fitness of the exporting countries would reveal a larger geological potential, including the scarcest minerals (by-products).

Finally, it should be noted that comparing the mining fitness/minerals' criticality of different years is meaningless, as mining fitness (or minerals' criticality) is a relative measure with respect to a specific product-country configuration, which changes from year to year. To address this issue, we introduced the same fixed point for each year to provide a constant benchmark for comparison. Specifically, we added one hypothetical benchmark country with RCAs = 1 in every mineral for every year, so that countries' mining fitness is estimated in relation to this top benchmark country (Mazzilli et al., 2024).

5. Results

Through the execution of the Fitness-Criticality Algorithm (FCa), we obtain a country-level vector measuring the Mining Fitness Index (MFI) and a mineral-level vector accounting for the Criticality Minerals Index (CMI). This section presents the annual results of the FCa execution for the period 1996–2018.

5.1. Mining Fitness Index (MFI)

The annual results of the Mining Fitness Index (MFI) for the 48 countries included in the sample for the period 1996–2018 are presented in Fig. 3. The MFI for each year is normalized by the benchmark country fitness (a hypothetical country with all RCAs = 1). The cells colored in dark blue, light blue, and orange/yellow/green represent countries with low, medium, and high fitness levels, respectively. The matrix is sorted from high-fitness to low-fitness levels based on the last year of the sample (2018). The top 10 most competitive countries for the period 1996–2018 (average) are: 1) South Africa, 2) Russia, 3) the United States, 4) China, 5) Australia, 6) Norway, 7) Canada, 8) Chile, 9) Brazil, and 10) Finland.

A first pattern that arises from Fig. 3 is the presence of four groups, which we will call: leaders, followers, emerging, and lagging. The group of the leaders (orange and yellow cells) consists of South Africa, Russia, and the United States. The group of the followers (yellow and green cells) includes China, Norway, Chile, Finland, Australia, Brazil, and Canada. The emerging group (light blue) includes Malaysia, Zimbabwe, Kazakhstan, India, Sweden, Ukraine, Peru, Turkey, the Philippines, Thailand, and Uzbekistan. Finally, the lagging group (blue and dark blue) ranges from Iran to Rwanda.[11]

[11] The ranking with the average fitness scores for the period 1996–2018 are presented in Annex B.

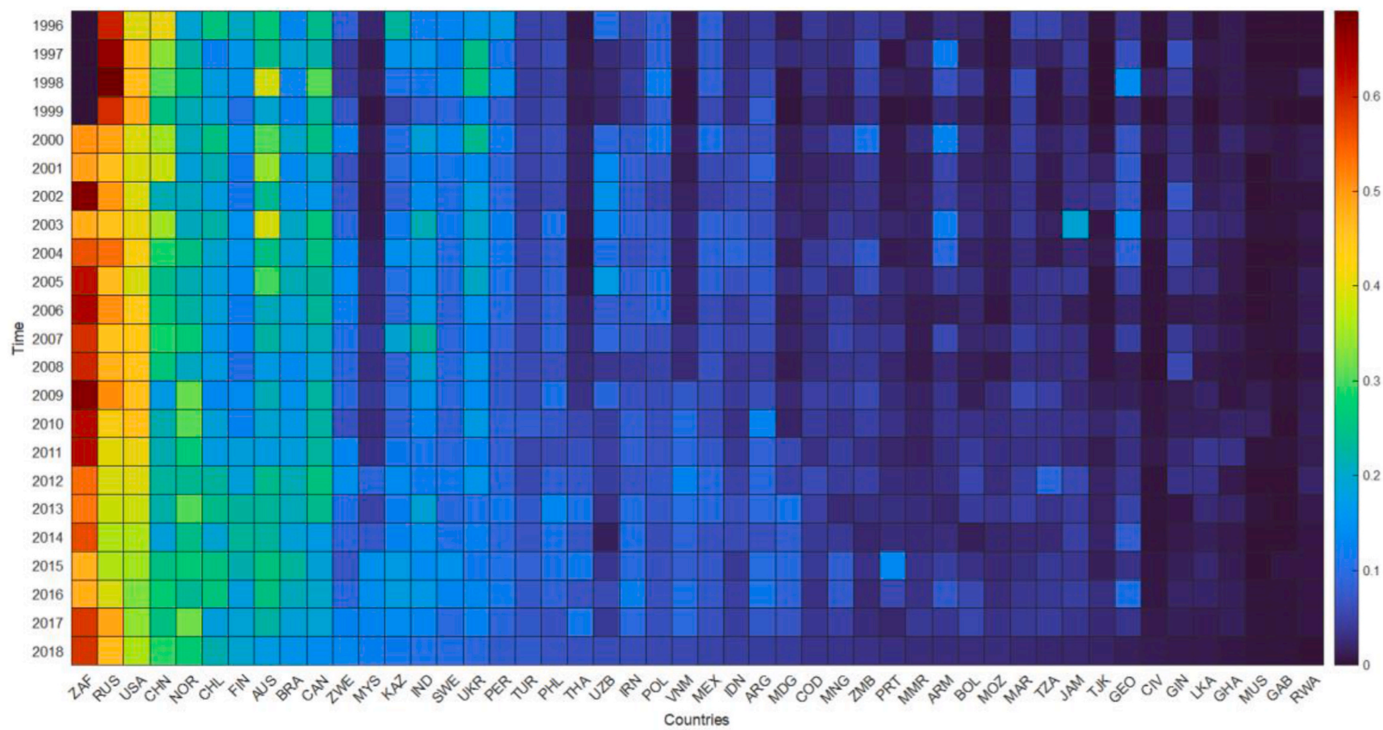

Fig. 3. Heatmap of the mining fitness index yearly based.
Source: Author's elaboration.

When looking at the evolution within countries, different patterns emerge. For instance, Australia and Canada, two major mining countries, have lost competitiveness over the period. China presents a U-shape trend, with a decline from 1996 to 2009 followed by a positive trend since then, reflecting its strategy to reduce dependency on foreign minerals to feed its metallurgical industry. Russia shows a downward trend with a slight reversal in recent years. Some emerging countries that were not previously specialized in the mining sector have rapidly gained competitiveness in recent years. Examples of these countries include Malaysia, Thailand, Vietnam, and Madagascar.

The previous results highlight the strategic importance of minerals for the two largest economies in the world, the United States and China,

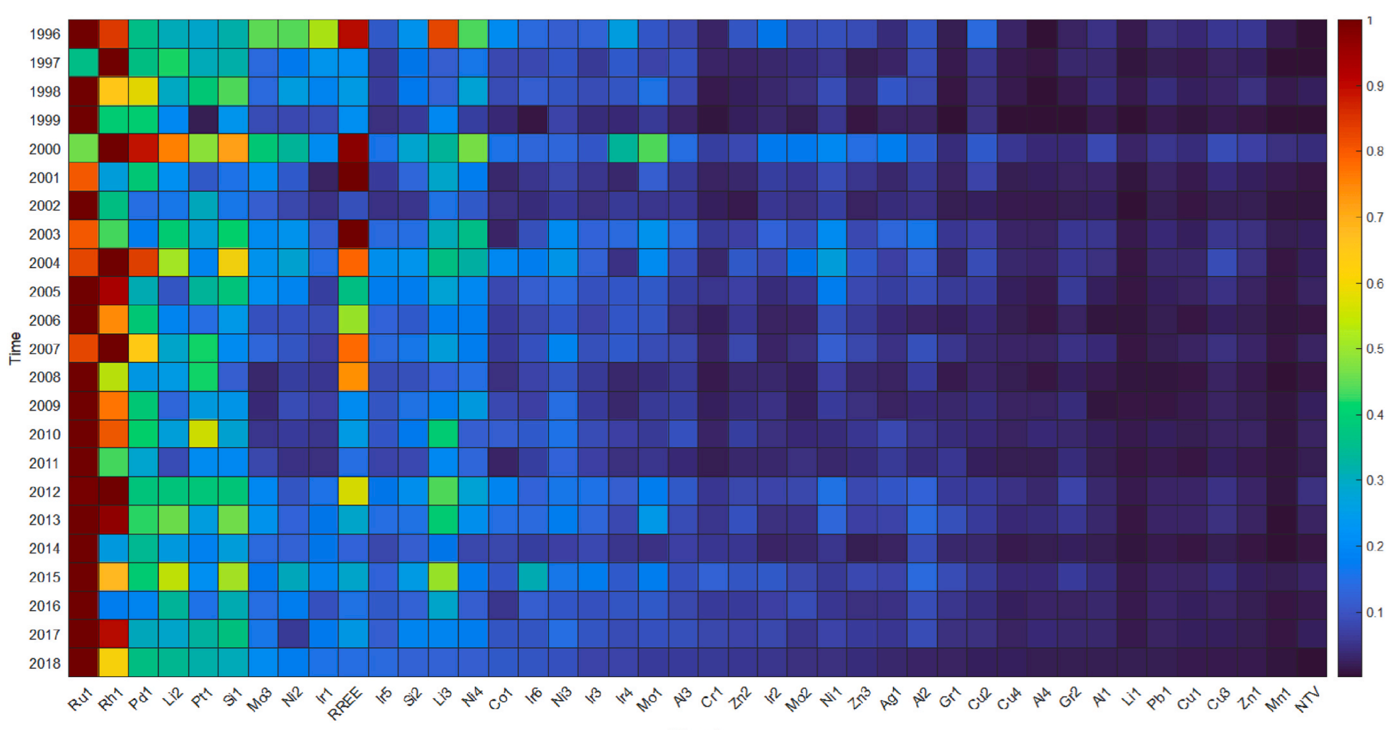

Fig. 4. Heatmap of the criticality minerals index yearly based.
Source: Author's elaboration.

and the relevance of geopolitics in these markets, reflected in the competitiveness of Russia and China vis-à-vis the United States and Western countries. In this context, Scandinavian countries stand out as the main source of critical minerals in Europe. Indeed, most European countries are not producing minerals on a large scale.

Meanwhile, Chile, Australia, and Brazil emerge as key "external" countries to ensure the supply chains of critical minerals for consumer countries that lack sufficient domestic resources. Additionally, several countries in the emerging group, such as Zimbabwe, Malaysia, Thailand, Vietnam, and Argentina, have increasingly gained competitiveness in recent years.

5.2. Critical Mineral Index (CMI)

The results of the Critical Mineral Index (CMI) for the 42 mineral goods included in the sample for the period 1996–2018 are presented in Fig. 4. The CMI for each year is normalized by the mineral with the highest criticality level, meaning that each year, the most critical mineral is assigned a value of 1. Each mineral is identified by its chemical symbol followed by a number, as there are multiple products for most minerals.[12] Analogous to the country analysis, cells colored in dark blue, light blue, and brown/orange/yellow/green represent mineral goods with low, medium, and high criticality levels, respectively. The matrix is sorted from high-criticality to low-criticality levels based on the last year of the sample (2018). The top 10 of most critical minerals for the period 1996–2018 (average)[13] are: 1) ruthenium (Ru1), 2) rhodium (Rh1), 3) rare earths (REE), 4) palladium (Pd1), 5) silicon, 6) lithium (Li2), 7) platinum (Pt1), 8) lithium (Li3), 9) nickel (Ni4) and 10) molybdenum (Mo3).

Fig. 4 illustrates that minerals belonging to the platinum-group metals (ruthenium, rhodium, palladium, and platinum) have consistently been the most critical minerals over time. In this group, platinum is the major mineral, while the others are by-products. As of 2022, global reserves of PGM are concentrated in five countries: South Africa (90%), Russia (7.8%), Zimbabwe (1.7%), the United States (1.3%), and Canada (0.4%).[14] Until 2008, rare earths exhibited criticality levels like those of platinum-group metals; however, their criticality has diminished since then. In 2022, global reserves of rare earths were concentrated in China (33.8%), Vietnam (16.9%), Russia (16.1%), and Brazil (16.1%).[15] Behind this leading group are silicon and lithium goods (colored green), which have exhibited medium-high and consistent levels of criticality throughout the entire period. While there are no statistics on silicon reserves, they are ample in the main producer countries. The production shares of the leading producers are China (68.1%), Russia (7.2%), Brazil (4.5%), and Poland (4%).[16] In 2022, global reserves of lithium were concentrated in Chile (35.7%), Australia (23.8%), Argentina (10.3%), and China (7.7%).[17] A third group is composed of minerals with medium levels of criticality (colored light blue), such as nickel, molybdenum, cobalt, and iron. Finally, the dark blue section of the matrix represents critical minerals with lower and constant criticality levels, including mineral goods such as copper, zinc, graphite, lead, and manganese.

Fig. 4 also allows us to explore specific minerals over time and examine the overall evolution of criticality across years. For example, rare earths (REE) were highly critical during the 2000s but have lost criticality since then, except for the year 2012. This trend aligns with the evolution of the rare earth industry, where China's monopolistic power and trade policies (e.g., export bans) induced new countries to enter the market, thereby reducing criticality. The criticality increase in 2012 coincides with the stricter restrictions that China applied in 2010 and 2011. In fact, China's export quota declined by 50% during the period 2008–2014 (Mancheri, 2015).

On the time dimension, it is interesting to note that some years appear more critical than others. For instance, the years following global economic crises, such as the Asian Financial (1999) and the Global Financial (2009), are darker than the adjacent years. Meanwhile, years of recovery and economic expansion (e.g., 2000, 2004, and 2007) are lighter. This pattern reflects the procyclical evolution of criticality.

These results are consistent with other methodologies that separately estimate countries' mining competitiveness and minerals' criticality. However, some divergences can be explained by the scope of the assessments, the variables used to measure competitiveness and criticality, and the timing of the assessments.

In this regard, the Fraser Institute's Annual Surveys[18] has estimated mining competitiveness since 1997 through the Investment Attractiveness Index, which combines the Mineral Potential Index (geological variables) with the Policy Potential Index (institutional variables). This survey is conducted with mining and exploration companies, asking for their perceptions on several topics related to mineral endowment and the institutional framework (Fredricksen, 2002). While the ranking produced by the Investment Attractiveness Index differs partly from ours for the years considered (1996–2018), some regularities exist. The United States, Canada, and Australia consistently lead the rankings, with other countries such as Chile, Finland, and Sweden also among the most competitive—consistent with our results (Fig. 3). Conversely, Venezuela, Bolivia, Argentina, the Democratic Republic of Congo, and Indonesia frequently stay at the bottom of the ranking, again aligning with our estimates.

However, there are some countries where we find opposite results. To illustrate, India and China rank above the mean in our ranking, while the Fraser Institute classifies them among the least competitive. This discrepancy may be due to the Fraser Institute's focus on investment attractiveness, which may bias the analysis against non-Western countries such as China, India, and Russia. Our MFI, which is based on the RCAs of countries exporting critical minerals, accounts for the actual output produced by each country.

Consequently, we believe that our Mining Fitness Index (MFI) provides a more accurate approach for estimating countries' competitiveness since it is based on real data rather than perceptions and focuses on exports rather than foreign direct investment, thereby offering an unbiased comparison for countries leveraging domestic resources to invest in the mining sector.

On the minerals side, the European Commission provides a ranking of minerals' criticality for its countries based on the economic importance of minerals in European production systems and the supply risks each mineral faces. Although this report has a broader scope than our research (as it examines 70 potential critical minerals, not just those linked to the energy transition), it serves as a useful benchmark. In the latest version of this report (Grohol and Veeh, 2023), 34 of the 70 minerals assessed are considered critical. Of these 34, 14 are included in our critical list, and only 6 are not, meaning there is a 70% match. In both assessments, platinum-group metals and rare earths are ranked as the most critical, while copper, lead, and zinc are considered the least critical.

We conducted a formal analysis of the similarity between the EC2023 report and CMI2018 by calculating their correlation. Specifically, we computed the Pearson correlation for our Critical Minerals Index (CMI) from 2018 and the simple average between the economic importance index and the supply risk index reported by the European Commission for 2023 (EC-CRM). The result shows a positive linear

[12] Annex A shows the full name and the respective code for each mineral good.

[13] The ranking with the average criticality scores for the period 1996–2018 are presented in Annex C.

[14] https://pubs.usgs.gov/periodicals/mcs2023/mcs2023-platinum-group.pdf.

[15] https://pubs.usgs.gov/periodicals/mcs2023/mcs2023-rare-earths.pdf.

[16] https://pubs.usgs.gov/periodicals/mcs2023/mcs2023-silicon.pdf.

[17] https://pubs.usgs.gov/periodicals/mcs2023/mcs2023-lithium.pdf.

[18] https://www.fraserinstitute.org/categories/mining accessed July 12, 2023.

correlation of 0.62 between CMI2018 and EC2023 (Fig. 5), which remains relatively high (0.54) even when the two minerals with the highest CMI values are excluded to avoid potential bias.

It should be noted that we are comparing MFI (2018) with EC-CRM (2023), which introduces a temporal mismatch that biases the comparison. This is because previous assessments by the European Union did not provide the detailed information required for a comparison over the same period. Despite this, the correlation between the two indicators remains significant.

Therefore, we hold that our Critical Minerals Index (CMI) is a more efficient indicator of minerals' criticality since it employs minimal information compared to the EC-CRM ranking, and it also allows annual estimates. Moreover, the CMI is agnostic regarding other considerations, as it does not use arbitrary parameters to calibrate the final index, unlike the EC index.

6. Robustness check

In this section, we perform three analyses to check whether the Fitness-Criticality Algorithm (FCa) is robust to the methodological specifications and consistent with the theoretical framework. First, we examine how the results differ if the FCa is run using the original EFC approach. Second, we assess whether the MFI captures more than just the diversity of specialization. Third, we evaluate whether the CMI reflects factors beyond the mineral's ubiquity.

6.1. Fitness-Criticality algorithm (FCa) computed by using the original economic Fitness-Complexity (EFC) approach

Our algorithm starts from the premise that specializing in mineral goods is a function of the specialization of countries in other sectors, as specializations are determined in a general equilibrium scheme. This is why we use the RCAs calculated for the entire range of products and countries. However, we maintain that mineral criticality and countries' mining fitness depend solely on mining sector dynamics. In other words, mineral criticality is shaped only by the fitness of mining countries. Otherwise, we would be incorporating the effects of the rest of the economy twice in determining mineral criticality: first when calculating the RCAs and second when running the algorithm.

By contrast, the original EFC approach calculates sectoral fitness indexes based on the full range of goods and countries, and then adds the product complexities of interest to obtain sector-country values (Caldarola et al., 2023). Although we believe this original approach provides biased results, it is pertinent to test how different the results are when applying this method.

Therefore, this subsection presents the results of computing the FCa using the original EFC approach and compares them with the results previously shown. In summary, the methodology consists of running the algorithm for the entire bipartite specialization network of countries and products using binary RCA matrices. This method yields product complexities and country fitness for the 5040 products and 147 countries included in our sample. The Criticality Mining Index (CMI) corresponds to the product complexities of our selected products. Meanwhile, the Mining Fitness Index (MFI) is calculated as the weighted sum of the RCAs for each country, with the critical mineral values serving as the weights. The results for the period 1996–2018 are presented in the same format used in Section V.

6.1.1. Mining Fitness Index (MFI)

When we look at the average MFI for the entire period, both estimation approaches deliver very similar values. This is reflected in the high correlation (0.98) of the MFI average values for the period 1996–2018. Fig. 6 illustrates the correlation between MFI (FCa) and MFI (EFC), where most of the data points are clustered around the fitted line (with China as the outlier).

However, when we analyze the MFI year by year, some notable differences emerge. Fig. 7 illustrates the yearly evolution of the MFI for our 48 countries during the period 1996–2018, using the original EFC approach. The matrix is sorted from high-fitness to low-fitness levels based on the last year of the sample (2018), similar to Fig. 3. When we observe the ranking for the base year (2018), we can see some major shifts compared to Fig. 3.

For instance, China moves up from 4th to 2nd place, surpassing Russia and the United States. Other countries not highly specialized in the mining sector climb several positions in the ranking. For example, the Philippines, Sri Lanka, and Argentina move up 10, 12, and 14 places, respectively. Meanwhile, countries that are highly specialized in the mining sector, such as Australia, Poland, Peru, Zambia, and the Democratic Republic of Congo, lose several positions (6, 6, 10, 10, and 17 positions, respectively). These ranking shifts are due to the inclusion of all products and goods in the mineral criticality computation (total countries' fitness influences mineral criticality), which biases the results against countries with lower development levels (lower total fitness).

6.1.2. Critical Mineral Index (CMI)

Analogous to the countries' fitness, both estimation approaches deliver very similar CMI average values for the entire period. Fig. 8 shows the correlation between CMI (EFC) and CMI (FCa) for the period 1996–2018, which reaches 0.91. Without the point [1,1], the correlation increases to 0.96.

However, the differences become more pronounced when we look at the annual results. Fig. 9 illustrates the yearly evolution of the CMI for our 42 mineral goods during the period 1996–2018, using the original

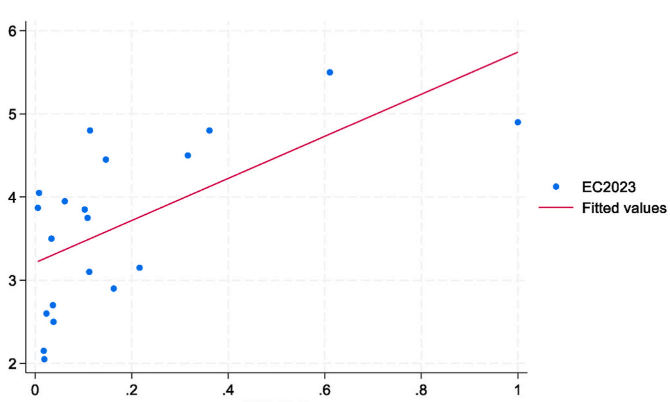

Fig. 5. Critical raw material index of European Commission (EC, 2023) versus critical minerals index (CMI, 2018).
Source: Author's elaboration.

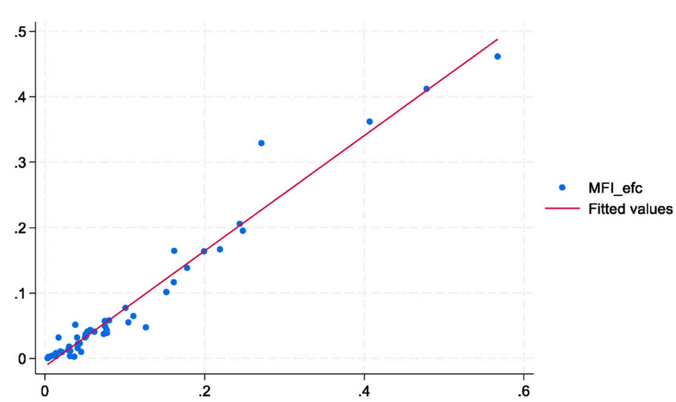

Fig. 6. MFI (FCa) versus MFI (EFC), average levels (1996–2018).
Source: Author's elaboration.

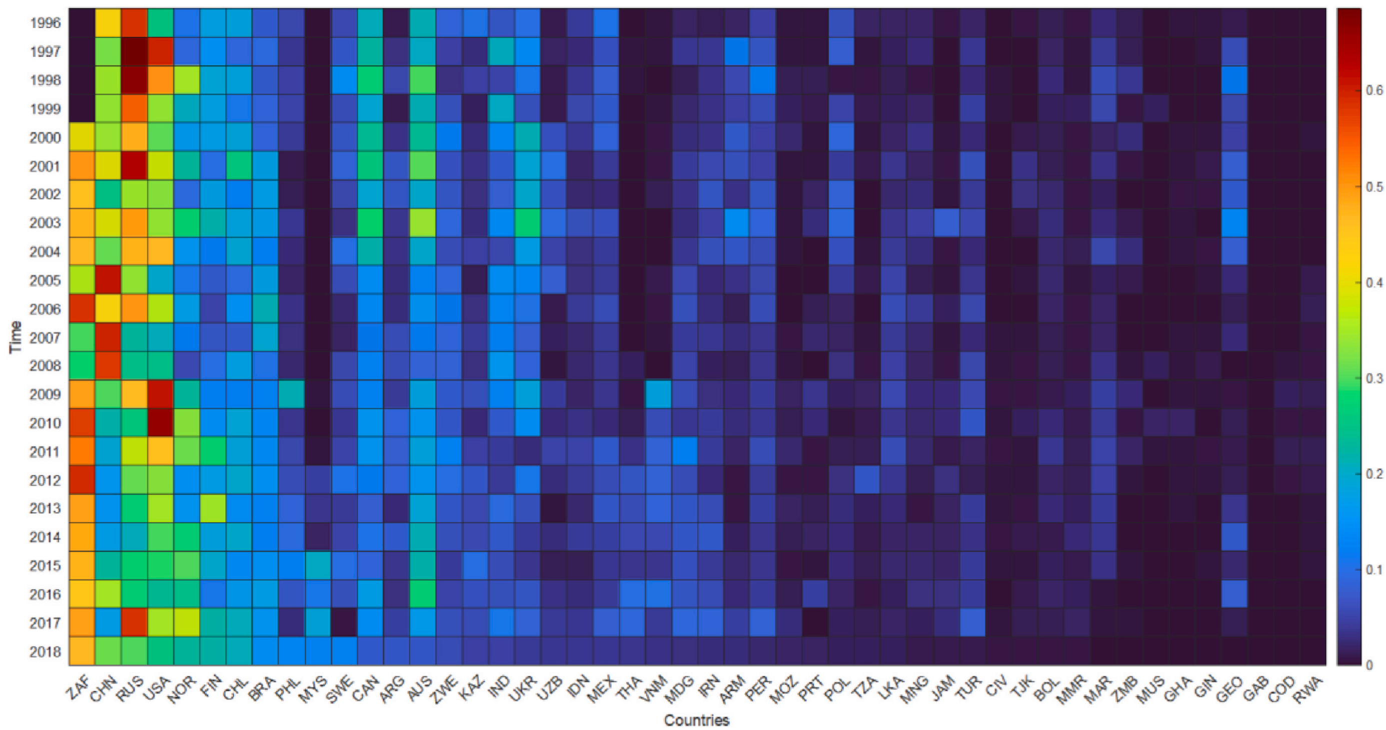

Fig. 7. Yearly-based mining fitness index by using original EFC approach.
Source: Author's elaboration.

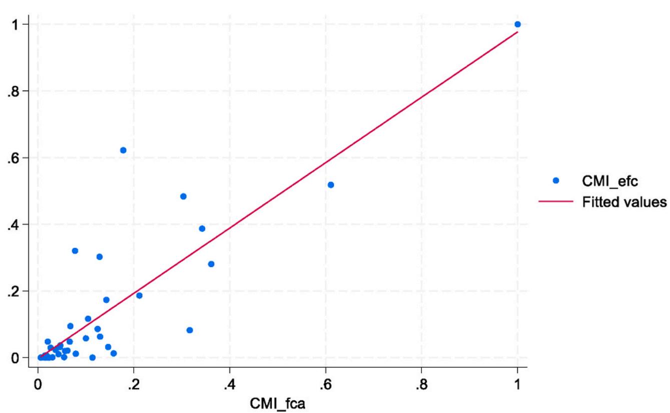

Fig. 8. CMI (FCa) versus CMI (EFC), average levels (1996–2018).
Source: Author's elaboration.

EFC approach. The matrix is sorted from high-criticality to low-criticality levels based on the last year of the sample (2018), similar to Fig. 4. When comparing the 2018 ranking with that of Fig. 4, significant changes emerge.

To illustrate, nickel (Ni2), molybdenum (Mo2), zinc (Zn1), and iron (Ir4) climb 5, 8, 11, and 13 positions, respectively. Meanwhile, palladium (Pd1), platinum (Pt1), rare earths (REE), and cobalt (Co) drop 5, 9, 10, and 25 places, respectively. In this case, the bias introduced by estimating the CMI through the original EFC approach becomes clearer, as mineral goods intensively exported by less developed countries (with lower total fitness) lose significant criticality. This outcome does not align with the literature, previous estimates, or the results provided by our Fitness-Criticality Algorithm (FCa).

6.2. *Mining Fitness Index (MFI) versus diversity*

We test whether the MFI measures something beyond just the diversity of specialization, as mining fitness would be redundant if it were solely explained by the number of mineral goods in which countries specialize. To perform this analysis, we regress the MFI against the diversity of specializations in critical minerals for the base year 2018. If all observations fell on the regression line, mining fitness and diversity would reflect the same information.

Fig. 10 shows the scatter plot with a regression line between the MFI and diversity, which indicates a high positive fit ($R^2 = 0.59$). However, 41% of the variability in the MFI is not explained by changes in diversity, which is attributed to mineral criticality. Therefore, the MFI provides additional and useful information, as it incorporates both the diversity and criticality levels of the exported mineral goods.

6.3. *Critical Mineral Index (CMI) versus ubiquity*

We also tested whether the CMI measures something beyond just mineral ubiquity. If minerals' criticality were solely explained by ubiquity, the algorithm would not add any additional information. To test this, we performed a linear regression between the CMI and mineral ubiquity. If the observations aligned with the regression line, it would indicate that the CMI is equivalent to minerals' ubiquity.

Fig. 11 illustrates the relationship between the CMI and minerals' ubiquity for the base year 2018. Specifically, five fit lines are traced between CMI and ubiquity, showing that there is not a strong relationship between the two variables. Furthermore, the scatter plot shows that the linear correlation is close to zero, while the fit improves with higher degrees of non-linear specifications, reflecting the non-linear nature of the algorithm. Thus, the CMI captures something different from mineral ubiquity, confirming that mineral criticality and mineral ubiquity are two distinct dimensions.

Overall, our robustness checks confirm the following.

- There are differences in terms of fitness and criticality when running the FCa using our approach compared to the original EFC approach. We explain why we consider our approach more appropriate.

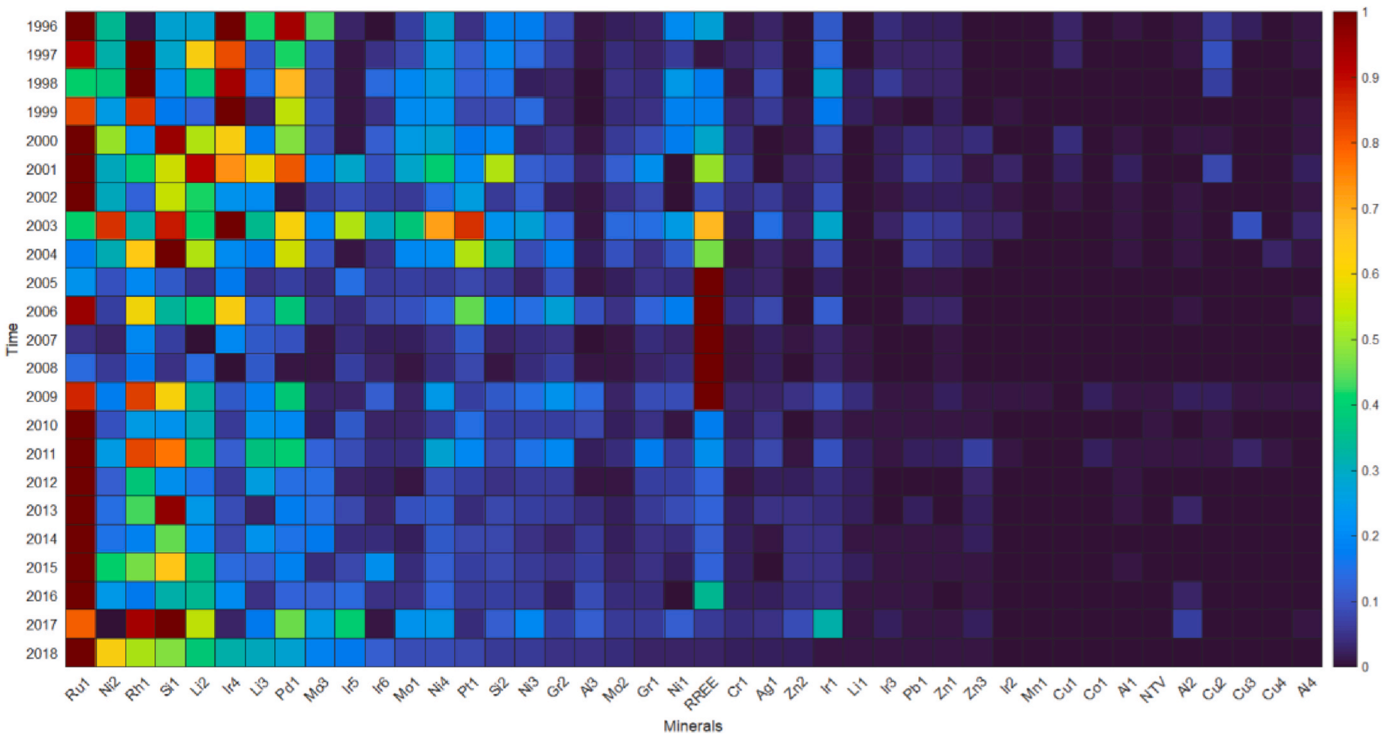

Fig. 9. Yearly-based critical mineral index by using original EFC approach.
Source: Author's elaboration.

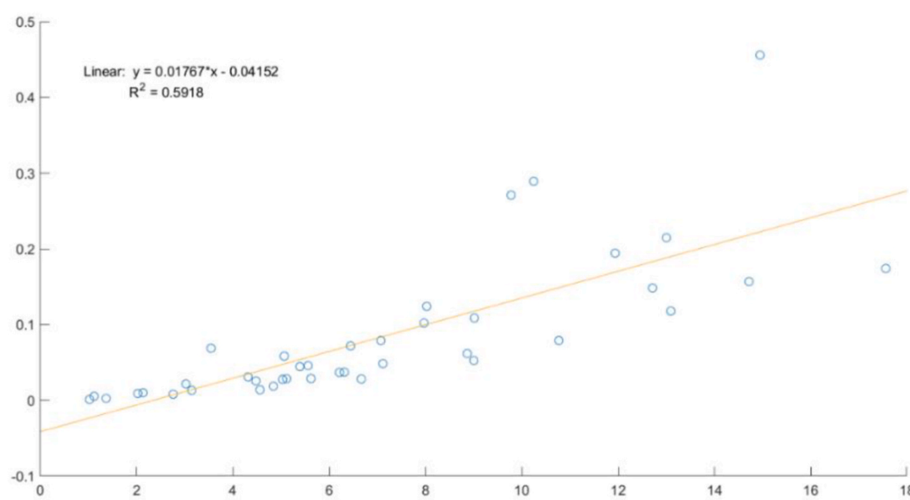

Fig. 10. MFI versus diversity (2008–2018).
Source: Author's elaboration.

- The MFI provides additional and useful information, as it incorporates not only the diversity of exported mineral goods but also the criticality levels of those goods.
- The CMI captures something distinct from mineral ubiquity, confirming that mineral criticality and mineral ubiquity are two separate dimensions.

7. Concluding remarks

This paper contributes to the literature by providing a theoretical framework that links mining competitiveness and mineral criticality, and it proposes a novel methodology to simultaneously estimate both dimensions. This framework represents an innovation in mineral economics, as these variables have traditionally been studied independently through unconnected theoretical frameworks. The primary contribution lies in the positive relationship between countries' competitiveness and mineral criticality, as predicted by our model. This relationship is based on our definition of countries' mining competitiveness, which states that it is an increasing function of the variety of exported mineral goods, and the exogenous fact that the most critical minerals are typically by-products of major minerals. Therefore, the more ore veins of major minerals a country possesses, the higher the chances of producing by-products.

From an empirical perspective, the methodology based on the Fitness-Criticality Algorithm (FCa) provides a straightforward and efficient data-driven approach to assess minerals' criticality and mining

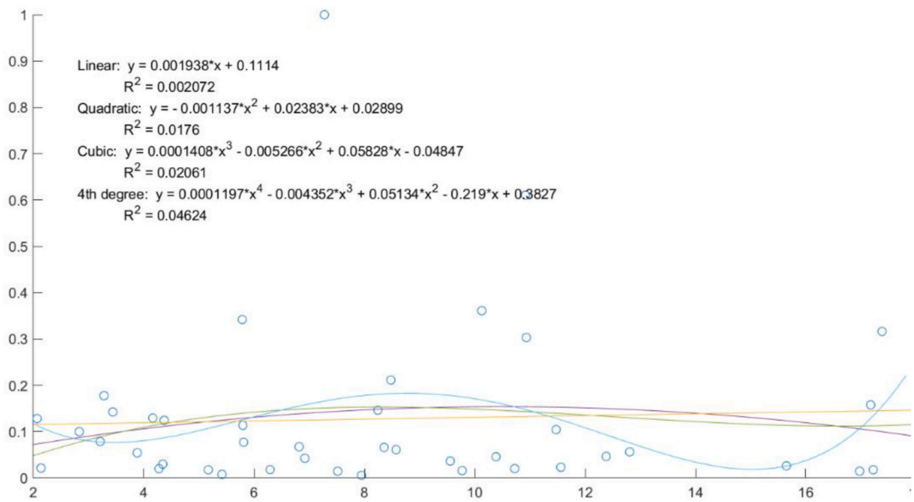

Fig. 11. CMI versus minerals' ubiquity (2008–2018).
Source: Author's elaboration.

competitiveness. It does not require a large set of variables and avoids using arbitrary parameters to calibrate the final indexes. As such, it emerges as an appealing tool for policymakers' assessments.

On countries mining competitiveness, our results allow us to classify countries into four groups: leaders, followers, emerging, and lagging. The leader countries are South Africa, Russia, and the United States, while China, Norway, Chile, Finland, Australia, Brazil, and Canada are among the followers. Although it is unsurprising to find countries like the United States, South Africa, Canada, or Australia in these groups, the inclusion of Russia and China represents a novelty compared to other indexes. This is because we use a direct measure of competitiveness, whereas mainstream literature often relies on proxy variables, such as foreign direct investments, which can bias results against non-Western and less integrated countries.

Through our results, we can observe the evolution of countries' competitiveness, identify key actors in the critical mineral market, and determine which countries could become relevant providers of these critical minerals in the future. In this regard, the Mining Fitness Index (MFI) shows that traditionally strong mining countries, such as Russia, Australia, and Canada, have lost competitiveness in recent decades. Meanwhile, non-mining emerging countries, such as Malaysia, Thailand, Argentina, and Vietnam, have made significant strides in competitiveness in recent years.

On minerals' criticality, our results suggest that the most critical minerals are the platinum group metals (PGM), silicon, rare earths, and lithium, while copper, zinc, lead, and manganese exhibit the lowest criticality levels. Although these results align with previous rankings in the literature, the Criticality Mineral Index (CMI) incorporates a time-series dimension that allows us to observe changes in criticality trends and the effects of specific shocks. For instance, the criticality of rare earths has decreased since 2010 (except for 2012), coinciding with increased export restrictions imposed by China in the late 2000s. Although higher export bans from China, which holds monopolistic power, would typically imply higher criticality levels for rare earths, these restrictions led to the entry of new producers in the global market, thereby reducing criticality.

Finally, this new methodology for estimating minerals' criticality and countries' mining competitiveness opens a research agenda that could be complemented by other information sources. For example, our analysis could be enhanced by incorporating demand-side criticality determinants, such as the number of technologies that use each mineral, the resource availability of each mineral, and the substitution options for each mineral.

CRediT authorship contribution statement

Jorge Valverde-Carbonell: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Carlo Pietrobelli:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **María de las Mercedes Menéndez:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Annex A. List of Critical Minerals

Product Name	Short Name	HS Code
Unroasted iron pyrites	Ir1	250200
Natural graphite in powder or in flakes	Gr1	250410
Natural graphite, except powder or flakes	Gr2	250490
Mineral substances nes (spodumene)	Li1	253090
Iron ores and concentrates, other than roasted iron pyrites: - Non-agglomerated	Ir2	260111
Iron ores and concentrates, other than roasted iron pyrites: - Agglomerated	Ir3	260112
Manganese ores and concentrates	Mn1	260200
Copper ores and concentrates.	Cu1	260300

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Product Name	Short Name	HS Code
Nickel ores and concentrates.	Ni1	260400
Cobalt ores and concentrates.	Co1	260500
Aluminium ores and concentrates.	Al1	260600
Lead ores and concentrates.	Pb1	260700
Zinc ores and concentrates.	Zn1	260800
Chromium ores and concentrates.	Cr1	261000
Molybdenum concentrates, roasted	Mo1	261310
Molybdenum ores and concentrates, except roasted	Mo2	261390
Niobium, tantalum and vanadium ores and concentrates	NTV	261590
Silver ores and concentrates	Ag1	261610
Silicon: - Containing by weight not less than 99.99 % of silicon	Si1	280461
Silicon: other	Si2	280469
Rare-earth metals, scandium and yttrium, whether or not intermixed or interalloyed	RREE	280530
Aluminium oxide; other than artificial corundum	Al2	281820
Aluminium hydroxide	Al3	281830
Iron oxides and hydroxides	Ir4	282110
Lithium oxide and hydroxide	Li2	282520
Nickel oxides and hydroxides	Ni2	282540
Molybdenum oxides and hydroxides	Mo3	282570
Other: - Lithium carbonates	Li3	283691
Platinum: - Unwrought or in powder form	Pt1	711011
Palladium: - Unwrought or in powder form	Pd1	711021
Rhodium: - Unwrought or in powder form	Rh1	711031
Iridium, osmium and ruthenium: - Unwrought or in powder form	Ru1	711041
Non-alloy pig iron containing by weight 0.5 % or less of phosphorus	Ir5	720110
Non-alloy pig iron containing by weight more than 0.5 % of phosphorus	Ir6	720120
Copper mattes	Cu2	740110
Unrefined copper; copper anodes for electrolytic refining.	Cu3	740200
Refined copper: - Cathodes and sections of cathodes	Cu4	740311
Nickel unwrought, not alloyed	Ni3	750210
Nickel powders and flakes.	Ni4	750400
Aluminium, not alloyed	Al4	760110
Zinc, not alloyed: Containing by weight 99.99 % or more of zinc	Zn2	790111
Zinc, not alloyed: - Containing by weight less than 99.99 % of zinc	Zn3	790112

Annex B. Ranking of Mining Fitness Index (1996–2018)

COUNTRY	MFI
ZAF	0.566978
RUS	0.478055
USA	0.406719
CHN	0.271113
AUS	0.247842
NOR	0.243893
CAN	0.21919
CHL	0.199181
BRA	0.177883
FIN	0.161774
UKR	0.161288
IND	0.151984
KAZ	0.126295
SWE	0.110613
PER	0.104369
ZWE	0.100794
PHL	0.080203
POL	0.07766
IRN	0.077084
ARG	0.075157
MEX	0.074969
UZB	0.073563
TUR	0.061895
GEO	0.056689
ARM	0.053126
IDN	0.051733
VNM	0.050825
MYS	0.050117
ZMB	0.045267
THA	0.043582
MNG	0.041058
JAM	0.040915
MAR	0.040167
MDG	0.037937

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COUNTRY	MFI
COD	0.03663
TZA	0.031647
GIN	0.031261
BOL	0.030286
PRT	0.029003
MMR	0.021214
MOZ	0.019145
LKA	0.016932
GHA	0.013799
TJK	0.013721
RWA	0.009037
CIV	0.006047
MUS	0.004147
GAB	0.003261

Annex C. Ranking of Criticality Minerals Index (1996–2018)

MINERAL NAME	CMI
Iridium, osmium and ruthenium: - Unwrought or in powder form	0.915099
Rhodium: - Unwrought or in powder form	0.682835
Rare-earth metals, scandium and yttrium, whether or not intermixed or interalloyed	0.446094
Palladium: - Unwrought or in powder form	0.399901
Silicon: - Containing by weight not less than 99.99 % of silicon	0.332664
Lithium oxide and hydroxide	0.313395
Platinum: - Unwrought or in powder form	0.286204
Other: - Lithium carbonates	0.28195
Nickel powders and flakes.	0.209704
Molybdenum oxides and hydroxides	0.169873
Nickel oxides and hydroxides	0.164493
Silicon: other	0.159319
Unroasted iron pyrites	0.13973
Nickel unwrought, not alloyed	0.13378
Molybdenum concentrates, roasted	0.127042
Non-alloy pig iron containing by weight 0.5 % or less of phosphorus	0.116429
Non-alloy pig iron containing by weight more than 0.5 % of phosphorus	0.108634
Nickel ores and concentrates.	0.102654
Iron oxides and hydroxides	0.100456
Iron ores and concentrates, other than roasted iron pyrites: - Agglomerated	0.096132
Cobalt ores and concentrates.	0.096117
Aluminium oxide; other than artificial corundum	0.085445
Aluminium hydroxide	0.082995
Iron ores and concentrates, other than roasted iron pyrites: - Non-agglomerated	0.066911
Silver ores and concentrates	0.064158
Molybdenum ores and concentrates, except roasted	0.063151
Zinc, not alloyed: Containing by weight 99.99 % or more of zinc	0.06267
Zinc, not alloyed: - Containing by weight less than 99.99 % of zinc	0.061703
Copper mattes	0.056123
Chromium ores and concentrates.	0.043866
Natural graphite in powder or in flakes	0.040736
Unrefined copper; copper anodes for electrolytic refining.	0.038105
Natural graphite, except powder or flakes	0.038041
Aluminium ores and concentrates.	0.03199
Zinc ores and concentrates.	0.028376
Lead ores and concentrates.	0.026052
Refined copper: - Cathodes and sections of cathodes	0.026045
Aluminium, not alloyed	0.023099
Copper ores and concentrates.	0.021386
Niobium, tantalum and vanadium ores and concentrates	0.019461
Mineral substances nes (spodumene)	0.012069
Manganese ores and concentrates	0.011314

Data availability

Data will be made available on request.

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