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Pauline Bucciarelli
Emmanuel Hache
Valérie Mignon

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EconomiX - UMR 7235 Bâtiment Maurice Allais
Université Paris Nanterre 200, Avenue de la République
92001 Nanterre Cedex

Site Web : economix.fr
Contact : secreteriat@economix.fr
Twitter : @EconomixU

cnrs Université Paris Nanterre

Evaluating criticality of strategic metals: Are the Herfindahl–Hirschman Index and usual concentration thresholds still relevant?

Pauline Bucciarelli[a,b], Emmanuel Hache[a,b,c], and Valérie Mignon[b,d]

[a]IFP Energies nouvelles, 1 et 4 avenue de Bois Préau, 92852 Rueil-Malmaison, France
[b]EconomiX-CNRS, University of Paris Nanterre, France
[c]The French Institute for International and Strategic Affairs (IRIS), France
[d]CEPII, France

Abstract

This paper aims to evaluate the criticality of strategic metals by (i) investigating the validity of the Herfindahl-Hirschman Index (HHI) for assessing the supply risk aspect of criticality and (ii) determining an appropriate threshold for using this indicator in the context of criticality studies. Relying on a large panel of 33 strategic metals over the 1995-2021 period, our findings show that the variation of HHI has more impact on metal prices at lower HHI levels and question the existence of a threshold that clearly distinguishes high-risk markets from less risky ones based on their concentration levels. Overall, we show that using the HHI as a supply risk indicator, especially in conjunction with a threshold, may result in underestimating risks in less concentrated markets.

JEL classification: Q02 ; Q34 ; C23 ; C24

Keywords: Strategic metals; Criticality; Herfindahl–Hirschman Index; Metal prices; Panel regression

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Corresponding author: Valérie Mignon, EconomiX-CNRS, University of Paris Nanterre, 200 avenue de la République, 92001 Nanterre cedex, France. Email: valerie.mignon@parisnanterre.fr

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1 Introduction

Over the last decades, the growing number of raw material criticality assessments reflects the renewed interest in the supply security of these resources, particularly for countries and companies heavily dependent on international commodity flows.

The first decade of the 21^{st} century witnessed remarkable economic growth and industrialization, mainly driven by emerging economies such as China, which became a dominant force in the global marketplace. As China's demand for metals and minerals surged, global markets tightened, leading to historic price increases and heightened concerns over potential shortages and scarcity (Schmidt, 2019). The imposition of Chinese export restrictions on rare earth elements (REE) over the 2009-2011 period—especially in 2010[1]—further exacerbated these fears, leading highly import-dependent industrialized countries to develop their criticality assessment methodology in order to secure their raw material supply chains (Frenzel et al., 2017). More recently, the COVID-19 pandemic and the war in Ukraine have had significant implications for global supply chains, including those related to metals and minerals. The pandemic's disruptive impact on production, transportation, and distribution of raw materials led to temporary shutdowns of mines and processing facilities (Gupta et al., 2020). This crisis has also highlighted the existence of tensions between economic powers, which could lead to non-cooperative trade policies in the future (Jaravel and Méjean, 2021). As a result, there is a renewed focus on building more resilient and diversified supply chains to mitigate future risks and ensure a steady flow of critical resources.[2] Moreover, the ongoing global energy transition, aimed at reducing greenhouse gas emissions and shifting towards low-carbon technologies, has led to substantial demand for specific metals and minerals. As underlined by the International Energy Agency (IEA), such technologies have a higher metal content than their traditional counterparts and require a greater diversity of metals. Consequently, the availability of metal and mineral resources has become a central concern in the energy transition dynamic, as these resources could potentially become limiting factors to net zero ambition in the future.[3]

[1] See Seaman (2019).

[2] In August 2022, the United States passed the Inflation Reduction Act, which promotes the development of more robust supply chains and domestic production of various minerals. In particular, it introduces the New Advanced Manufacturing Production Credit, a 10% tax credit granted to domestic producers of specified critical minerals (IEA, 2023). A few months later, the European Commission proposed the Critical Raw Materials Act, a set of actions aimed to ensure "the EU's access to a secure, diversified, affordable and sustainable supply of critical raw material" (European Commission, 2023).

[3] In March 2022, the Departments of Energy, State, and Defense of the United States collaborated to integrate minerals that are necessary for a clean energy transition into the National Defense Stockpile of critical minerals, in addition to those required for defense purposes (IEA, 2022b).

Within this context, correctly measuring the criticality of minerals and metals is crucial, and this is the aim of the present paper. This is not straightforward since, as highlighted by Graedel et al. (2015), defining criticality is a difficult task because "criticality depends not only on geological abundance, but on a host of other factors such as the potential for substitution, the degree to which ore deposits are geopolitically concentrated, the state of mining technology, the amount of regulatory oversight, geopolitical initiatives, governmental instability, and economic policy".

Originally developed by states to ensure their military-strategic positions and later to sustain economic growth and contemporary lifestyles, criticality studies are now conducted by a multitude of actors at different scales (state, industry, company, or even technology scale) (Schrijvers et al., 2020). As a result, multiple criticality assessment methodologies have been developed to identify materials of concern and assist decision-making processes, drawing on the pioneering work of the National Research Council (2008) and the European Commission (2010). Two key aspects are commonly used as criteria to identify critical raw materials: (i) their economic and/or strategic importance, and (ii) the likelihood of supply disruptions, often referred to as 'supply risk' (Frenzel et al., 2017). However, the measurement of these criteria varies from one study to another, from the selection of the indicators used to the way they are aggregated (Gleich et al., 2013).

The absence of a standardized theoretical framework for criticality measurement and the proliferation of such studies has led to the emergence of a distinct field in the scientific literature reviewing the various criticality assessment methods and their relevance (Erdmann and Graedel, 2011; Achzet and Helbig, 2013; Glöser et al., 2015; Frenzel et al., 2017; Hatayama and Tahara, 2018; Schrijvers et al., 2020). It is commonly observed that certain indicators lack sufficient relevance. Therefore, experts and researchers recommend identifying best practices (Schrijvers et al., 2020), primarily through acquiring more robust empirical evidence on widely used indicators (Helbig et al., 2021).

One of the most commonly used indicators for assessing the supply risk of a material is the country production concentration. Helbig et al. (2021) conduct a thorough review of different indicators employed to measure supply risk and find that country's production concentration appears in about 75% of the 88 assessment analyses presented in their paper and has been in use since 1977. The rationale behind using such an indicator is that as the production of a given raw material becomes more concentrated in a few countries, the likelihood of supply disruptions increases due to various factors, including economic, political, or environmental considerations (Frenzel et al., 2017).[4] Moreover, "in the context

[4]In recent years, a third important consideration has been added: the environmental implications

of global studies, 'production' is used as a proxy for 'supply"' (Brown, 2018). Therefore, world production by country is used to evaluate supply diversity (Thomas et al., 2022), which is known in the literature as a significant factor in supply resilience and, consequently, supply risk (Sprecher et al., 2015; Sato et al., 2017).[5] The Herfindahl–Hirschman Index (HHI) (Herfindahl, 1950; Hirschman, 1945) is the dominant measure for assessing this indicator (Helbig et al., 2021; Brown, 2018). The HHI is a widely recognized measure of market concentration. It was initially developed in the field of industrial organization to assess market structure and quantify market power and has since been extensively used, particularly in the field of competition law. The HHI is calculated by summing the squares of individual firms' market shares, thereby assigning greater weight to larger market shares.[6] As a result, the HHI approaches zero when a market consists of numerous firms of relatively equal size, while reaching its maximum value of 10,000 points when a single firm dominates the market.

In the metal and mineral production sector, various HHIs are available to evaluate concentration. The HHI can be assessed at different scales, either based on the national production of countries (referred to as country HHI) or by focusing on the production of specific firms. Moreover, the HHI can be computed at various points along the value chain, including ore extraction, smelting, and refining. Indeed, minerals undergo a multi-stage transformation process before they can be utilized in final applications. Initially, the raw minerals are extracted from deposits through mining activities, which are classified as upstream operations. Subsequently, the extracted minerals are transferred to smelters or refiners, where chemical refining and processing take place, known as midstream operations, transforming the minerals into fine particles with high purity levels, rendering them suitable for use in the final products. Finally, the refined metals are passed on to downstream actors who incorporate them into the manufacturing process to create the end products (Castillo, 2022). Most criticality analyses focus on the country's concentration of mineral production at the extraction stage, a choice driven primarily by data availability considerations.

(Graedel et al., 2015).

[5] In recent years, the study of network resilience has become a significant subfield in network science (Liu et al., 2022), referring to the ability to withstand and rapidly recover from environmental changes or disruptions. An essential component of resilience, as highlighted by recent research, is redundancy, denoting the use of multiple pathways, functions, or components within a system (Kharrazi et al., 2020). In the context of trade systems, redundancy refers to the diversity of supply, which involves having multiple suppliers for a specific product, as emphasized by Sprecher et al. (2015) and Kharrazi et al. (2020).

[6] According to Le Coq and Paltseva (2009), the HHI emphasis on the larger suppliers, makes it "suited to reflect the risks, associated with the non-diversified energy portfolio".

In many cases, criticality studies are used to identify which minerals are subject to relatively higher supply risk, thereby distinguishing between different materials and identifying which markets require more vigilant monitoring. Although supplier diversity is generally considered in the literature to be a robust indicator of supply risk, it remains important to determine whether it is effective as a discriminative criterion for classifying different metals and minerals. This is a recurring observation in the literature reviewing criticality methodologies, consistently highlighting the lack of empirical evidence for widely used indicators (Achzet and Helbig, 2013; Frenzel et al., 2017; Helbig et al., 2021).

Only a few studies have highlighted the relevance of the HHI of production in this context, using different methodologies. Buchholz et al. (2022) focus on the largest mines for 12 mineral commodities over 1.5 years. They use big data analytics to investigate how specific risk events disrupt these mines. They analyze the impact of events such as COVID-19 measures taken by different countries and conclude that a global market with few suppliers would be more vulnerable to risk than a market with a large supplier base. However, their conclusion depends largely on their underlying assumption: "the potential impact has been quantified based on the global share of production from mines at risk". Furthermore, the study only looks at 12 raw materials over a relatively short period of time. Brown (2018), though, shows that assessing supply concentration using only a snapshot index taken at a single point in time may inadequately measure potential supply concentration concerns. Therefore, examining the impact of HHI over such a truncated time period (less than two years) could lead to misleading results. Gleich et al. (2013) assess the relevance of the indicator by examining its impact on raw material prices. This methodology is grounded in the efficient market hypothesis, assuming that prices reflect current and future risks, i.e., economic scarcity, and thus capture a degree of criticality. This approach offers a more comprehensive perspective, encompassing a larger set of metals and minerals (42) over an extended period (26 years). However, the study adopts a time series perspective, considering every material independently. Furthermore, the authors investigate whether the HHI of a metal's production has an effect on its price but do not demonstrate whether it is a relevant indicator for the entirety of metals and minerals, and thus a suitable means of differentiation.

In the United States, the Federal Trade Commission has established benchmark values, as outlined in their guidelines, to identify markets of concern (Federal Trade Commission, 2006): markets are categorized into three groups based on the HHI—unconcentrated markets (HHI below 1500), moderately concentrated markets (HHI between 1500 and 2500), and highly concentrated markets (HHI above 2500). Mineral criticality studies frequently incorporate the thresholds specified in the American Merger Guidelines when utilizing the HHI to quantify production concentration. This is done in two ways. Firstly, the thresholds are mentioned in the introduction to the analysis, which creates a framing bias for the reader but does not directly affect the results (Al Barazi et al., 2021; Buchholz et al., 2022). Secondly, some studies include these thresholds in their methodology. For instance, in their paper on supply risk for mineral commodities, Schneider et al. (2014) set a threshold for each selected indicator, including the HHI of production, above which supply risk is expected. The supply risk for each resource is then calculated by considering its proximity to this threshold. For the HHI of production, the threshold is set at 1500, in line with the thresholds defined by the US Department of Justice in the Merger Guidelines. Similarly, Rosenau-Tornow et al. (2009) use these thresholds to define their benchmarks for HHI values related to country concentration. However, these thresholds were established in the context of using the HHI as a proxy for the monopolistic structure of an industry, rather than for measuring the redundancy of the trading system, which is a more pertinent criterion in criticality studies. Furthermore, even in the context of mergers, these thresholds have been criticized for being arbitrary. The arbitrary nature of thresholds is also emphasized by Brown (2018) within the context of criticality studies. She highlights that the specific level at which the threshold for defining "high concentration" is established can significantly influence the interpretation of results in criticality assessments of minerals.

While the scientific community is generally less inclined towards adopting a sharply defined threshold value for criticality determination, policymakers tend to employ such values since they lead to easily understandable outcomes, as in the case of enumerative inventories of critical raw materials (Schrijvers et al., 2020). Consequently, it is essential to provide empirical evidence to support the validity of such indicators and the relevance of the thresholds used (Brown, 2018).

This paper tackles this crucial issue. Specifically, it aims to empirically assess the validity of a country production concentration indicator for evaluating the supply risk aspect of criticality and to examine whether a threshold exists within the HHI values to assign the criticality of specific non-fuel minerals. We go further than the aforementioned literature since, to the best of our knowledge, no study has assessed the relevance of the HHI of production as an indicator for distinguishing among various metals and minerals, nor has any study empirically attempted to determine an appropriate threshold for utilizing this indicator in the context of criticality studies. Our paper fills these gaps by investigating the impact of the production HHI on metal prices from a panel perspective and seeking to identify the presence of a threshold. To this end, we adopt the approach outlined in Gleich et al. (2013), which attempts to assess the validity of certain indicators, by examining their relationship with raw material prices.

Our results challenge the commonly held assumption that the variation of HHI has a greater impact on prices at higher HHI levels. Additionally, our findings suggest that a clear threshold does not exist to distinguish high-risk markets from less risky ones based on their concentration levels. Therefore, using the HHI as a supply risk indicator, particularly in conjunction with a threshold, may result in underestimating risks in less concentrated markets.

The rest of the paper is organized as follows. Section 2 comprehensively describes the HHI data used in the model while Section 3 outlines our chosen models. The results are presented and discussed in Section 4. Finally, Section 5 summarizes our main findings and draws some policy implications.

2 The Herfindahl–Hirschman Index (HHI): calculation and stylized facts

2.1 HHI calculation

We construct a database that tracks the evolution of the HHI for a set of 63 metals and minerals that are key to today's economy (see Table 8 in Appendix A). The database spans the period from 1994 to 2021 at an annual frequency. To measure these concentrations, we use country-specific production data for these materials. Our primary sources for this purpose are the United States Geological Survey (USGS) and the British Geological Survey (BGS), both recognized as global references for minerals and metals data and statistics.

The USGS publishes an annual report called *The Minerals Yearbook*, which reviews the mineral and metal industries of both the United States and foreign countries. This yearbook comprises statistical data on various metals and minerals and offers information on economic and technical trends. First published in 1933, digital versions have been available on the USGS website since 1996. In the publication for year i, the USGS provides data of global primary production by country for a wide variety of raw materials for year $i-2$. Consequently, we can extract production data from 1994 to 2021. This data availability defines the period of our study. For most materials listed, the data pertains to primary production (extracted from mining operations), while refining data is available for some metals.

Similarly, the BGS maintains its own database on the production and trade of minerals named the *World Mineral Statistic Datasets*.This data is published annually in three reports, including *World Mineral Production*, which contains production statistics, categorized by country, for a range of economically significant mineral commodities, encompassing ferrous and non-ferrous metals, industrial minerals, and hydrocarbons. The first publication of this dataset dates to 1913. While data for some metals are available before to 1994, we opt to extract data from 1994 to ensure comparability with the USGS dataset.

While primarily relying on data from the USGS, we use BGS data in cases where USGS data is missing, and it serves as a robustness check for our HHI calculations. The HHI for row material m at stage s and year i is defined as follows:

$$\mathrm{HHI}_{m,s,i} = \sum_{c \,\in\, P_{m,s}} (S_{c,m,s,i})^2$$

where:

- $P_{m,s}$ is the set of all countries c that produce raw material m at stage s.
- $S_{c,m,s,i}$ is the share of country c in the global supply of the raw material m at stage s in the specified year i.
- s corresponds either to mine production, refinery, or smelter activities.

In the USGS reporting, for some raw materials, minor producers are aggregated into the 'Other Country' category, resulting in a combined production denoted as p_{other}. In this case, we assume that each country within the 'Other Country' category produces less than the country with the lowest production (p_{min}) among the available data.[7] Applying this methodology, we obtained HHI data for 63 metals and minerals at various stages of their value chain. Most of these data points represent market concentration at the extraction level, but for certain metals, we also have data on concentration at the refining or smelting stages (see Table 8 in Appendix A).

2.2 Stylized facts: trends in HHI over the 1994-2021 period

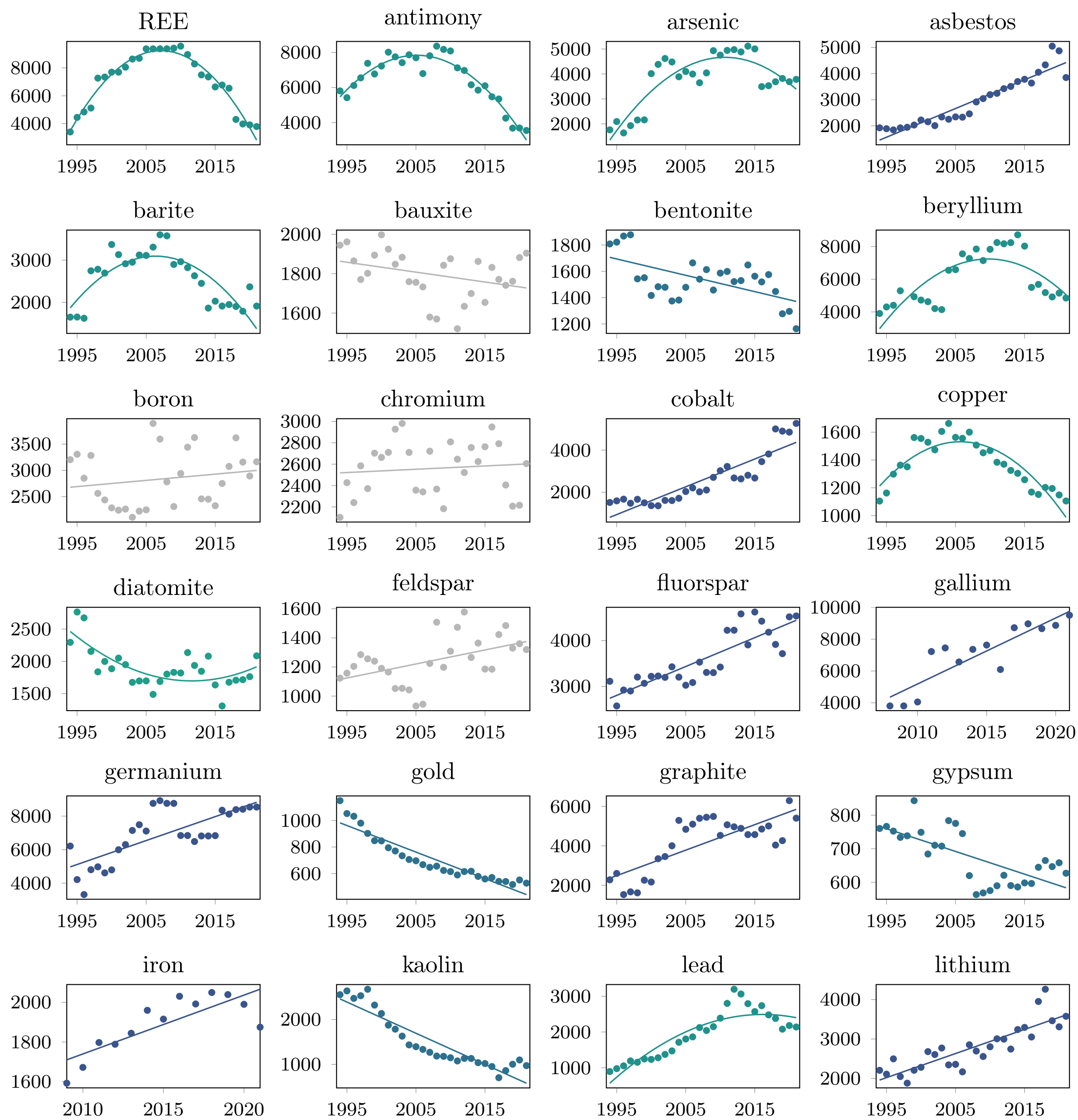
2.2.1 HHI at the extraction stage

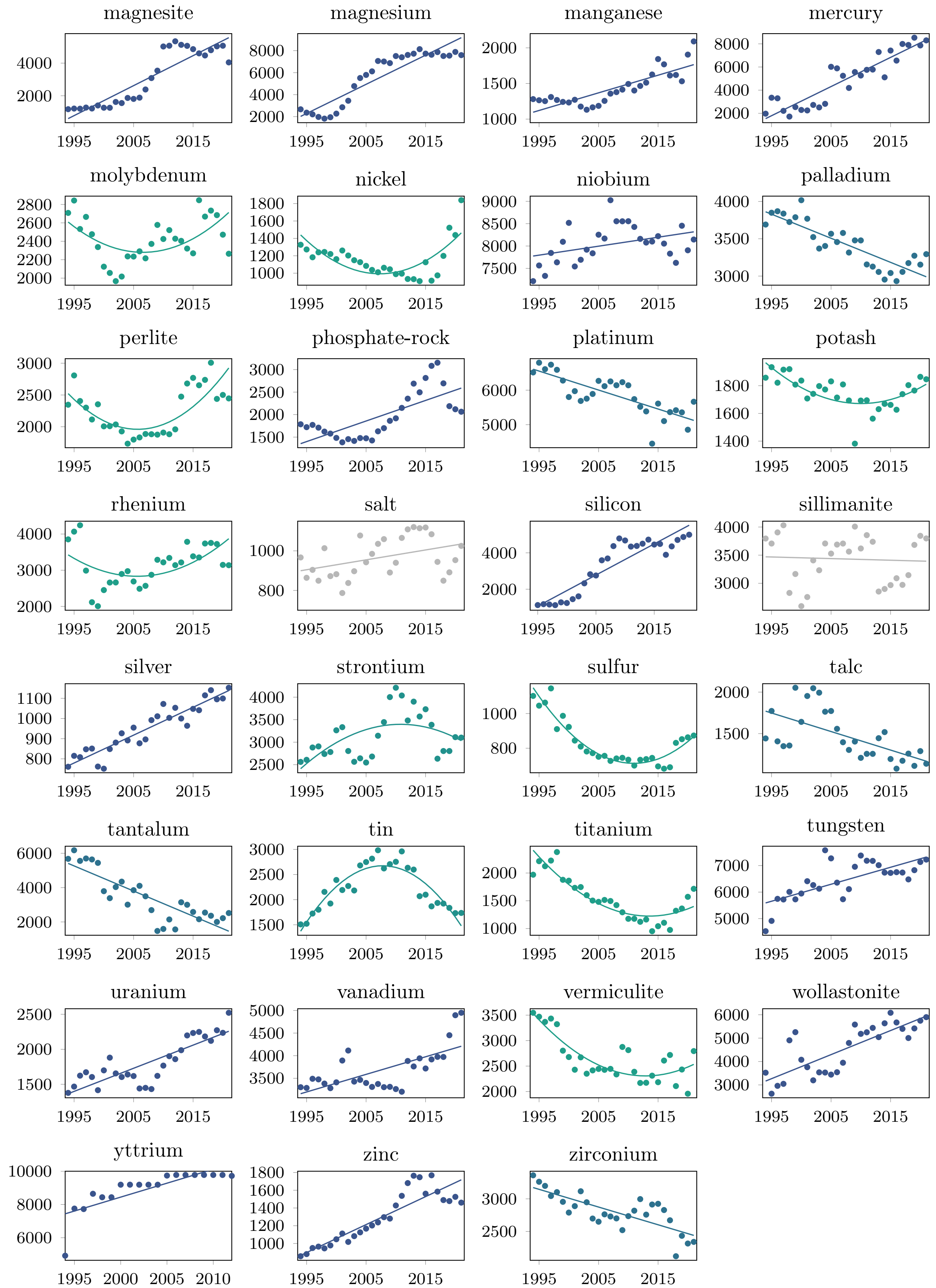
The time evolution of HHI at the extraction stage exhibits diverse patterns across the studied metals and minerals (Figure 1). Specifically, we observe five distinct categories of

[7] All the details as well as robustness checks are provided in Appendix A.

HHI trends. First, certain metals and minerals exhibit continuous HHI growth, indicating a rising market dominance over time. Second, another group maintains relatively stable HHI values, pointing a consistent market share throughout the years. Third, some raw materials experience a decreasing trend in HHI, implying increased competition between countries within their respective markets. Fourth, there are cases where materials initially undergo growth before experiencing a subsequent decline. Fifth, conversely, we find instances where materials exhibit the reverse pattern, initially declining before witnessing growth.

Figure 1: Evolution of the HHI at the extraction stage over the 1994-2021 period





Note: These graphs illustrate the evolution of the HHI values calculated at the mining stage using the USGS and BGS data, as described in section 2.1

In the period under study, most HHI series exhibit an increasing trend (40% of the analyzed series) indicating a concentration of primary production for a significant number of metals and minerals over the past two decades. This intensification in concentration occurs at varying rates, with the HHI for silver increasing only by 13 points per year on average, while for gallium,[8] the rise amounts to over 400 HHI points annually (Table 1). Several factors contribute to this phenomenon, including geological considerations as countries possess differing mineral endowments and prioritize the extraction of highly concentrated ores. For instance, the Democratic Republic of the Congo (DRC) is a prominent cobalt producer due to its possession of nearly half of the world's cobalt reserves (USGS, 2023). Economies of scale and expertise are additional drivers of production concentration. Lastly, environmental, and social regulations (ecological and social dumping) can also lead to significant concentration in the production of certain metals.

Table 1: Regression coefficients of HHI series

Raw material	Regression coefficient	Trend	Raw material	Regression coefficient	Trend
tantalum	−146.281	decreasing	phosphate-rock	45.737	increasing
kaolin	−69.571	decreasing	lithium	61.131	increasing
platinum	−54.949	decreasing	fluorspar	62.978	increasing
palladium	−32.278	decreasing	tungsten	64.060	increasing
zirconium	−27.161	decreasing	wollastonite	102.845	increasing
talc	−22.322	decreasing	asbestos	109.864	increasing
gold	−20.033	decreasing	graphite	129.243	increasing
bentonite	−12.414	decreasing	cobalt	131.806	increasing
gypsum	−6.788	decreasing	germanium	142.685	increasing
silver	13.809	increasing	yttrium	167.491	increasing
niobium	20.059	increasing	silicon	171.143	increasing
manganese	24.751	increasing	magnesite	183.807	increasing
iron	29.663	increasing	mercury	251.764	increasing
zinc	31.527	increasing	magnesium	265.179	increasing
uranium	33.052	increasing	gallium	414.387	increasing
vanadium	38.926	increasing			

Note: This table presents the linear regression coefficients calculated for the HHI data of raw materials that exhibit a monotone HHI trend throughout the specified period (Figure 1). Metals and minerals are arranged in ascending order based on their regression coefficients. Most of these trends show an upward trajectory, and the rate at which the HHI evolves varies significantly among the different elements studied.

A sustained decrease in HHI over the same period is relatively rare, representing only 16% of the studied series. Notably, this subset comprises gold, palladium, and platinum, three metals categorized as precious metals.[9] This can be attributed to consistently high prices that make extraction profitable, even when deposits are not highly concentrated. For instance, artisanal and small-scale gold mining, which contributes to about 20% of

[8]Gallium data is available only for the period 2007-2021.

[9]Silver is the only element in the precious metals category within our dataset that does not exhibit a declining HHI; nevertheless, as previously mentioned, its growth remains sluggish.

global production and operates in 80 countries (Kumah, 2022), plays a role in lowering the gold HHI value. Some minerals such as talc, kaolin, bentonite, and gypsum, also exhibit a sustained decrease in HHI. In these cases, the decreasing trend can be explained by their large and well-distributed resources among various producing countries, contributing to a more balanced concentration of production across the globe (USGS, 2023). In 16% of cases, the HHI series display a pattern of growth followed by a subsequent decline over time. Notably, when we examine the leading producer of these materials at the point where the HHI reaches its maximum before decreasing, China emerges as the predominant producer in the majority of cases (Table 2). Also, the decline in HHI is often attributed to either a governmental decision to reduce production, typically in response to curbing domestic pollution, or a significant natural disaster that necessitated a substantial reduction in production.

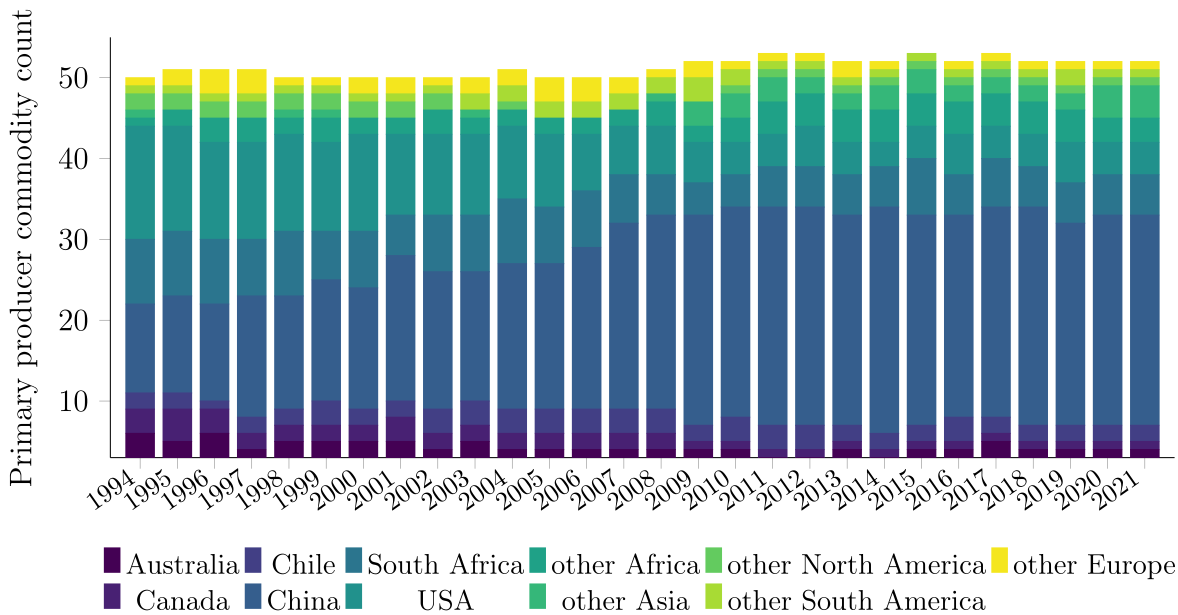
Table 2: HHI peak year and leading producer's market share

Raw material	Year of max HHI	First producer country	Market share	Regression coefficient
REE	2010	China	97.7	−550
antimony	2008	China	91.3	−399
arsenic	2011	China	66.6	−168
barite	2008	China	57.1	−108
beryllium	2014	USA	93.1	−440
copper	2006	Chile	35.5	−32
lead	2013	China	52.8	−114
strontium	2011	China	50.7	−119
tin	2011	China	49.2	−113

Note: The 'Year of max HHI' column indicates the specific year when the Herfindahl-Hirschman Index reaches its highest value before starting to decrease. The 'Market Share' represents the proportion of production held by the leading producer country in that specific year.

Antimony serves as a pertinent case study exhibiting a decreasing HHI from the period of 2008-2010 onwards. Classified as a metalloid, antimony plays a crucial role as an alloying element in the production of flame retardants, lead-acid batteries, and semiconductors. The reduction in HHI for antimony is explicitly linked to China's pivotal position as the world's leading antimony producer since the early 1980s. A government-driven decision to curtail antimony mining operations in 2010, in response to environmental concerns and safety issues, significantly contributed to this decline (USGS, 2023). Given China's dominance, accounting for nearly 90% of global antimony production at the time, the production disruptions led to a substantial price surge in 2011. Similarly, the decline in HHI for lead, tin, REEs, and molybdenum in the 2010s can be attributed to production curtailments implemented as part of an environmental clean-up initiative led by Beijing (USGS, 2023). Additionally, the decline in HHI for REEs, starting in 2010, is also linked to China's export restrictions on these elements, justified as a measure to conserve resources and protect the environment. This policy shift resulted in a substantial price surge for REEs in international markets, sparking increased investments in rare earth developments outside China. Consequently, despite China's production rebound from 2016 onwards, the country's market share declined due to growing exploitation in other regions of the world, which contributed to the rapid decrease in REE's HHI since 2010 at a rate of -550 points per year (Table 2). The reduction in barite's HHI is also attributed to the decrease in China's production, although in this case, it is not due to a governmental decision but rather the result of extreme climatic conditions that significantly impacted Chinese production from 2009 to 2011. Coupled with increased fuel costs and robust global demand for barite, these circumstances led to a sharp increase in prices for Chinese barite. Consequently, the higher prices encouraged the entry of new players into the barite mining sector, particularly India, which resulted in a sustained decline in HHI (USGS, 2023).

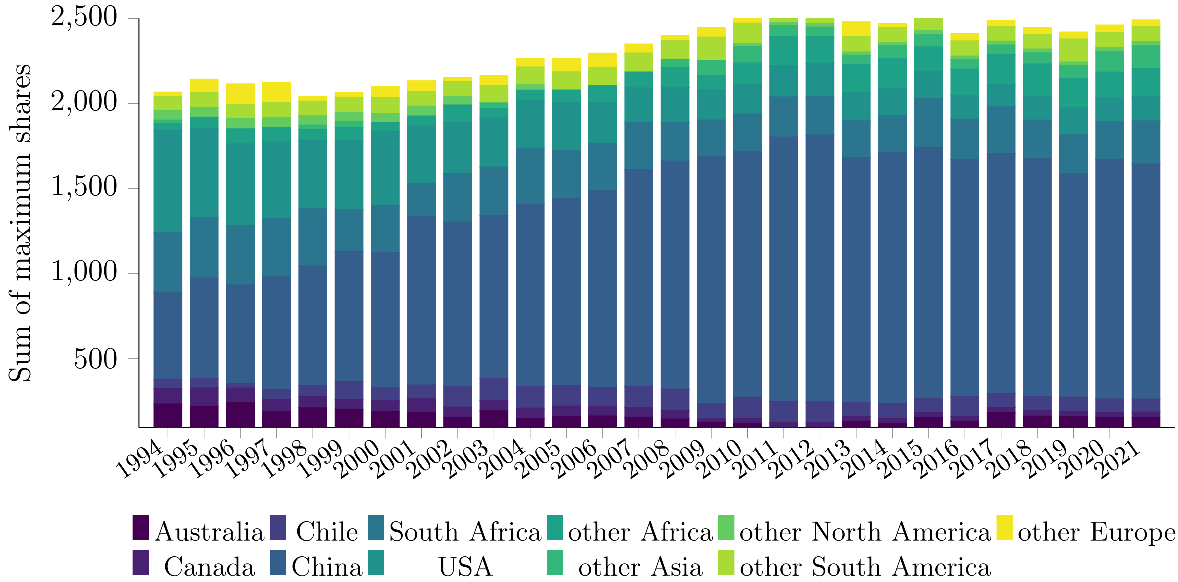
Figure 2: Global primary resource producers



Note: The graph presents the number of primary commodities within our panel, for which each country holds the position of the leading producer at the upstream stage. Only countries leading in at least 3 commodities are individually listed, while all others are grouped under the 'Other' category based on their respective continents. This analysis is based on the raw mineral production data from the USGS and BGS datasets presented in section 2.1.

Since the 1990s, a select group of countries have emerged as major players in primary resource production, dominating the supply of essential materials. Notably, China's role as a significant producer experienced substantial growth from the 2010s onwards, leading to a shift in the dynamics at the expense of the United States. By 2009, China had claimed the top position as the leading producer of over half of all metals and minerals in our panel (Figure 2). This shows that we have not only observed an increase in the concentration of global production for various commodities, but also a significant overall concentration of resources within China. However, despite China's continued dominance as a primary resource producer, there has been a decline in its market share since 2012, reflecting the impact of environmental policies implemented by the government (Figure 3).[10] Also, contextualizing Chinese production in relation to its consumption is essential as China is both the primary producer of metals and minerals and the largest consumer of these commodities (Frenzel et al., 2017).

Figure 3: Total maximum market shares by country



Note: The graph displays the sum of the maximum market shares, representing the market share held by the first producer of each commodity, for each respective country. This analysis is based on the raw mineral production data from the USGS and BGS datasets presented in section 2.1.

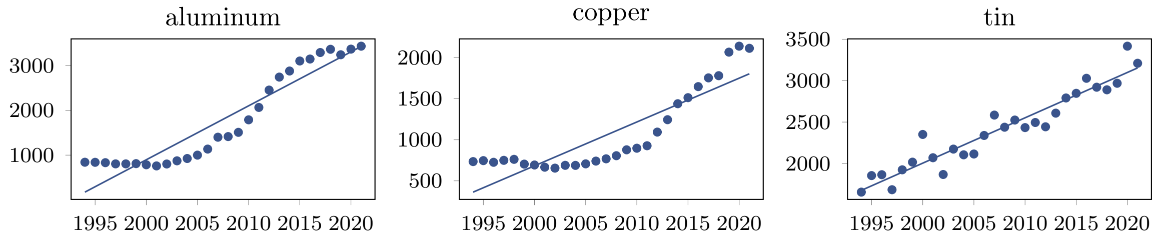
2.2.2 HHI at the smelting stage

The concentration of smelter production for aluminum, copper, and tin exhibits an upward trend over the studied period (Figure 4). In all three cases, the rise in HHI can be attributed to the expanding influence of the Chinese market on total production. China emerged as the leading player in tin smelting as early as 1993, with its market share steadily growing over time (Bonnet et al., 2022). Similarly, for aluminum and copper, China became the top producer in 2001 and 2004, respectively, leading to a noticeable

[10] The rationalization of industrial activities in China since 2010 should also be mentioned, with a wish to eliminate small actors for better control activities (Hache, 2019).

shift in the HHI curves, coinciding with the moment when the country attained the position of the primary producer with an increasingly dominant market share.

Figure 4: Evolution of the HHI at the smelting stage over the 1994-2021 period

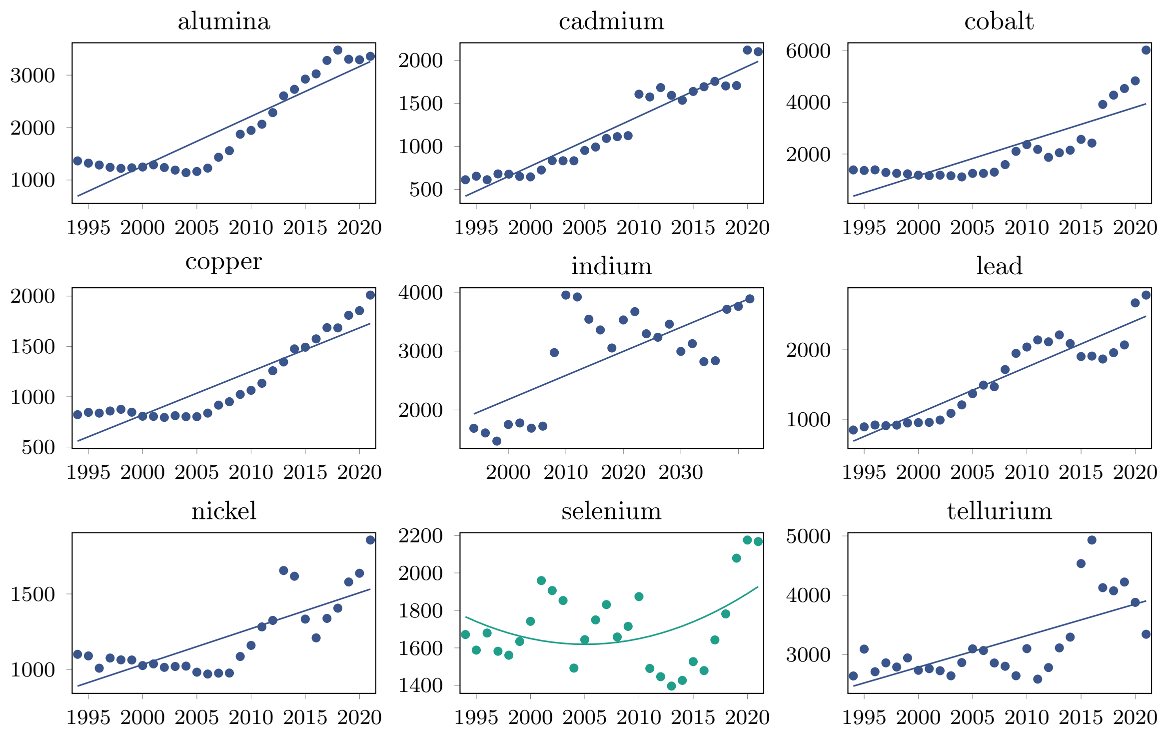


Note: These graphs illustrate the evolution of the HHI values calculated at the smelting stage using the USGS and BGS data, as described in section 2.1

2.2.3 HHI at the refinery stage

Likewise, the HHI series at the refinery stage for all metals with available refining data (metals shown in Figure 5) exhibit an increasing trend. Notably, this upward trajectory in HHI values is consistently attributed to China's production activities, signifying its progressive dominance in the refining processes of these metals.

Figure 5: Evolution of the HHI at the refinery stage over the 1994-2021 period



Note: These graphs illustrate the evolution of the HHI values calculated at the refinery stage using the USGS and BGS data, as described in section 2.1

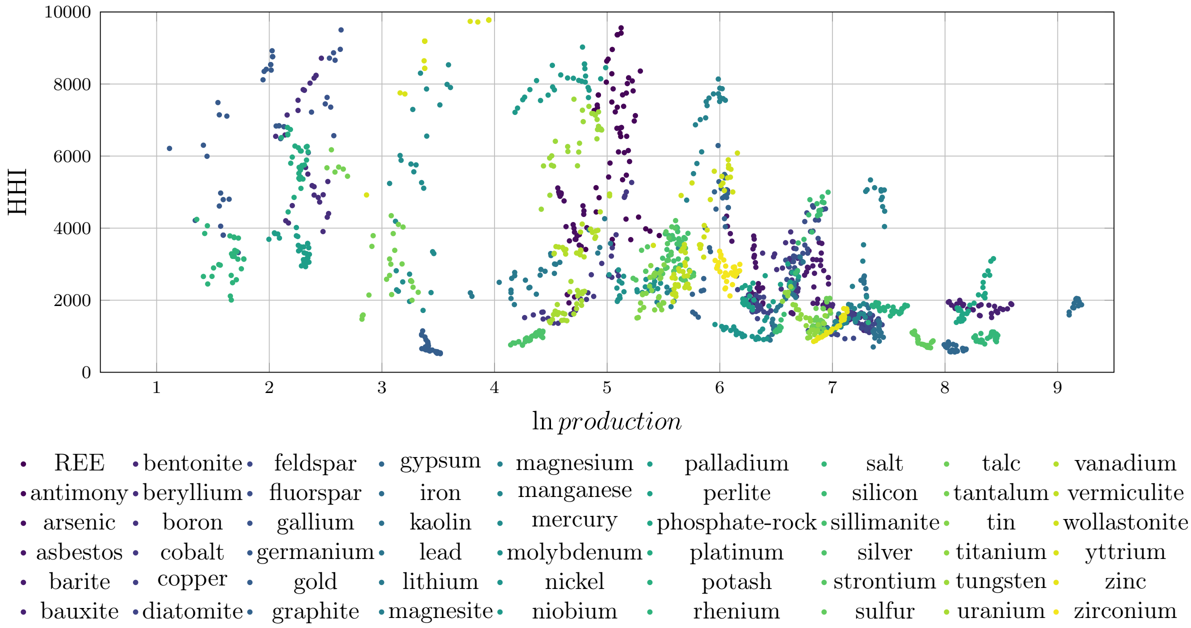
It is noteworthy to compare the HHI values between the upstream and midstream stages.[11] Taking copper and tin as examples, the concentration of production at the extraction stage has been decreasing for over 15 years, while the concentration at the refining stage is increasing. This dynamic is primarily driven by China's growth in the refining sector, even though China's tin extraction is declining. Regarding cobalt, both the extraction and refining HHIs show a comparable increasing trend, but the primary producer differs. The DRC dominates cobalt extraction, while China refines over 76% of global cobalt production in 2021. This reflects China's determination to secure its supplies and assert its hegemony in the global resources market. It also underscores its aim to move up the value chain and capture additional value downstream from ore, a sentiment echoed by many resource-producing countries. Notably, many countries have begun to restrict the export of unprocessed minerals. Indonesia banned the export of raw nickel ore in 2020 and has been followed by several lithium-rich African countries, including Ghana, Namibia, and Zimbabwe. The primary goal of these nations is to encourage investments in on-site ore processing, with a long-term objective of developing batteries within their territories. The Chinese dominance in the permanent magnet market is a successful example of value chain ascent, spanning from mining to the development of final technology. In his work, Pitron (2018) describes the Chinese strategy, starting with establishing a dominant position in rare earth mining and refining, and later assimilating foreign expertise in permanent magnet production.

2.3 Concentration as a function of total production

When examining the relationship between mining production concentration and total raw material production within the panel, we observe a negative relationship in the pooled regression. This implies that as the total quantity of mined mineral increases, its production concentration decreases. This initial finding suggests that metals or minerals produced in larger quantities tend to be shared among a greater number of actors. However, when we consider the individuality of each metal and conduct a within-panel regression, the coefficient of regression between HHI and global production is positive (Figure 6). This aligns with the earlier qualitative analysis, where we observed that the HHI of metals and minerals extraction generally shows a growing trend over time, while the production of metals and minerals also generally increases through time. As a result,

[11] Given the proximity of HHI values between smelting and refining data, we can combine these two categories in the analysis. Although there is a slight difference for copper and tin, where the refining data accounts for secondary production, this has a negligible impact on the overall HHI.

Figure 6: HHI vs log of total production



Note: This plot illustrates the relationship between the HHI and the logarithm of the total annual production (measured in metric tons of metal or mineral content per year), of metals and minerals in our panel. [12]

we would expect to find a positive relationship between HHI and production.

3 Data and methodology

Our analysis focuses on evaluating the HHI of a country's production concentration as a reliable indicator for measuring supply risk, specifically in distinguishing between different materials. Furthermore, we aim to analyze the presence of a distinct threshold in the HHI values for assigning the criticality of particular metals. Based on the hypothesis that metal prices can indicate to some degree their criticality (Gleich et al., 2013), we rely a panel regression analysis to examine the impact of HHI on metal prices. The use of a panel data framework provides the significant advantage of working with a sizable dataset, thereby enhancing the statistical robustness of our findings. Furthermore, it is necessary to rely on a panel data approach because using a single metal's HHI values over time is insufficient for determining a consistent threshold due to their limited variability.

[12] In this analysis, we have excluded chromium from our panel due to data inconsistency, as its production data is expressed in gross weight rather than element content. To ensure consistency, we have retained only elements with production data expressed in element content.

3.1 Data

Our dependent variable is the annual price of metals. Metal prices are measured in US dollars per metric ton and have been sourced from the USGS.[13] Note that the prices reflect rates in the United States, serving as a representative estimate for the average cost of these raw materials in the country. As stated in the IRENA report (IRENA, 2023), not all metals and minerals have a fully global market presence. Nevertheless, after thoroughly comparing the USGS-derived prices with metal market rates obtained from alternative sources, a remarkable level of similarity is observed. The differences between these price series, on a median basis, tend to hover around a modest 3%, and their variations exhibit an even narrower median difference of approximately 0.3%. Detailed statistics are available in Appendix B (Table 10). Based on this empirical evidence, it is reasonable to consider the metal prices under examination as indicative of global market prices. However, this assumption cannot be uniformly applied to minerals such as salt, talc, and asbestos due to the lack of comprehensive global price data. Consequently, minerals have been excluded from the subsequent econometric analysis. This choice can also be justified by the fact that metals are more relevant than minerals in low-carbon technologies which deserve particular attention.[14] Overall, our (unbalanced) panel is composed of 33 metals over the 1995-2021 period, corresponding to a total of 821 observations (see the list and descriptive statistics in Appendix C - Table 11). Following the common practice in the literature that examines commodity prices (Akram, 2009; Issler et al., 2014; Rubaszek et al., 2020), the metal prices have been transformed into real prices by deflating them by the US consumer price index (CPI).

The explanatory variable is the country HHI computed at the mine production level, presented in detail in the previous section.

Turning to the control variables, we use the five variables most found in the literature that investigates the dynamics of metal prices, and more generally, commodity prices. First, we consider the real price of Brent crude oil, which exerts its influence on metal prices through two primary channels.[15] On the one hand, oil can be regarded as a proxy for global economic growth, thus impacting metal prices through its effect on demand. This relationship is supported by the literature, which indicates that commodities used

[13]Data sources for all series are provided in Appendix D (Table 12).

[14]Additionally, none of the parameters obtained from the panel regression exclusively conducted on mineral data attains statistical significance.

[15]The Brent crude oil price benchmark was chosen over the WTI because it is the world's most important crude oil benchmark, responsible for pricing nearly 70% of globally traded crude oil (Imsirovic and Chapman, 2022). As shown in Appendix G, using WTI leads to similar results, illustrating the robustness of our findings to the choice of the oil price series.

as inputs in the production process typically escalate during periods of strong global economic activity (Erten and Ocampo, 2013). On the other hand, the extraction and refining processes of metals require a significant amount of energy, predominantly derived from fossil fuels. Therefore, fluctuations in oil prices have an impact on the production costs of metals, creating potential cost-push effects on metal prices (Akram, 2009; Lombardi et al., 2012).

Second, fluctuations in the US dollar can also act as a driver of metal prices. Since metals are commonly traded in US dollars, a depreciation of the US currency leads to a lower price for importers. Consequently, importers' demand for commodities increases, ultimately resulting in higher prices. Conversely, when the US dollar appreciates, it becomes costlier for importers to purchase commodities, leading to potentially reduced demand and lower commodity prices (Akram, 2009). We use the broad US dollar real effective exchange rate from the FRED database.

Third, metals and minerals are fundamental inputs in industrial production. Therefore, an increase in industrial production triggers higher consumption of metals and minerals, which, in turn, has an impact on their prices. To capture this relationship as an explanatory variable, several proxies are considered:

- Shipping freight cost (Baltic Dry Index): Reflecting shipping rates for major raw materials, this index serves as a gauge of global demand for commodities, providing insights into the overall economic activity.
- Industrial production index of OECD, China, Brazil, India, and Russia: These indices measure the output of industrial sectors in the respective countries.
- US Real Manufacturing and Trade Industries Sales.

Fourth, commodity prices can also be influenced by short-term interest rates. Frankel (2008) presents the theoretical link between interest rates and commodity prices, demonstrating a negative relationship between them. This negative correlation can be attributed to several factors. Firstly, a lower interest rate encourages a shift in investments from financial markets to commodity assets. Then, it increases the incentive to hold inventories due to reduced carrying costs and diminishing the motivation for early extraction of exhaustible commodities. These combined effects lead to an increase in commodity demand and a decrease in commodity supply, ultimately resulting in higher commodity prices. We use the US LIBOR rate as a proxy for the US interest rate, as in Akram (2009).

Fifth, the influence of uncertainty on metal prices has been widely explored in the literature. Uncertainty can impact commodity prices by amplifying the effects of an economic recession, as global economic growth is a key driver of commodity prices. Moreover, heightened uncertainty may induce increased risk aversion among investors, leading to a rise in the desired risk premium, subsequently hampering investment prospects (Byrne et al., 2013; Chen et al., 2022). The volatility index (VIX) traded in the Chicago Board Options Exchange can be used to proxy uncertainty, as a measure of the implied volatility of S&P 500 index options and reflects the uncertainty of the stock market.

Finally, the concentration of minerals is often cited as one of the primary factors influencing production costs, which, in turn, can ultimately impact metal prices. However, several studies have shown that there is no direct link between resource scarcity and market prices, indicating that current market prices are not reliable indicators of resource depletion (Seyhan et al., 2012; Henckens et al., 2016). Vidal (2021) explains this phenomenon by highlighting that technological innovation has thus far offset the decline in mineral concentration. As a result, we do not consider the concentration of minerals in deposits as an explanatory variable in our model.

With the exception of the interest rate, all series are transformed into first-logarithmic differences to ensure stationarity.[16]

3.2 Panel regressions

To address our research questions, we consider four panel regression models:

$$\begin{aligned}\Delta \ln price_{i,t} = {} & \alpha_i + \beta_1 \, \Delta \ln \mathrm{HHI}_{i,t} + \\ & \beta_2 \, \Delta \ln oil_t + \beta_3 \, \Delta \ln er_t + \beta_4 \, ir_t + \beta_5 \, \Delta \ln vix_t + \beta_6 \, \Delta \ln is_t + \epsilon_{i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}\Delta \ln price_{i,t} = {} & \alpha_i + \beta_{11} \, \Delta \ln \mathrm{HHI}_{i,t} + \beta_{12} \, \mathrm{I}_{\mathrm{HHI}_{i,t}} + \\ & \beta_{13} \, \Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} + \\ & \beta_2 \, \Delta \ln oil_t + \beta_3 \, \Delta \ln er_t + \beta_4 \, ir_t + \beta_5 \, \Delta \ln vix_t + \beta_6 \, \Delta \ln is_t + \epsilon_{i,t}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta \ln price_{i,t} = {} & \alpha_i + \beta_{11} \, \Delta \ln \mathrm{HHI}_{i,t} + \beta_{12} \, \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} + \\ & \beta_{13} \, \Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} + \\ & \beta_2 \, \Delta \ln oil_t + \beta_3 \, \Delta \ln er_t + \beta_4 \, ir_t + \beta_5 \, \Delta \ln vix_t + \beta_6 \, \Delta \ln is_t + \epsilon_{i,t}\end{aligned} \tag{3}$$

[16] We used the second-generation unit root test for panel data proposed by Demetrescu et al. (2006) that allows for cross-dependence across the panel units. We applied this test to the price series and HHI series, which are the only ones that vary according to the N individuals of the panel (metals). The remaining variables depend solely on the time section of the panel. This test is a modification of Choi's inverse-normal combination test that can be used when the N p-values are not independent. The results, reported in Appendix E Table 13, show that the logged price series cannot be considered stationary, as the test fails to reject the null at a 10% significance level. The outcomes for the logged HHI series are dependent on the chosen specification, yet the test never displays significance at the 5% level.

$$
\begin{aligned}
\Delta \ln price_{i,t} = \alpha_i &+ \beta_{11}\, \Delta \ln \mathrm{HHI}_{i,t} + \beta_{121}\, \mathrm{I}_{\mathrm{HHI}_{i,t}} + \beta_{122}\, \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} + \\
&\beta_{131}\, \Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} + \beta_{132}\, \Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} + \\
&\beta_{14}\, \Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} + \\
&\beta_2\, \Delta \ln oil_t + \beta_3\, \Delta \ln er_t + \beta_4\, ir_t + \beta_5\, \Delta \ln vix_t + \beta_6\, \Delta \ln is_t + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

The variable $price_{i,t}$ represents the price of metal i at time t, while $\mathrm{HHI}_{i,t}$ denotes the corresponding country HHI computed at the mine production level. The variables oil_t, er_t ,vix_t, ir_t and is_t represent the oil price, exchange rate, VIX index, interest rate, and industries sales,[17] respectively, at time t, all independent of i. The constant vector α_i reflects the unobserved effects. The random error terms are denoted by $\epsilon_{i,t}$. Model 1 simply examines the effect of a change in HHI on the metal price. In the other models, two dummy variables are introduced: $\mathrm{I}_{\mathrm{HHI}_{i,t}}$ takes the value of 0 when $\mathrm{HHI}_{i,t}$ is below a certain threshold and 1 otherwise. Similarly, $\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$ is derived from the absolute value of $\Delta \ln \mathrm{HHI}_{i,t}$. Mathematically, this is expressed as:

$$
\mathrm{I}_{\mathrm{HHI}_{i,t}} = \begin{cases} 0 & \text{if } \mathrm{HHI}_{i,t} < t_{\mathrm{HHI}} \\ 1 & \text{if } \mathrm{HHI}_{i,t} \geq t_{\mathrm{HHI}} \end{cases} \quad \text{with } t_{\mathrm{HHI}} \in [0, 10000] \tag{5}
$$

$$
\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}} = \begin{cases} 0 & \text{if } |\Delta \ln \mathrm{HHI}_{i,t}| < t_{\Delta \ln \mathrm{HHI}} \\ 1 & \text{if } |\Delta \ln \mathrm{HHI}_{i,t}| \geq t_{\Delta \ln \mathrm{HHI}} \end{cases} \quad \text{with } t_{\Delta \ln \mathrm{HHI}} \in [0, 1] \tag{6}
$$

Incorporating these variables into Equations (2) to (4) enables differentiation of the effects of an HHI variation on prices based not only on the HHI level but also on the magnitude of this variation. In Model 2 we include the interaction dummy variable $\mathrm{I}_{\mathrm{HHI}_{i,t}}$ alongside $\Delta \ln \mathrm{HHI}_{i,t}$, in order to explore the interplay between the level of the HHI and the fluctuation of the HHI on price changes. Similarly, within Equation (3), a corresponding investigation is made by including the dummy variable $\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$. The latter represents the absolute value of the annual HHI variation and aims to capture the impact of pronounced HHI fluctuations. In Model 4 , we take into account the interaction of the three variables: $\Delta \ln \mathrm{HHI}_{i,t}$, $\mathrm{I}_{\mathrm{HHI}_{i,t}}$, and $\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$, which enables us to examine how a metal price responds to changes in HHI, considering the extent of the variation and HHI's level. This specification outlines four regimes as detailed in Table 3.

Moreover, the inclusion of the dummy variable $\mathrm{I}_{\mathrm{HHI}_{i,t}}$ can provide evidence of the

[17] We have selected the US Real Manufacturing and Trade Industries Sales as the proxy for industrial production because it exhibits the highest significance in our model.

Table 3: Metal price fluctuation regimes delineated in Model 4

$\mathrm{I}_{\mathrm{HHI}_{i,t}}$	HHI level	$\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$	HHI variation	Model parameters	Regime effect
0	low	0	low	β_{11}	$\beta_{low,low}$
0	low	1	high	$\beta_{11} + \beta_{132}$	$\beta_{low,high}$
1	high	0	low	$\beta_{11} + \beta_{131}$	$\beta_{high,low}$
1	high	1	high	$\beta_{11} + \beta_{131} + \beta_{132} + \beta_{14}$	$\beta_{high,high}$

Note: Model 4 delineates four regimes based on the levels and variations of HHI. The effect of HHI variations on prices for each regime is captured by the parameters of Equation (4) in the 'Model parameters' column. The overall name for these parameters is provided in the 'Regime effect' column.

existence of a threshold within the HHI values. We check all the possible thresholds by performing a loop over the values of the variable t_{HHI}, ranging from 0 to 10,000. Differences in the results based on the value of t_{HHI} could be a positive indication of a threshold. The chosen value would be the one leading to the most empirically significant results The same method can be used for the dummy variable $\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$.[18]

In this analysis, we did not use a dynamic model because the results did not show significance when incorporating the lagged endogenous variable (see Appendix G). Similarly, the outcomes lack significance when accounting for the lagged variable of interest ($\Delta \ln \mathrm{HHI}_{i,t-1}$). However, the issue of endogeneity is not a substantial concern within the scope of our econometric model due to several factors. Mining, the first stage in the value chain of metal production, depends on external factors unrelated to the price of raw materials. These factors include the mining endowment of the producing country and prevailing environmental and social regulations. Moreover, the start of mine operations is primarily a government decision driven by sovereignty considerations rather than economic concerns. In addition, although mining investment is highly correlated with metal prices, its effect on production and, consequently, on the HHI, may take several years to materialize. According to IEA (2022a), the average lead time from discovery to production is about 17 years. The period from discovery through exploration to feasibility accounts for most of this time, with the remaining period (construction planning and construction to production) averaging about 4.5 years.

4 Empirical results and discussion

Table 4 presents the results of the four regression models considered, estimated for the thresholds set at $t_{\mathrm{HHI}} = 2700$ and $t_{\Delta \ln \mathrm{HHI}} = 0.1$. In the first panel regression model,

[18]Although the Panel Smooth Regression Model specification would have been an interesting alternative approach at a first sight, it cannot be implemented in our context as demonstrated in Appendix H.

Table 4: Linear estimation results using the fixed effects regression

	Model 1	Model 2	Model 3	Model 4
$\Delta \ln \mathrm{HHI}_{i,t}$	-0.04	0.04	-0.38	-0.75^{**}
	(0.09)	(0.12)	(0.24)	(0.31)
$\Delta \ln oil_t$	0.14^{**}	0.14^{**}	0.14^{**}	0.14^{**}
	(0.07)	(0.07)	(0.06)	(0.06)
$\Delta \ln er_t$	-1.70^{***}	-1.70^{***}	-1.69^{***}	-1.71^{***}
	(0.35)	(0.36)	(0.35)	(0.36)
$\Delta \ln is$	0.89^{***}	0.88^{***}	0.89^{***}	0.88^{***}
	(0.31)	(0.32)	(0.31)	(0.31)
$\Delta \ln vix_t$	0.02	0.01	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
ir_t	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
$\mathrm{I}_{\mathrm{HHI}_{i,t}}$		-0.01		-0.00
		(0.03)		(0.04)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}}$		-0.12		0.70
		(0.18)		(0.48)
$\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$			-0.03	-0.01
			(0.02)	(0.04)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$			0.41	0.95^{***}
			(0.26)	(0.34)
$\mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$				-0.02
				(0.05)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$				-0.96^{*}
				(0.52)
Num. obs.	821	821	821	821

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: The dependent variable is the log differentiated prices of metals $\Delta \ln price$. The variables $\Delta \ln oil$, $\Delta \ln er$, $\Delta \ln vix$, and $\Delta \ln is$ denote the variation rate of oil price, exchange rate, VIX index, and Industries sales, respectively. ir denotes the US interest rate. $\Delta \ln \mathrm{HHI}$ is the variation rate of the country metal production concentration and $\mathrm{I}_{\mathrm{HHI}}$ and $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ are the dummy variables computed for the threshold values of $t_{\mathrm{HHI}} = 2700$ and $t_{\Delta \ln \mathrm{HHI}} = 0.1$. These thresholds are chosen according to the methodology presented in the previous section, and the decision relies on the results presented in Appendix F. To provide consistent results, we apply the Newey and West robust covariance estimators, the corresponding standard errors are in parentheses.

the HHI has no impact on price dynamics. This is also the case in Models 2 and 3. Furthermore, the interaction terms in both models are not significant; a result which remains consistent regardless of the considered threshold (see Figure 7 and 8 in Appendix F).[19] The most interesting findings concern Model 4. Indeed, the parameters associated

[19]We obtain the same results (available upon request to the authors) when testing homogeneity against the Panel Smooth Transition Regression alternative.

with $\Delta \ln \mathrm{HHI}_{i,t}$, $\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$, and $\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$ are statistically significant at conventional confidence levels. Based on this finding, to examine the impact of metal production concentration on their prices, it is essential to consider both the HHI level and the extent of HHI variation. In this context, the estimated value of the parameter β_{11} related to the variable $\Delta \ln \mathrm{HHI}_{i,t}$ is negative (-0.75). This implies that for HHI values below 2700 and for HHI fluctuations below 10%, HHI fluctuations and commodity price fluctuations have an inverse relationship. The estimated parameter value associated with the interaction variable $\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$ is positive and greater than the absolute value of the preceding parameter ($\beta_{11} + \beta_{132} = 0.2$). This suggests that when the HHI is below 2700 and the HHI variation is above 10%, the HHI variation has a positive effect on price variation. The estimated parameter value associated with the interaction variable $\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}}$ is also positive but lower than the absolute value of the first parameter ($\beta_{11} + \beta_{131} = -0.05$). However, it is not statistically significant at conventional confidence levels ($pvalue = 14\%$). Finally, the parameter linked with the variable $\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$ is significant and the overall effect of HHI variation when the HHI is above 2700 and the HHI variation exceeds 10% is captured by : $\beta_{11} + \beta_{131} + \beta_{132} + \ \beta_{14} = -0.06$. Therefore, in that case, the HHI variation has a negative impact on price variation. Additionally, we observe that the effect of HHI on prices is more pronouced for lower HHI levels, where a 1-point HHI variation results in a price change of either 0.2 points or 0.75 points, depending on the magnitude of the variation.

Table 5 summarizes our main findings. For relatively low concentrations of mining production (HHI below 2700) and modest concentration variations ($< 10\%$), an increase in HHI generally leads to a downward effect on prices. However, when the HHI is low (< 2700) and concentration variation is large ($> 10\%$), the effect is reversed and a rise in HHI tends to increase commodity prices. Finally, when both the HHI level and the HHI variation are high, a negative coefficient is observed, indicating that a decrease in HHI leads to higher prices.[20]

We have shown that the effect of HHI variation on commodity prices depends on the magnitude of the HHI change, irrespective of whether we examine high or low HHI values. If commodity production is diversified, a small change in HHI (less than 10%) will negatively impact prices. This can be illustrated by commodities characterized by low HHI values and high prices, such as precious metals, where a price increase induces even small producers (e.g., gold) to augment production, leading to a reduction in HHI.

[20] These results hold for other HHI threshold values (see Figures 9 to 12).The threshold 2700 was chosen as it is the value that gives the most empirically significant results.

Table 5: Effect of HHI fluctuations on prices based on HHI level and magnitude of variation

HHI level	low	low	high	high
HHI variation	low	high	low	high
parameter	$\beta_{low,low}$	$\beta_{low,high}$	$\beta_{high,low}$	$\beta_{high,high}$
effect on price	-0.75	0.2	-0.05	-0.06

Note: This table summarizes the results of Model 4, with $t_{\text{HHI}} = 2700$ and $t_{\Delta \ln \text{HHI}} = 0.1$.

In cases of larger HHI variations, the inverse effect is observed.

Within the scope of our analysis, the dummy variable $\text{I}_{\Delta \ln \text{HHI}_{i,t}}$ can be considered a proxy for disturbances or shocks to material production. A minor fluctuation in HHI indicates the absence of market disruption, while a substantial fluctuation signifies market disturbance. A significant HHI shift can be traced back to a sudden drop in major producers' production or a decline in output from smaller producers, which magnifies the dominance of the leading producer. Among the six geopolitical risks to the supply of materials listed by IRENA, five have the potential to cause production disruptions that could impact HHI. These risks include resource nationalism, mineral cartels, political instability and social unrest, export restrictions, as well as external shocks (IRENA, 2023).[21] Consequently, our findings indicate that a disruption in markets with lower concentration positively affects prices but has a negative effect in markets with higher concentration. This latter phenomenon can be illustrated by cases such as antimony and REEs, where a significant decline in HHI can be attributed to a reduction in production by the dominant producer, leading to shortages in the market. Under the assumption that a major commodity producer can more easily reduce the HHI in the short term by lowering production than increase it, market participants may view a negative impact as riskier. This is due to the potential increase in prices resulting from the decisions of a few key players. This underscores the rationale for avoiding excessively concentrated commodity markets.

Nonetheless, disruption has a four-fold greater impact in less concentrated markets compared to their more concentrated counterparts in absolute terms. This apparently paradoxical result can be explained by the stabilizing effect on prices provided by cartels' market power. Thus, while a decrease in redundancy can make a network more vulnerable to disruptions, in commodity markets, higher production concentration leads to increased price stability and reduces the material's criticality. A notable example is Indonesia, a major producer of tin, which established a commodity exchange, the Indonesia Commod-

[21] The final risk type is market manipulation, which refers to phenomena like short squeezing, market cornering, spoofing, and insider trading. However, these risks do not affect production and are thus not accounted for in our models.

ity and Derivatives Exchange, in 2013 with the aim of stabilizing the price of tin (Pitron, 2018). Thus, a higher degree of market concentration can lead to greater price stability. A comparable situation can be observed for other raw materials like oil, where OPEC strives to maintain prices at a fair level, a phenomenon highlighted in the literature (Brémond et al., 2012; Pescatori and Nazer, 2022).

5 Conclusion

The Herfindahl–Hirschman Index applied to world production of a given commodity by country is a fundamental component of most raw material criticality assessments. This operates on the premise that analyzing mineral supply concentration is crucial since increased concentration heightens the potential risk of supply disruption.

In the present paper, we rely on a large panel of 33 metals to analyze the influence of HHI on market prices. Interestingly, our results challenge the commonly held assumption since they indicate that the variation of HHI has more impact on prices at lower HHI levels. Furthermore, our findings question the existence of a threshold that clearly distinguishes high-risk markets from less risky ones based on their concentration levels. Hence, using the HHI as a supply risk indicator, especially in conjunction with a threshold, may result in underestimating risks in less concentrated markets. Additionally, our paper highlights the importance of assessing the potential for fluctuations in production concentration, since it directly influences the impact of HHI on prices. This variable, which poses a challenge to measurement, has yet to be included in studies on criticality.

Our paper can be extended in several ways. First, it would be relevant to weight the HHI measured at the country level by the country's level of governance, to account for institutional quality considerations. Second, our study does not consider the recycling of metals, as it assesses concentration at the mining level. Although recycling rates for many metals are still low, recycling has the potential to significantly affect the concentration of metal production (at the refining stage) and provide a measure of sovereignty over these materials for countries without significant mining resources. Therefore, it would be instructive to replicate our study with HHI values calculated at the refining stage, allowing for the inclusion of recycling data when assessing the impact of concentration on commodity prices. Finally, since all world production may not be available for consumption by any country (Thomas et al., 2022), it would be interesting to consider market availability instead of production concentration as a measure of supply diversity. These avenues are left for future research.

Appendix A HHI calculation

A.1 USGS 'Other Country' category

In the USGS reporting, for some raw materials, minor producers are aggregated into the 'Other Country' category, resulting in a combined production denoted as p_{other}. In this case, we assume that each country within the 'Other Country' category produces less than the country with the lowest production (p_{min}) among the available data. To account for this, we introduce n fictitious countries, each hypothetically producing $\frac{p_{min}}{2}$ of the commodity. The value of n is determined as the floor of the ratio $p_{other}/\frac{p_{min}}{2}$. Employing the previously mentioned formula, we calculate what we refer to as the 'HHI Fictitious Country Adjustment'.

Table 6: HHI statistics with and without HHI adjustment

	HHI Adjustment	HHI wo Adjustment	HHI w Adjustment	HHI Adjustment %
mean	11.223	3075.467	3086.690	7.520
std	29.076	2152.209	2146.427	2.119
min	0.000	497.691	517.388	0
25%	0.015	1518.263	1530.770	0.003
50%	1.348	2382.732	2391.428	0.048
75%	7.828	3917.357	3917.382	0.440
max	321.394	9776.956	9776.962	22.022

Note:
- HHI wo Adjustment is the result of the calculation without considering the 'Other Country' category.
- HHI w Adjustment is the sum of HHI wo Adjustment and HHI Adjustment.
- HHI Adjustment % represents the proportion of the HHI contributed by the fictitious country adjustment.

The 'HHI Fictitious Country Adjustment' has a minimal effect on the overall HHI calculation, with an average adjustment value of 11.2 and a standard deviation of 29 observed across all materials and throughout the entire period (Table 6). Despite its seemingly negligible impact, the adjustment retains importance, particularly for certain metals. Specifically, in cases where the 'Other Country' category significantly contributes to the total production, the fictitious country adjustment can have a more notable influence on the HHI calculation. Accurately accounting for these smaller producers through the introduction of fictitious countries becomes essential to preserve the integrity of the HHI analysis and ensure a comprehensive representation of market concentration. Moreover, in the case of comparable data between the USGS and the BGS, the relative difference between the datasets is observed to be lower when considering the inclusion of the 'HHI Fictitious Country Adjustment', as depicted in Table 7.

Table 7: Relative differences with and without adjustment

	Relative Difference wo Adjustment	Relative Difference w Adjustment
mean	10.179	9.657
std	11.739	11.277
min	0.017	0.012
25%	2.609	2.424
50%	6.637	6.022
75%	13.883	13.277
max	143.370	142.242

Note: The *Relative Difference* represents the percentage difference between USGS and BGS data with and without considering the HHI Adjustment. Lower relative differences indicate better alignment and comparability between the datasets when the HHI Adjustment is considered

This suggests that accounting for the fictitious country addition in the HHI calculation leads to a reduced disparity between USGS and BGS data, enhancing the comparability and alignment of their results. In this paper, we will refer to the Herfindahl-Hirschman Index calculation that incorporates the 'HHI Fictitious Country Adjustment' simply as HHI.

A.2 Final data

In total, we obtained HHI data for 63 metals and minerals at various stages of their value chain. Most of these data points represent market concentration at the extraction level, but for certain metals, we also have data on concentration at the refining or smelting stages. By considering both the raw material and the stage of the value chain, we have a total of 69 HHI series. The distribution of these values between our two sources is shown in Table 8.

A.3 Robustness checks

The calculations conducted in Table 7 serve as a preliminary assessment of the robustness of the obtained results by comparing the HHIs obtained from the USGS and BGS sources. Additionally, a third source, the World Mining Data (WMD), an annual publication of the Federal Ministry Republic of Austria, is used. This publication reports the productions of 65 minerals and computes the HHI values between 2013 and 2021, utilizing data from various sources, including the USGS. We analyze the difference between the HHIs obtained solely from USGS and BGS data and those from WMD over this period. On average, the difference is approximately 10%, indicating that the calculations based solely on USGS or BGS data are relatively reliable (Table 9).

Table 8: Data source by material and stage in the supply chain

Stage	USGS	BGS
Mine	REE, antimony, asbestos, barite, bauxite, bentonite, beryllium, boron, chromium, cobalt, copper, diatomite, feldspar, fluorspar gallium gold, graphite, gypsum, iron, lead, lithium, magnesite, magnesium, manganese, mercury, molybdenum, nickel, niobium, palladium, perlite, phosphate-rock, platinum, potash, rhenium, salt, silicon, silver, strontium, sulfur, talc, tantalum, tin, titanium, tungsten, vanadium, vermiculite, yttrium, zinc.	arsenic, bentonite, gallium, germanium kaolin sillimanite, uranium, wollastonite zirconium.
Smelting		aluminum, copper, tin.
Refinery	cadmium, indium, tellurium.	alumina, cobalt, copper, lead, nickel, selenium, tellurium.

Note: Certain metals, namely bentonite, gallium, and tellurium, appear in both the 'USGS' and 'BGS' columns. This occurrence is due to our data collection process, where for some years, we consider BGS data when USGS data are either unavailable or deemed non-exploitable.

Table 9: Relative HHI differences with WMD data

	Relative difference	Relative difference abs
mean	−0.019	0.111
std	0.184	0.148
min	−1.098	0
25%	−0.064	0.024
50%	0.004	0.065
75%	0.067	0.136
max	0.344	1.098

Note: The 'Relative difference' represents the percentage difference between final and WMD data.

Appendix B Price benchmark

Table 10: Relative price differences between USGS and other sources

Metal	Source	*price* diff	$\Delta \ln price$ diff
REE	Dysprosium Metal Dy/ TREM=99% Dom. - SMM	−0.303	0.014
aluminum	Aluminium 99.7% Cash U$/MT - LME	0.084	0.090
antimony	Antimony 99.65% CIF NWE U$/MT- Refinitiv	0.046	0.008
arsenic	Arsenic Metal =99.5% Domestic – SMM	0.168	0.349
bauxite	Bauxite Australia Al:48-50,Si:6-7- SMM	0.740	1.669
bismuth	China Bismuth Ingot 99.99% - SMM	0.093	−0.147
cadmium	Cadmium 99.99% CIF NWE U$/LB – Refinitiv	−0.120	0.610
chromium	Chromium =99.2%, Coarse Particle - SMM	−36.084	−0.068
cobalt	Cobalt Cash - LME	0.076	0.096
copper	Copper Grade A Cash U$/MT - LME	0.031	−0.046
gallium	Gallium Ingots CIF NWE U$/KG - Refinitiv	0.356	−0.315
germanium	Germanium 50ohm CIF NWE U$/KG- Refinitiv	0.053	−0.500
gold	Gold Spot - LME	0.007	0.025
graphite	Graph spherical 99.9 FOB China - Fastmarket MB	−1.039	0.758
indium	Indium CIF NWE U$/KG - Refinitiv	0.182	0.460
lead	Lead Cash U$/MT - LME	0.240	−3.783
lithium	Lithium Metal =99%, Battery Grade - SMM	0.036	0.948
magnesium	Magnesium Ingot Shanghai-Wenxi - SMM	0.495	1.310
manganese	EMM =99.7% Major Prodctn Region – SMM	−422.723	−0.322
mercury	China Mercury Metal 99.999% EXW - Bloomberg	0.998	0.216
molybdenum	Molybdenum Cash Comp U$/MT - LME	0.051	1.125
nickel	Nickel Cash U$/MT - LME	−0.001	0.008
selenium	Selenium CIF NWE U$/LB - Refinitiv	0.107	−0.449
silicon	Silicon Lumps CIF NWE U$/MT- Refinitiv	−0.016	0.435
silver	Silver, Handy&Harman (NY) U$/Troy OZ - Handy&Harman	−0.096	0.066
strontium	China Strontium Metal 99% EXW - Bloomberg	−76.269	0.681
tantalum	China Tantalum Pentoxide 99.5% EXW - Bloomberg	−0.163	−1.019
tellurium	Tellurium =99.99% Domestic - SMM	−0.131	0.149
tin	Tin 99.85% Cash U$/MT - LME	0.038	0.130
tungsten	Tungsten Ferro CIF NWE U$/KG- Refinitiv	−0.108	1.094
yttrium	China Yttrium Metal 99.9% - Bloomberg	0.093	0.030
zinc	SHG Zinc 99.995% Cash U$/MT - LME	0.074	−0.280
zirconium	China Zirconium Carbonate ZrHfO2 40% EXW - Bloomberg	−1.533	−1.889

Note: '*price* diff' and '$\Delta \ln price$ diff' columns denote the average relative difference between the metal price data sourced from the USGS and the metal price data obtained from the source indicated in the 'Source' column. The differences are calculated respectively on the raw level data and after applying logarithmic differentiation.

Appendix C Descriptive statistics

Table 11: Descriptive statistics of panel data

	HHI				$\Delta \ln \text{HHI}$				$\Delta \ln price$			
Metal	mean	std	min	max	mean	std	min	max	mean	std	min	max
REE	7061	2041	3409	9559	0.004	0.129	−0.418	0.349	0.087	0.439	−0.850	1.229
antimony	6479	1428	3547	8359	−0.018	0.092	−0.229	0.139	0.049	0.317	−0.468	0.834
arsenic	3768	1086	1636	5116	0.028	0.167	−0.360	0.620	−0.009	0.291	−0.535	0.562
bauxite	1795	123	1520	1997	−0.001	0.074	−0.210	0.160	−0.016	0.093	−0.213	0.146
beryllium	6073	1576	3906	8716	0.012	0.141	−0.378	0.458	0.027	0.141	−0.266	0.376
chromium	2560	249	2102	2982	0.008	0.107	−0.149	0.252	−0.007	0.248	−0.404	0.721
cobalt	2590	1207	1361	5268	0.046	0.116	−0.185	0.271	−0.029	0.404	−0.810	0.788
copper	1372	173	1105	1663	0.000	0.054	−0.073	0.145	0.035	0.223	−0.324	0.564
germanium	6898	1587	3321	8923	0.012	0.149	−0.388	0.369	−0.018	0.282	−0.513	0.430
gold	712	177	517	1150	−0.029	0.036	−0.088	0.064	0.035	0.127	−0.182	0.275
graphite	4105	1382	1530	6292	0.032	0.194	−0.531	0.436	0.007	0.177	−0.344	0.463
iron	1888	144	1592	2049	0.014	0.042	−0.060	0.072	0.036	0.153	−0.149	0.394
lead	1941	673	894	3195	0.032	0.082	−0.135	0.159	0.043	0.181	−0.320	0.503
lithium	2785	585	1880	4263	0.018	0.127	−0.208	0.275	0.019	0.234	−0.545	0.529
magnesium	5602	2386	1820	8138	0.039	0.105	−0.121	0.327	−0.002	0.180	−0.311	0.446
manganese	1431	245	1132	2091	0.018	0.067	−0.093	0.219	0.007	0.341	−0.421	1.328
mercury	4940	2252	1718	8533	0.053	0.261	−0.399	0.758	0.032	0.321	−0.518	0.829
molybdenum	2418	241	1967	2846	−0.007	0.074	−0.115	0.227	0.005	0.436	−0.888	1.122
nickel	1157	204	909	1839	0.012	0.106	−0.209	0.246	0.027	0.292	−0.605	0.466
niobium	8046	418	7214	9025	0.004	0.050	−0.122	0.103	0.000	0.205	−0.257	0.253
palladium	3426	311	2932	4017	−0.004	0.044	−0.097	0.059	0.084	0.309	−0.598	0.677
platinum	5866	571	4450	6796	−0.005	0.079	−0.191	0.232	0.016	0.147	−0.275	0.334
rhenium	3134	566	2006	4243	−0.008	0.130	−0.350	0.200	−0.027	0.385	−0.479	1.605
silicon	3293	1486	1125	4997	0.057	0.111	−0.143	0.369	0.028	0.189	−0.408	0.452
silver	952	122	751	1152	0.015	0.058	−0.111	0.122	0.037	0.194	−0.283	0.526
strontium	3132	505	2548	4210	0.007	0.103	−0.251	0.160	0.019	0.207	−0.306	0.802
tantalum	3435	1428	1474	6175	−0.030	0.253	−0.601	0.699	0.015	0.554	−1.810	1.834
tin	2227	450	1508	2983	0.005	0.103	−0.228	0.218	0.046	0.236	−0.304	0.636
tungsten	6456	741	4526	7579	0.017	0.075	−0.135	0.213	0.060	0.268	−0.372	0.979
vanadium	3684	474	3203	4950	0.015	0.070	−0.183	0.193	0.031	0.495	−0.915	0.999
yttrium	8947	1188	4921	9777	0.038	0.110	−0.024	0.455	−0.035	0.334	−0.517	1.080
zinc	1292	290	856	1769	0.020	0.062	−0.112	0.125	0.021	0.249	−0.589	0.830
zirconium	2806	289	2120	3361	−0.013	0.071	−0.231	0.138	0.033	0.312	−0.948	1.025

Note: This table presents descriptive statistics for each individual in the panel. The panel consists solely of metals and metalloids from the materials described in Figure 1, except for two: bauxite, a mineral containing alumina and thus representing aluminum (a metal), and graphite, which, although not classified as a metal, is essential to battery technologies (for which market data is available). Additionally, the panel excludes four metals, namely boron, uranium, gallium, and titanium, due to limited data availability.

Appendix D Sources

Table 12: Sources

Variable	Source
Metal and mineral HHI	USGS and BGS
Metal price	USGS
BRENT crude Oil price	FRED - code: POILBREUSDM
Broad US dollar real effective rate	FRED – code: RTWEXBGS
Industries sales	FRED - code: CMRMTSPL
Baltic dry index	Bloomberg
US LIBOR	FRED - code: IR3TIB01USM156N
VIX	Bloomberg
US consumer price index	FRED - code: CPIAUCSL

Appendix E Second-generation stationarity test

Table 13: Panel unit root tests – p values

Variable	With linear trend	With constant	Without constant
$\ln price$	0.17	0.38	0.77
$\Delta \ln price$	1.7×10^{-5}	1.2×10^{-6}	1.8×10^{-8}
ln(HHI)	0.71	0.09	1
Δ ln(HHI)	2.3×10^{-73}	7.19×10^{-83}	1.95×10^{-116}

Note: p-values of the second-generation unit root test for panel data proposed by Demetrescu et al. (2006) applied to price and HHI series. The test is based on the p values from N independent ADF tests. The number of lags has been set according to AIC. The null hypothesis is the unit root. The columns correspond to the deterministic kernel used in the test

Appendix F Empirical results

Figure 7: Parameter estimation of Equation (2) based on dummy variable threshold

t_{HHI}	$\Delta \ln \mathrm{HHI}$	*dummy*	$\Delta \ln oil$	$\Delta \ln er$	$\Delta \ln vix$	ir	$\Delta \ln is$
1500	-0.25	0.22	0.14	-1.69	0.02	0.00	0.90
1600	-0.16	0.12	0.14	-1.70	0.01	0.00	0.88
1700	-0.17	0.13	0.14	-1.71	0.01	0.00	0.91
1800	-0.11	0.07	0.14	-1.70	0.01	0.00	0.91
1900	-0.07	0.03	0.14	-1.70	0.02	-0.00	0.90
2000	-0.09	0.06	0.14	-1.70	0.02	0.00	0.91
2100	-0.11	0.08	0.14	-1.70	0.02	-0.00	0.91
2200	0.04	-0.09	0.14	-1.70	0.02	-0.00	0.87
2300	0.10	-0.18	0.14	-1.70	0.01	-0.00	0.87
2400	0.07	-0.15	0.14	-1.69	0.01	-0.00	0.88
2500	0.04	-0.11	0.14	-1.71	0.01	-0.00	0.88
2600	0.01	-0.07	0.14	-1.70	0.01	-0.00	0.89
2700	0.04	-0.12	0.14	-1.70	0.01	-0.00	0.88
2800	-0.02	-0.05	0.14	-1.69	0.01	0.00	0.88
2900	0.00	-0.08	0.14	-1.69	0.01	-0.00	0.89
3000	0.01	-0.09	0.14	-1.69	0.01	-0.00	0.89
3100	0.01	-0.09	0.14	-1.69	0.01	-0.00	0.89
3200	0.02	-0.11	0.14	-1.68	0.01	-0.00	0.87
3300	0.01	-0.12	0.14	-1.69	0.01	0.00	0.89
3400	0.03	-0.17	0.14	-1.69	0.01	0.00	0.89
3500	0.01	-0.15	0.14	-1.70	0.01	0.00	0.89
3600	0.02	-0.17	0.14	-1.70	0.01	0.00	0.89
3700	0.01	-0.16	0.13	-1.71	0.01	0.00	0.89
3800	-0.09	0.13	0.14	-1.71	0.02	-0.00	0.91
3900	-0.09	0.12	0.14	-1.71	0.02	-0.00	0.90
4000	-0.07	0.09	0.14	-1.71	0.02	-0.00	0.89
4100	-0.08	0.13	0.14	-1.71	0.02	-0.00	0.90
4200	-0.08	0.13	0.14	-1.70	0.02	-0.00	0.90
4300	-0.09	0.15	0.14	-1.70	0.02	-0.00	0.90

Note: The rows indicate the threshold value t_{HHI} applied to the $\mathrm{I}_{\mathrm{HHI}}$ variable, while the columns represent the explanatory variables in our model. Column *dummy* corresponds to $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\mathrm{HHI}}$. Each cell represents the estimated parameter in the random panel regression corresponding to the threshold and variable. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Figure 8: Parameter estimation of Equation (3) based on dummy variable threshold

$t_{\Delta HHI}$	$\Delta \ln \mathrm{HHI}$	$dummy$	$\Delta \ln oil$	$\Delta \ln er$	$\Delta \ln vix$	ir	$\Delta \ln is$
0.05	-0.27	0.24	0.14	-1.70	0.02	-0.00	0.89
0.06	-0.34	0.32	0.14	-1.70	0.02	0.00	0.88
0.07	-0.41	0.40	0.14	-1.70	0.02	0.00	0.89
0.08	-0.38	0.37	0.14	-1.72	0.02	0.00	0.89
0.09	-0.27	0.27	0.14	-1.69	0.02	-0.00	0.88
0.1	-0.38	0.41	0.14	-1.69	0.02	-0.00	0.89
0.11	-0.23	0.24	0.14	-1.69	0.02	-0.00	0.89
0.12	0.00	-0.04	0.14	-1.69	0.01	-0.00	0.89
0.13	-0.10	0.08	0.14	-1.70	0.02	-0.00	0.89
0.14	-0.11	0.09	0.14	-1.70	0.02	-0.00	0.89
0.15	-0.07	0.05	0.14	-1.70	0.02	-0.00	0.89
0.16	-0.10	0.07	0.14	-1.71	0.02	-0.00	0.89
0.17	-0.05	0.00	0.14	-1.70	0.02	-0.00	0.89
0.18	-0.07	0.04	0.14	-1.71	0.02	-0.00	0.89
0.19	-0.07	0.04	0.14	-1.71	0.02	-0.00	0.89
0.2	-0.08	0.04	0.14	-1.72	0.01	-0.00	0.89
0.21	-0.03	-0.03	0.14	-1.72	0.01	-0.00	0.90
0.22	-0.03	-0.03	0.14	-1.71	0.01	-0.00	0.90
0.23	-0.02	-0.05	0.14	-1.71	0.02	-0.00	0.89
0.24	-0.04	-0.02	0.14	-1.70	0.02	-0.00	0.90
0.25	-0.01	-0.08	0.14	-1.70	0.02	-0.00	0.90

Note: The rows display the threshold value $t_{\Delta \ln \mathrm{HHI}}$ used to compute the $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable, while the columns represent the explanatory variables in our model. Column *dummy* corresponds to $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\Delta \ln \mathrm{HHI}}$. Each cell represents the estimated parameter in the random panel regression corresponding to the threshold and variable. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Figure 9: Parameter estimation for variable $\Delta \ln \mathrm{HHI}$ in Equation (4) based on dummy variable thresholds.

t_{HHI} \ $t_{\Delta HHI}$	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15
1500	-1.14	-1.03	-0.64	-0.58	-0.42	-0.37	-0.30	-0.30	-0.34	-0.34	-0.34
1600	-1.17	-0.84	-0.54	-0.47	-0.33	-0.28	-0.21	-0.26	-0.29	-0.29	-0.34
1700	-1.13	-0.82	-0.54	-0.44	-0.36	-0.46	-0.37	-0.43	-0.43	-0.43	-0.47
1800	-1.13	-0.77	-0.30	-0.36	-0.32	-0.40	-0.32	-0.39	-0.38	-0.38	-0.41
1900	-1.11	-0.87	-0.40	-0.45	-0.43	-0.47	-0.37	-0.44	-0.42	-0.42	-0.44
2000	-1.31	-1.00	-0.59	-0.59	-0.55	-0.58	-0.46	-0.45	-0.42	-0.42	-0.45
2100	-1.18	-0.98	-0.59	-0.60	-0.65	-0.67	-0.55	-0.51	-0.49	-0.45	-0.47
2200	-1.05	-0.91	-0.57	-0.60	-0.66	-0.63	-0.53	-0.36	-0.36	-0.28	-0.30
2300	-1.13	-0.98	-0.55	-0.46	-0.59	-0.58	-0.29	-0.18	-0.20	-0.13	-0.15
2400	-1.10	-0.92	-0.54	-0.45	-0.57	-0.56	-0.27	-0.17	-0.19	-0.16	-0.19
2500	-1.02	-0.87	-0.53	-0.69	-0.70	-0.68	-0.38	-0.26	-0.27	-0.21	-0.23
2600	-0.98	-0.89	-0.62	-0.76	-0.79	-0.76	-0.46	-0.23	-0.26	-0.21	-0.22
2700	-0.98	-0.88	-0.65	-0.78	-0.78	-0.75	-0.44	-0.19	-0.24	-0.20	-0.21
2800	-0.89	-0.82	-0.63	-0.76	-0.68	-0.71	-0.43	-0.21	-0.25	-0.24	-0.24
2900	-0.67	-0.67	-0.50	-0.65	-0.60	-0.73	-0.47	-0.15	-0.19	-0.19	-0.20
3000	-0.59	-0.47	-0.37	-0.52	-0.50	-0.64	-0.40	-0.11	-0.15	-0.16	-0.17
3100	-0.45	-0.38	-0.34	-0.54	-0.52	-0.65	-0.41	-0.12	-0.17	-0.17	-0.18
3200	-0.51	-0.42	-0.35	-0.53	-0.51	-0.64	-0.39	-0.11	-0.16	-0.17	-0.18
3300	-0.26	-0.27	-0.28	-0.47	-0.47	-0.61	-0.36	-0.09	-0.13	-0.15	-0.16
3400	-0.18	-0.23	-0.24	-0.41	-0.43	-0.62	-0.37	0.04	-0.01	-0.03	-0.05
3500	-0.21	-0.27	-0.28	-0.43	-0.44	-0.64	-0.39	0.02	-0.03	-0.06	-0.08
3600	-0.42	-0.40	-0.27	-0.38	-0.41	-0.60	-0.36	0.03	-0.02	-0.04	-0.06
3700	-0.44	-0.42	-0.28	-0.39	-0.41	-0.64	-0.40	-0.00	-0.05	-0.07	-0.07
3800	-0.48	-0.43	-0.28	-0.39	-0.41	-0.63	-0.43	-0.04	-0.08	-0.10	-0.09
3900	-0.52	-0.46	-0.30	-0.40	-0.42	-0.55	-0.36	0.02	-0.03	-0.06	-0.05
4000	-0.43	-0.40	-0.26	-0.40	-0.41	-0.54	-0.36	0.01	-0.04	-0.07	-0.06
4100	-0.39	-0.29	-0.19	-0.34	-0.36	-0.50	-0.31	0.05	-0.01	-0.04	-0.04
4200	-0.38	-0.28	-0.21	-0.35	-0.38	-0.51	-0.32	0.04	-0.01	-0.05	-0.04
4300	-0.42	-0.36	-0.25	-0.38	-0.40	-0.53	-0.34	0.02	-0.03	-0.06	-0.06

Note: The rows display the threshold values applied to the $\mathrm{I}_{\mathrm{HHI}}$ variable, while the columns represent the threshold values applied to the $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable. Each cell signifies the estimated parameter of $\Delta \ln \mathrm{HHI}$ variable in the random panel regression for the corresponding thresholds. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Figure 10: Parameter estimation for variable $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\mathrm{HHI}}$ in Equation (4) based on dummy variable thresholds.

t_{HHI} \ $t_{\Delta HHI}$	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15
1500	1.18	0.88	0.30	0.27	0.19	-0.02	0.09	0.37	0.29	0.27	0.31
1600	1.23	0.64	0.16	0.12	0.07	-0.13	-0.04	0.31	0.22	0.20	0.30
1700	1.24	0.65	0.17	0.11	0.15	0.12	0.19	0.58	0.44	0.41	0.49
1800	1.26	0.60	-0.16	-0.02	0.07	0.02	0.12	0.52	0.38	0.35	0.43
1900	1.29	0.77	-0.01	0.10	0.24	0.13	0.19	0.62	0.45	0.42	0.49
2000	1.65	1.00	0.27	0.32	0.41	0.28	0.33	0.65	0.48	0.44	0.51
2100	1.49	1.00	0.29	0.35	0.57	0.42	0.46	0.77	0.58	0.50	0.57
2200	1.35	0.95	0.28	0.35	0.62	0.40	0.46	0.59	0.42	0.27	0.35
2300	1.52	1.06	0.24	0.13	0.54	0.33	0.11	0.32	0.18	0.05	0.14
2400	1.52	0.98	0.23	0.11	0.51	0.30	0.07	0.31	0.16	0.11	0.20
2500	1.39	0.89	0.20	0.53	0.77	0.53	0.28	0.50	0.32	0.22	0.30
2600	1.35	0.94	0.36	0.66	0.95	0.67	0.42	0.45	0.32	0.22	0.29
2700	1.41	1.00	0.46	0.76	1.02	0.70	0.43	0.42	0.32	0.23	0.30
2800	1.25	0.93	0.43	0.73	0.84	0.65	0.41	0.46	0.33	0.29	0.37
2900	0.84	0.67	0.21	0.56	0.73	0.77	0.53	0.37	0.24	0.22	0.30
3000	0.71	0.29	-0.09	0.31	0.56	0.61	0.40	0.28	0.15	0.13	0.22
3100	0.42	0.11	-0.16	0.38	0.63	0.65	0.44	0.33	0.18	0.17	0.25
3200	0.62	0.23	-0.12	0.40	0.64	0.67	0.42	0.33	0.18	0.18	0.27
3300	-0.06	-0.20	-0.34	0.21	0.51	0.55	0.32	0.25	0.09	0.11	0.21
3400	-0.46	-0.47	-0.56	-0.05	0.32	0.52	0.29	-0.18	-0.30	-0.25	-0.11
3500	-0.27	-0.28	-0.41	0.08	0.42	0.65	0.41	-0.07	-0.21	-0.17	-0.02
3600	0.33	0.05	-0.49	-0.07	0.30	0.55	0.33	-0.14	-0.27	-0.23	-0.07
3700	0.42	0.10	-0.46	-0.04	0.33	0.67	0.44	-0.04	-0.19	-0.16	-0.05
3800	0.65	0.22	-0.45	-0.01	0.38	0.73	0.59	0.10	-0.08	-0.05	0.04
3900	0.83	0.31	-0.40	0.04	0.42	0.51	0.41	-0.05	-0.21	-0.15	-0.07
4000	0.60	0.23	-0.45	0.11	0.50	0.58	0.47	0.02	-0.16	-0.10	-0.02
4100	0.48	-0.10	-0.71	-0.08	0.35	0.46	0.33	-0.10	-0.27	-0.20	-0.09
4200	0.42	-0.14	-0.68	-0.06	0.38	0.47	0.34	-0.09	-0.27	-0.19	-0.09
4300	0.57	0.06	-0.55	0.02	0.46	0.53	0.40	-0.05	-0.23	-0.16	-0.06

Note: The rows display the threshold values applied to the $\mathrm{I}_{\mathrm{HHI}}$ variable, while the columns represent the threshold values applied to the $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable. Each cell signifies the estimated parameter of $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\mathrm{HHI}}$ variable in the random panel regression for the corresponding thresholds. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Figure 11: Parameter estimation for variable $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\Delta \ln \mathrm{HHI}}$ in Equation (4) based on dummy variable thresholds.

t_{HHI} \ $t_{\Delta HHI}$	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15
1500	1.00	0.91	0.49	0.44	0.26	0.19	0.09	0.09	0.18	0.18	0.18
1600	1.06	0.73	0.43	0.36	0.20	0.15	0.05	0.14	0.20	0.20	0.30
1700	1.02	0.71	0.42	0.32	0.23	0.37	0.25	0.35	0.35	0.35	0.40
1800	1.07	0.73	0.22	0.29	0.26	0.36	0.27	0.37	0.34	0.34	0.40
1900	1.10	0.88	0.39	0.45	0.46	0.53	0.41	0.53	0.52	0.53	0.58
2000	1.29	1.01	0.57	0.59	0.57	0.63	0.50	0.53	0.50	0.50	0.54
2100	1.14	0.97	0.56	0.59	0.68	0.72	0.59	0.59	0.56	0.52	0.56
2200	1.15	1.03	0.69	0.74	0.84	0.83	0.73	0.56	0.58	0.47	0.51
2300	1.29	1.16	0.72	0.63	0.82	0.83	0.50	0.39	0.42	0.33	0.36
2400	1.22	1.06	0.67	0.58	0.75	0.76	0.43	0.33	0.35	0.34	0.37
2500	1.11	0.97	0.62	0.82	0.87	0.87	0.54	0.42	0.43	0.38	0.40
2600	1.03	0.95	0.68	0.85	0.93	0.92	0.59	0.33	0.38	0.33	0.35
2700	1.06	0.98	0.75	0.92	0.96	0.95	0.61	0.32	0.39	0.36	0.38
2800	0.91	0.86	0.67	0.83	0.78	0.85	0.54	0.28	0.33	0.34	0.36
2900	0.70	0.72	0.56	0.73	0.71	0.90	0.61	0.24	0.29	0.31	0.33
3000	0.63	0.52	0.42	0.59	0.61	0.80	0.53	0.18	0.24	0.26	0.28
3100	0.48	0.43	0.39	0.62	0.63	0.81	0.54	0.20	0.26	0.28	0.30
3200	0.55	0.47	0.40	0.61	0.61	0.79	0.51	0.20	0.25	0.28	0.30
3300	0.29	0.31	0.33	0.54	0.57	0.75	0.47	0.16	0.22	0.25	0.26
3400	0.22	0.27	0.30	0.48	0.53	0.78	0.50	-0.00	0.06	0.10	0.12
3500	0.23	0.30	0.32	0.49	0.52	0.77	0.50	0.01	0.07	0.10	0.13
3600	0.46	0.45	0.31	0.44	0.49	0.73	0.48	-0.00	0.06	0.09	0.12
3700	0.47	0.46	0.32	0.45	0.49	0.77	0.52	0.04	0.09	0.12	0.13
3800	0.40	0.36	0.20	0.32	0.36	0.63	0.41	-0.07	-0.02	0.01	0.00
3900	0.45	0.40	0.23	0.35	0.37	0.55	0.34	-0.12	-0.07	-0.03	-0.04
4000	0.38	0.36	0.21	0.37	0.39	0.56	0.36	-0.09	-0.04	0.01	-0.02
4100	0.32	0.22	0.11	0.28	0.32	0.50	0.29	-0.14	-0.09	-0.04	-0.05
4200	0.31	0.22	0.14	0.30	0.33	0.51	0.30	-0.14	-0.08	-0.03	-0.05
4300	0.35	0.29	0.18	0.33	0.35	0.52	0.31	-0.12	-0.07	-0.03	-0.04

Note: The rows display the threshold values applied to the $\mathrm{I}_{\mathrm{HHI}}$ variable, while the columns represent the threshold values applied to the $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable. Each cell signifies the estimated parameter of $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable in the random panel regression for the corresponding thresholds. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Figure 12: Parameter estimation for variable $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\mathrm{HHI}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}}$ in Equation (4) based on dummy variable thresholds.

t_{HHI} \ $t_{\Delta HHI}$	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15
1500	-1.07	-0.78	-0.15	-0.13	-0.02	0.23	0.14	-0.19	-0.15	-0.12	-0.16
1600	-1.16	-0.56	-0.07	-0.02	0.05	0.29	0.21	-0.24	-0.16	-0.13	-0.30
1700	-1.17	-0.56	-0.07	0.00	-0.03	-0.00	-0.06	-0.55	-0.40	-0.37	-0.48
1800	-1.24	-0.57	0.23	0.09	-0.01	0.04	-0.06	-0.57	-0.39	-0.36	-0.47
1900	-1.33	-0.81	0.01	-0.12	-0.27	-0.16	-0.23	-0.79	-0.61	-0.57	-0.69
2000	-1.68	-1.03	-0.27	-0.33	-0.44	-0.32	-0.36	-0.81	-0.61	-0.57	-0.67
2100	-1.48	-1.01	-0.27	-0.33	-0.61	-0.46	-0.50	-0.92	-0.71	-0.62	-0.72
2200	-1.50	-1.11	-0.42	-0.51	-0.84	-0.59	-0.67	-0.87	-0.71	-0.52	-0.63
2300	-1.77	-1.31	-0.46	-0.35	-0.84	-0.61	-0.36	-0.66	-0.51	-0.34	-0.46
2400	-1.73	-1.19	-0.41	-0.27	-0.75	-0.51	-0.26	-0.58	-0.43	-0.39	-0.50
2500	-1.54	-1.04	-0.32	-0.70	-1.00	-0.74	-0.47	-0.77	-0.59	-0.48	-0.59
2600	-1.46	-1.05	-0.45	-0.81	-1.16	-0.86	-0.59	-0.65	-0.53	-0.42	-0.52
2700	-1.58	-1.17	-0.63	-0.97	-1.29	-0.96	-0.66	-0.69	-0.59	-0.51	-0.61
2800	-1.33	-1.02	-0.52	-0.86	-1.01	-0.83	-0.57	-0.65	-0.52	-0.50	-0.61
2900	-0.94	-0.79	-0.32	-0.71	-0.92	-0.99	-0.73	-0.58	-0.45	-0.45	-0.56
3000	-0.82	-0.40	-0.01	-0.45	-0.74	-0.81	-0.59	-0.48	-0.35	-0.35	-0.47
3100	-0.53	-0.21	0.05	-0.54	-0.82	-0.87	-0.64	-0.55	-0.41	-0.41	-0.53
3200	-0.75	-0.36	-0.01	-0.57	-0.85	-0.90	-0.64	-0.58	-0.42	-0.44	-0.57
3300	-0.06	0.08	0.23	-0.37	-0.70	-0.77	-0.52	-0.48	-0.33	-0.36	-0.50
3400	0.30	0.32	0.40	-0.15	-0.55	-0.80	-0.56	-0.01	0.11	0.05	-0.13
3500	0.13	0.14	0.28	-0.26	-0.63	-0.91	-0.66	-0.11	0.02	-0.03	-0.23
3600	-0.51	-0.23	0.34	-0.12	-0.52	-0.81	-0.58	-0.05	0.08	0.03	-0.18
3700	-0.60	-0.27	0.32	-0.14	-0.53	-0.95	-0.71	-0.17	-0.03	-0.07	-0.20
3800	-0.52	-0.08	0.64	0.15	-0.24	-0.64	-0.49	0.07	0.26	0.23	0.13
3900	-0.71	-0.18	0.57	0.10	-0.29	-0.42	-0.30	0.23	0.40	0.33	0.25
4000	-0.51	-0.12	0.60	-0.01	-0.40	-0.52	-0.40	0.11	0.31	0.23	0.16
4100	-0.34	0.27	0.92	0.25	-0.20	-0.34	-0.19	0.29	0.49	0.40	0.30
4200	-0.27	0.31	0.90	0.22	-0.22	-0.35	-0.21	0.29	0.48	0.40	0.30
4300	-0.40	0.14	0.80	0.17	-0.26	-0.36	-0.21	0.28	0.49	0.42	0.32

Note: The rows display the threshold values applied to the $\mathrm{I}_{\mathrm{HHI}}$ variable, while the columns represent the threshold values applied to the $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable. Each cell signifies the estimated parameter of $\Delta \ln \mathrm{HHI} * \mathrm{I}_{\mathrm{HHI}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}}$ variable in the random panel regression for the corresponding thresholds. The color of the cell indicates the level of significance: blue indicates 10% significance, green indicates 5% significance, and yellow indicates 1% significance.

Appendix G Robustness tests

Table 14: Estimations - Robustness tests

	difference GMM		individual fixed effects	
	Model 1 lag	Model 4 lag	Model wo CV	Model WTI
$\Delta \ln price_{i,t-1}$	0.01	0.02		
	(0.06)	(0.06)		
$\Delta \ln \mathrm{HHI}_{i,t}$	-0.02	-1.04^{***}	-0.54	-0.76^{**}
	(0.08)	(0.39)	(0.35)	(0.31)
$\Delta \ln \mathrm{HHI}_{i,t-1}$	0.10	0.10		
	(0.08)	(0.08)		
$\Delta \ln oil_t$	0.17^{**}	0.17^{**}		0.11
	(0.07)	(0.07)		(0.07)
$\Delta \ln er_t$	-1.43^{***}	-1.54^{***}		-1.87^{***}
	(0.37)	(0.36)		(0.37)
$\Delta \ln is$	1.05^{***}	1.03^{***}		0.92^{***}
	(0.35)	(0.33)		(0.31)
$\Delta \ln vix_t$	0.03	0.04		0.01
	(0.04)	(0.04)		(0.04)
ir_t	-0.00	-0.00		0.00
	(0.01)	(0.01)		(0.00)
$\mathrm{I}_{\mathrm{HHI}_{i,t}}$		-0.08	-0.00	0.00
		(0.07)	(0.04)	(0.04)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}}$		1.14^{**}	0.65	0.71
		(0.46)	(0.52)	(0.48)
$\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$		-0.00	-0.03	-0.01
		(0.06)	(0.04)	(0.04)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$		1.30^{***}	0.85^{**}	0.95^{***}
		(0.42)	(0.38)	(0.34)
$\mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$		-0.02	-0.01	-0.02
		(0.07)	(0.05)	(0.05)
$\Delta \ln \mathrm{HHI}_{i,t} * \mathrm{I}_{\mathrm{HHI}_{i,t}} * \mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}$		-1.39^{***}	-1.06^{*}	-0.97^{*}
		(0.50)	(0.56)	(0.52)
Num. obs.	898	898	821	821
Num. obs. used	753	753		

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: The dependent variable is the log differentiated prices of metals $\Delta \ln price$. The variables $\Delta \ln oil$, $\Delta \ln er$, $\Delta \ln vix$, and $\Delta \ln is$ denotes the variation rate of oil price, exchange rate, VIX index, and Industries sales, respectively. ir denotes the US interest rate. $\Delta \ln \mathrm{HHI}$ denotes the variation rate of the country metal production concentration, and $\mathrm{I}_{\mathrm{HHI}}$ and $\mathrm{I}_{\Delta \ln \mathrm{HHI}}$ are the dummy variables computed for the threshold values of $t_{\mathrm{HHI}} = 2700$ and $t_{\Delta \ln \mathrm{HHI}} = 0.1$. Model 1 lag and Model 4 lag correspond to the dynamic form of Model 1 and Model 4, respectively. Model wo CV corresponds to Model 4 without the control variables, and Model WTI uses the WTI price benchmark for oil instead of Brent in Model 4. To provide consistent results, we apply the Newey and West robust covariance estimators for the fixed effect specification, the corresponding standard errors are in parentheses.

Table 15: Effect of HHI fluctuations on prices based on HHI level and magnitude of variation - Robustness tests

	$\beta_{low,low}$	$\beta_{low,high}$	$\beta_{high,low}$	$\beta_{high,high}$
Model 4 lag	-1.11	0.31	0.08	-0.05
Model wo CV	-0.54	0.32	0.11	-0.10
Model WTI	-0.76	0.20	-0.04	-0.05

Note: This table corresponds to Table 5 for the models presented in Table 14.

Appendix H Panel Smooth Transition Regression (PSTR)

We first considered the possibility of using PSTR models to investigate the likely non-linear relationship between metal prices and HHI variations. However, our research shows statistical significance only with the inclusion of two threshold variables—the HHI level and the magnitude of HHI variations—which is not consistent with a PSTR specification, as further illustrated.

Within the PSTR framework (Gonzalez, A. et al., 2017), the additive model can account for two different transition variables. The model specification is presented as follows:

$$y_{it} = \theta_0\, x_{it} + \theta_1\, x'_{it}\, G_1(s_{1,it}; \gamma_1, c_1) + \theta_2\, x'_{it}\, G_2(s_{2,it}; \gamma_2, c_2)$$

where :

- y_{it} is the dependent variable
- x_{it} is the vector of explanatory variables
- x'_{it} is the vector of explanatory variables in the non-linear part
- $s_{k,it}$ is an observable transition variable
- $G_k(s_{k,it}; \gamma_k, c_k)$ is a transition function bounded between zero and one, where γ_k is the slope parameter indicating the speed of transition between the extreme values, whereas the threshold parameter c_k points to where the transition takes place.

If we apply this specification to our data, $s_{1,it}$ corresponds to HHI_{it} and $s_{2,it}$ to $|\Delta \ln \mathrm{HHI}_{i,t}|$. Then, our dummy variables correspond to the extreme values of the transition functions $G_1(s_{1,it}; \gamma_1, c_1)$ and $G_2(s_{2,it}; \gamma_2, c_2)$.

Table 16: Parameter correspondence with the PSTR additive model

$\mathrm{I}_{\mathrm{HHI}_{i,t}}/G_1$	$\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}\ /G_2$	Regime parameter	Article parameters	PSTR parameters
0	0	$\beta_{1,low,low}$	β_{11}	θ_0
0	1	$\beta_{1,low,high}$	$\beta_{11} + \beta_{132}$	θ_1
1	0	$\beta_{1,high,low}$	$\beta_{11} + \beta_{131}$	θ_2
1	1	$\beta_{1,high,high}$	$\beta_{11} + \beta_{131} + \beta_{132} + \beta_{14}$	$\theta_1 + \theta_2$

Hence, through correspondence, employing the additive model necessitates that the model satisfies the condition:

$$\beta_{11} + \beta_{132} + \beta_{11} + \beta_{131} = \beta_{11} + \beta_{131} + \beta_{132} + \beta_{14}$$

$$\beta_{11} = \beta_{14}$$

Conversely, the model with interaction variables developed in the paper gives:

$$\beta_{11} \neq \beta_{14}$$

Using the additive model does not offer sufficient degrees of freedom, making it unsuitable for our analysis.

This problem of multiple regimes has been addressed in a time series context in van Dijk and Franses (1999). The authors develop a Multiple Regime Smooth Transition AutoRegressive (MRSTAR) model that allows the definition of a four-regime model.[22]

$$\begin{aligned} y_t = &[\phi_1 x_t(1 - G_1(s_{1,t};\gamma_1, c_1)) + \phi_2 x_t G_1(s_{1,t};\gamma_1, c_1)][1 - G_2(s_{2,t};\gamma_2, c_2)] \\ &+ [\phi_3 x_t(1 - G_1(s_{1,t};\gamma_1, c_1)) + \phi_4 x_t G_1(s_{1,t};\gamma_1, c_1)]G_2(s_{2,t};\gamma_2, c_2) \end{aligned}$$

Table 17: Parameter correspondence with the MRSTAR additive model

$\mathrm{I}_{\mathrm{HHI}_{i,t}}/G_1$	$\mathrm{I}_{\Delta \ln \mathrm{HHI}_{i,t}}/G_2$	Regime parameter	Article parameters	MRSTAR parameters
0	0	$\beta_{1,low,low}$	β_{11}	ϕ_1
0	1	$\beta_{1,low,high}$	$\beta_{11} + \beta_{132}$	$\phi_2 - \phi_1$
1	0	$\beta_{1,high,low}$	$\beta_{11} + \beta_{131}$	$\phi_3 - \phi_1$
1	1	$\beta_{1,high,high}$	$\beta_{11} + \beta_{131} + \beta_{132} + \beta_{14}$	$\phi_4 - \phi_1$

The MRSTAR model could be adapted to our problem, though it has not yet been extended to panel data.

[22] Obtained by 'encapsulating' two different two-regime LSTAR models

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