No 2026-06 – July 2026

Working Paper

What Drives Mineral Commodity Prices? A Historical Perspective on Demand and Supply Dynamics

Romain Capliez, Carl Grekou, Emmanuel Hache & Valérie Mignon

Highlights

- A century of mineral commodity prices is analyzed using an incompletely identified SVAR.
- Metal-specific demand shocks explain most mineral price fluctuations.
- Supply responses remain weak, heterogeneous, and often short-lived.
- Historical price dynamics provide limited evidence of increasing scarcity.

Abstract

This paper investigates the historical determinants of real mineral commodity prices using a structurally identified vector autoregression (SVAR) with incomplete identification. Drawing on a large sample of mineral commodities covering more than a century of data, we identify supply, aggregate demand, and metal-specific demand shocks using economically motivated prior distributions. Historical decompositions show that price fluctuations are predominantly driven by demand-side forces, with metal-specific demand shocks accounting for the largest share of variation. Aggregate demand shocks also play an important role, particularly during periods of global instability, while the contribution of supply shocks is more limited and tends to decline over time. Elasticity estimates indicate that prices respond more strongly and more persistently to demand shocks than to supply shocks, whereas supply responses remain weak in the short run. We also document substantial heterogeneity across mineral commodities and over time, reflecting differences in adjustment mechanisms across markets. Overall, our findings highlight the central role of demand in mineral commodity price formation and provide little support for the view that increasing scarcity has been the dominant force shaping observed price dynamics over the period considered. Instead, fluctuations in mineral commodity prices appear to be primarily driven by demand-side factors rather than by tightening supply conditions.

Keywords

Mineral Commodities, Commodity Price Dynamics, Resource Scarcity, Structural VAR, Historical Decomposition.

JEL

Q31, Q32, C32.

Working Paper

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ISSN 2970-491X

July 2026

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What Drives Mineral Commodity Prices? A Historical Perspective on Demand and Supply Dynamics[1]

Romain Capliez*, Carl Grekou†, Emmanuel Hache‡, Valérie Mignon§

1. Introduction

Mineral commodities occupy a central position in modern economies. They are essential inputs for infrastructure, transportation, manufacturing, digital technologies, and energy systems. Their strategic importance has increased considerably in recent years as governments around the world pursue ambitious decarbonization objectives. The transition toward low-carbon energy systems is expected to generate a substantial increase in the demand for a wide range of minerals, including both so-called energy transition minerals (cobalt, lithium, rare earths, etc.) and more traditional industrial metals. Copper, nickel, zinc, tin, and many other mineral commodities are expected to play a crucial role in the deployment of renewable energy technologies, electricity networks, storage, and electrified transport systems.

A growing body of research has highlighted the unprecedented scale of future mineral demand associated with the energy transition (e.g., Vidal et al., 2013; Hund et al., 2020; Watari et al., 2019; IEA, 2021; Ku et al., 2024; Carr-Wilson et al., 2024; Shi et al., 2025). These studies emphasize not only the rapid increase in mineral requirements, but also the possibility that supply constraints, geographical concentration, and adjustment frictions may generate significant pressures on mineral markets in the coming decades. Achieving climate objectives, together with continued economic development, urbanization, and infrastructure expansion, is expected to require substantial increases in the production of numerous mineral commodities, raising questions about the ability of supply systems to adjust to rapidly expanding demand given the lag between mining investment and initial production. At the same time, many mineral markets remain characterized by a high geographical concentration of production and processing activities, long project development times, and significant environmental and regulatory constraints. As a result, mineral security and potential supply bottlenecks have become central policy concerns in many countries.

These developments have renewed interest in mineral commodity prices. In both policy discussions and academic debates, prices are often viewed as key indicators of tensions in commodity markets and of the availability of natural resources. Understanding the

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drivers of mineral price fluctuations is therefore essential for assessing whether observed price movements reflect increasing scarcity pressures or other economic forces.

The relationship between commodity prices and resource scarcity has long been a central question in the economics of non-renewable resources. The seminal contribution of Hotelling (1931) laid the foundations of the modern literature on exhaustible resources by showing that the depletion of such resources should generate increasing scarcity rents and ultimately rising real commodity prices. However, the extent to which observed commodity prices reflect increasing scarcity rather than other economic forces remains subject to debate. A large literature has shown that technological progress, resource discoveries, improvements in extraction techniques, substitution possibilities, recycling, and changes in demand may prevent physical resource depletion from translating into increasing scarcity rents and rising commodity prices (see, e.g., Krautkraemer, 2005; Svedberg and Tilton, 2006; and the references in Section 2). Consequently, observed price dynamics cannot be interpreted as evidence of resource scarcity without first identifying the underlying forces driving them.

A growing literature has therefore sought to understand the determinants of commodity prices. One strand focuses on estimating supply and demand elasticities in order to measure the responsiveness of producers and consumers to price changes (see Section 2). Another strand relies on structural econometric models to identify the shocks driving commodity price fluctuations. In particular, the Structural Vector Autoregression (SVAR) literature has emphasized the importance of distinguishing supply and demand shocks when analyzing commodity markets (e.g., Kilian, 2009; Baumeister and Hamilton, 2015; Baumeister and Hamilton, 2019). While this literature has generated important insights, most existing studies focus either on individual commodities, on relatively short time periods, or on energy markets. As a result, evidence remains limited regarding the long-run determinants of mineral commodity prices and the extent to which these determinants have evolved over time.

This paper addresses these questions by studying the historical determinants of real mineral commodity prices. More specifically, we seek to identify the relative importance of supply shocks, aggregate demand shocks, and metal-specific demand shocks in explaining mineral price fluctuations, and to examine whether the responses of prices and production to these shocks have changed over time. By doing so, we provide new evidence on the mechanisms underlying mineral price formation and on the extent to which observed price dynamics can be interpreted as reflecting increasing scarcity pressures.

Our paper contributes to the literature in several ways. First, we provide a long-run historical analysis of mineral commodity prices covering more than a century of data. Unlike most existing studies, which typically focus on a single commodity or on a small group of widely traded metals such as copper and other London Metal Exchange (LME) metals, our analysis covers a broad set of up to 65 mineral commodities. This wider coverage allows us to assess the extent to which common patterns emerge across mineral markets while accounting for substantial heterogeneity across commodities. The long time horizon further enables us to examine whether the determinants of mineral prices have changed over time and whether observed price dynamics are consistent with increasing scarcity pressures.

Second, we employ a structurally identified VAR framework with incomplete identification following Baumeister and Hamilton (2015), Baumeister and Hamilton (2018), and Baumeister and Hamilton (2019). Using economically motivated prior distributions, we identify supply shocks, aggregate demand shocks, and metal-specific demand shocks. This framework allows us to quantify their relative contributions to mineral price fluctuations and to distinguish common macroeconomic influences from commodity-specific demand forces.

Third, we complement the historical decomposition with an analysis of elasticities and adjustment mechanisms. Beyond identifying the sources of price fluctuations, we examine how prices and production respond to shocks and how these responses evolve over time.

More broadly, our analysis contributes to the long-standing debate on resource scarcity. By disentangling the respective roles of supply and demand forces, our framework provides a direct way to assess whether observed mineral price dynamics primarily reflect tightening supply conditions or fluctuations in demand.

Our results point to a clear and robust pattern. Historical decompositions indicate that demand-side forces dominate mineral commodity price fluctuations over the long run. Metal-specific demand shocks account for the largest share of price variation across periods and production groups, while aggregate demand shocks also play an important role, particularly during episodes of global economic disruption. By contrast, supply shocks contribute less to price fluctuations, and their importance tends to decline over time. The elasticity analysis reinforces this interpretation. Prices respond more strongly and more persistently to demand shocks than to supply shocks, while production responses to price signals remain limited in the short run. In addition, rolling estimates suggest that supply responsiveness has weakened over time, whereas price responses to shocks have become larger.

Taken together, these findings suggest that mineral commodity prices primarily reflect fluctuations in demand rather than persistent increases in scarcity pressures. While substantial heterogeneity exists across metals, the dominant role of demand emerges as a robust feature of mineral commodity markets over the long run. Contrary to the view that rising mineral demand should mechanically translate into increasing scarcity rents and sustained price increases, our results indicate that long-run mineral price dynamics are shaped primarily by demand fluctuations and heterogeneous adjustment mechanisms across markets.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the data and methodology. Section 4 reports the empirical results, while Section 5 provides various robustness checks. Section 6 concludes.

2. Literature review

As the world economy continues to develop, the demand for mineral resources is expected to increase substantially. This trend is not new, but it is now reinforced by the energy transition, which requires large quantities of both critical and traditional minerals. While particular attention has been devoted to minerals such as lithium, cobalt, and rare earths, the transition also relies heavily on more traditional industrial metals and metal alloys such as copper, nickel, zinc, and steel. Recent projections suggest that demand for many mineral commodities will increase sharply over the coming decades (IEA, 2025), raising concerns about the ability of supply to keep pace with this growth.

However, as emphasized by Vidal et al. (2022), the question of resource availability is largely a question of the economic and environmental costs that societies are willing to bear. From a geological perspective, the Earth may contain sufficient quantities of many mineral resources to support the energy transition. For example, Vidal et al. (2022) estimate ultimate recoverable copper resources at between 5 and 7.5 billion tonnes, well above projected transition needs. Nevertheless, as extraction progresses, producers must increasingly exploit lower-grade deposits and more difficult resources, raising extraction costs and potentially commodity prices. Consequently, the key issue is not necessarily physical exhaustion, but rather the economic conditions under which resources can be extracted.

This question has long occupied the economics of non-renewable resources. In this literature, commodity prices are often viewed as indicators of scarcity (Krautkraemer, 2005; Svedberg and Tilton, 2006). As previously mentioned, this intuition is formalized in the seminal contribution of Hotelling (1931), who showed that, under a set of restrictive assumptions, the scarcity rent associated with an exhaustible resource should increase at the market rate of interest.

Subsequent research has shown, however, that the Hotelling framework relies on assumptions that are unlikely to hold in practice. As discussed by Svedberg and Tilton (2006) and reviewed by Gaugler (2015), technological progress, reserve discoveries, market power, extraction costs, and demand fluctuations all influence commodity prices. Once these factors are taken into account, the relationship between depletion and prices becomes considerably less clear. In this perspective, the Hotelling rule should be viewed as one among several mechanisms affecting commodity prices rather than as a complete theory of price formation (Livernois, 2009).

Several theoretical contributions explicitly incorporate these additional mechanisms. For example, Pindyck (1978) allows for endogenous reserve discoveries and shows that commodity prices may follow a U-shaped path over time. During periods characterized by abundant discoveries and technological improvements, prices may decline despite ongoing extraction. Only when discoveries slow and extraction becomes increasingly costly do prices begin to rise. Similarly, Vidal et al. (2022) argue that declining ore grades imply growing energy requirements for extraction. Although technological progress has historically compensated for these effects, physical and thermodynamic constraints imply that such gains cannot continue indefinitely.

Despite these theoretical arguments, empirical evidence provides little support for a systematic increase in real mineral prices over the long run. Numerous studies have failed to identify a persistent upward trend in mineral commodity prices (Nordhaus, 1974; Slade, 1982; Krautkraemer, 1998; Howie, 2002; Svedberg and Tilton, 2006). Explanations range from the possibility that technological progress and reserve expansion have continued to dominate scarcity forces to measurement issues related to price deflators (Svedberg and Tilton, 2006). Consequently, the extent to which observed commodity prices genuinely reflect increasing scarcity remains an open question.

Understanding the determinants of commodity prices is therefore essential for assessing both the consequences of the energy transition and the potential emergence of supply constraints. Two strands of literature are particularly relevant.

A first strand focuses on estimating supply and demand elasticities. These studies aim to measure the responsiveness of production and consumption to price changes and thereby provide information on the adjustment mechanisms operating in commodity markets. With the exception of Shojaeddini et al. (2025), who consider the full set of minerals available in the USGS database, most studies focus on a limited group of metals. Methodologically, they typically rely on reduced-form approaches. Examples include OLS estimations (Hojman, 1981; Blomberg and Hellmer, 2000), panel-data methods (Evans and Lewis, 2002), panel ARDL models (Stuermer, 2017), instrumental-variable approaches (Fernandez, 2018; Shojaeddini et al., 2024), ARDL-ECM specifications (Al Rawashdeh, 2023), and local projections (Bogmans et al., 2024). Comprehensive reviews of commodity elasticities are provided by Dahl (2020) and Fally and Sayre (2018). While these studies provide valuable estimates of market responsiveness, they generally do not identify the underlying shocks driving commodity price fluctuations.

A second strand seeks to identify these shocks directly using SVARs. This literature has been particularly active in oil markets. Early contributions, such as Kilian (2009), relied on recursive identification schemes based on short-run restrictions. Subsequent studies increasingly adopted sign-restriction approaches. For example, Baumeister and Hamilton (2015) estimate a time-varying SVAR and show that declining supply elasticities contributed to rising oil price volatility after the mid-1980s. Their results suggest that smaller production responses require larger price adjustments to clear markets following shocks.

However, as emphasized by Kilian and Murphy (2012), sign restrictions alone often leave a large set of admissible models, many of which may be difficult to reconcile with economic intuition despite satisfying the imposed sign conditions. As a result, they may provide limited information regarding the magnitude of structural responses and offer little guidance for discriminating among alternative structural models. Some authors have therefore argued that additional economic information may be required to further narrow the set of admissible models. For example, Kilian and Murphy (2014) propose additional restrictions on impact elasticities, relative magnitudes, dynamic responses, and shape constraints. In the same spirit, the aforementioned Bayesian framework developed by Baumeister and Hamilton (2015), Baumeister and Hamilton (2018), and Baumeister and Hamilton (2019) incorporates prior economic information directly through probability distributions on structural parameters, allowing identification to be informed by economic knowledge in a transparent and flexible manner.

Despite their methodological differences, these studies generally reach a similar conclusion: demand shocks play a dominant role in commodity price fluctuations. This result has been documented extensively for oil markets and also appears in broader commodity analyses. For example, Jacks and Stuermer (2020) examine a large set of commodities and show that aggregate demand shocks play a central role in generating commodity supercycles and synchronized price movements across markets.

Existing evidence therefore points to an important role for demand-side factors in commodity markets. However, the respective roles of aggregate demand and commodity-specific demand remain much less understood, especially for mineral commodities and over long historical periods. One notable exception is Miller and Martinez (2025), who apply a sign-restricted SVAR to financial data for LME metals and conclude that demand shocks dominate price fluctuations, while long-run supply elasticities remain relatively low. By contrast, Boer et al. (2024), using sign and narrative sign restrictions following Antolín-Díaz and Rubio-Ramírez (2018), find larger long-run supply responses and predict substantial increases in metal prices under energy-transition scenarios.

More fundamentally, relatively little evidence exists on the respective contributions of supply shocks, aggregate demand shocks, and mineral-specific demand shocks over very long historical periods. Consequently, the extent to which observed mineral price dynamics can be interpreted as evidence of increasing scarcity remains largely unresolved.

3. Data and methodology

3.1. Data

We use mineral production and price data obtained from the United States Geological Survey (USGS, Historical Statistics on Mineral Commodities in the United States), which covers up to 65 mineral commodities from 1900 onwards, depending on data availability.[2] Aggregate economic activity is proxied by the Dry Freight Index compiled by Boer et al. (2024), which captures fluctuations in global demand conditions through developments in international shipping markets. Finally, recession periods are identified using the NBER recession indicator series provided by the Federal Reserve Bank of St. Louis (FRED), which records U.S. business-cycle downturns from peak to trough. These recession dates are used for descriptive purposes when analyzing the historical evolution of commodity prices and structural shocks (see Section 4).

3.2. Incomplete identification strategy

We adopt the incomplete identification approach for SVARs developed by Baumeister and Hamilton (2015), Baumeister and Hamilton (2018), and Baumeister and Hamilton (2019), in which identification is achieved through explicitly specified prior distributions on the contemporaneous coefficients. In contrast to pure sign-restriction approaches—which leave the influence of prior information largely implicit—this methodology makes such information explicit by specifying priors on the contemporaneous coefficients.

We consider a three-variable SVAR defined as follows. Let q_t denote the logarithm of world production of a given mineral, y_t the logarithm of the Dry Freight Index, and p_t the logarithm of the real unit value of the mineral. The structural model with four lags

[2] The complete list of the 65 mineral commodities included in the analysis is reported in Table A.1 in Appendix. For each mineral, we use annual world production and U.S. real unit values. As noted by Svedberg and Tilton (2006) in the case of copper, internationally traded mineral commodities are generally priced on integrated global markets rather than segmented regional markets. Consequently, U.S. prices can be viewed as reasonable proxies for world prices.

is given by:

$$
\begin{aligned}
q_t &= \alpha_y y_t + \alpha_p p_t + \sum_{i=1}^{4} \mathbf{B}_i \mathbf{X}_{t-i} + u_{qt} && (1)\\
y_t &= \beta_q q_t + \beta_p p_t + \sum_{i=1}^{4} \mathbf{B}_i \mathbf{X}_{t-i} + u_{yt} && (2)\\
p_t &= \gamma_q q_t + \gamma_y y_t + \sum_{i=1}^{4} \mathbf{B}_i \mathbf{X}_{t-i} + u_{pt} && (3)
\end{aligned}
$$

Equation (1) corresponds to the supply equation, Equation (2) to global economic activity, and Equation (3) to mineral-specific demand. The coefficient γ_q can be interpreted as the inverse of the price elasticity of demand (Baumeister and Hamilton, 2019). Structural shocks are interpreted as production, aggregate demand, and mineral-specific demand shocks, respectively.

Consistent with standard economic mechanisms governing supply, demand, and price formation in commodity markets, prior beliefs suggest that the contemporaneous relationships should satisfy the sign patterns summarized below. Unlike traditional sign-restriction approaches, these sign patterns are not imposed as exact identifying restrictions but are incorporated through prior distributions on structural parameters:

$$\alpha_y > 0, \quad \alpha_p > 0, \quad \beta_q > 0, \quad \beta_p < 0, \quad \gamma_q < 0, \quad \gamma_y > 0 \tag{4}$$

meaning that (i) production responds positively to both global demand and mineral prices, (ii) global economic activity responds positively to production and negatively to mineral prices, and (iii) mineral prices respond negatively to production and positively to aggregate demand.

The model can therefore be written in the following structural form:

$$\mathbf{A}\mathbf{X}_t = \sum_{i=1}^{4} \mathbf{B}_i \mathbf{X}_{t-i} + \mathbf{u}_t \tag{5}$$

where the contemporaneous matrix $\mathbf{A}$ is given by:

$$\mathbf{A} = \begin{pmatrix} 1 & -\alpha_y & -\alpha_p \\ -\beta_q & 1 & -\beta_p \\ -\gamma_q & -\gamma_y & 1 \end{pmatrix} \tag{6}$$

The resulting contemporaneous responses to structural shocks, represented by the matrix $\mathbf{A}^{-1}$, are expected to display the following sign patterns:

$$\text{Sign}(\mathbf{A}^{-1}) = \begin{pmatrix} + & + & + \\ + & + & - \\ - & + & + \end{pmatrix} \tag{7}$$

Using the identity $\mathbf{A}^{-1} = \frac{1}{\det(\mathbf{A})}\,\text{adj}(\mathbf{A})$, we obtain:

$$\det(\mathbf{A}) = 1 - \beta_p\gamma_y - \alpha_y\beta_q - \alpha_y\beta_p\gamma_q - \alpha_p\beta_q\gamma_y - \alpha_p\gamma_q \tag{8}$$

and

$$\text{adj}(\mathbf{A}) = \begin{pmatrix} 1 - \beta_p\gamma_y & \alpha_y + \alpha_p\gamma_y & \alpha_y\beta_p + \alpha_p \\ \beta_q + \beta_p\gamma_q & 1 - \alpha_p\gamma_q & \beta_p + \alpha_p\beta_q \\ \beta_q\gamma_y + \gamma_q & \gamma_y + \alpha_y\gamma_q & 1 - \alpha_y\beta_q \end{pmatrix} \tag{9}$$

Given the assumed sign patterns of the structural parameters, only a subset of the elements of adj($\mathbf{A}$) have signs that are unambiguously determined. This can be summarized as:

$$\text{Sign}(\text{adj}(\mathbf{A})) = \begin{pmatrix} + & + & ? \\ + & + & ? \\ ? & ? & ? \end{pmatrix} \tag{10}$$

Setting $\alpha_y = 0$ and $\beta_q = 0$ would fully determine the sign pattern of adj($\mathbf{A}$) in accordance with these sign assumptions, as in Baumeister and Hamilton (2019). However, such assumptions appear implausible in an annual framework, as they would imply no contemporaneous interaction between production and global economic activity. We now translate the theoretical sign assumptions on the contemporaneous relationships between variables—reflecting standard economic mechanisms—by specifying prior distributions on the structural parameters, in particular on $\mathbf{A}$, $\det(\mathbf{A})$, and selected elements of $\mathbf{A}^{-1}$.

3.3. Priors for A

We construct prior distributions for the coefficients of $\mathbf{A}$ based on a survey of empirical elasticities reported in the literature. Each type of elasticity is mapped to a corresponding coefficient of $\mathbf{A}$. Elasticities that are not statistically significant at the 5% level are set to zero. Summary statistics reported in Table 1 include the mean, standard deviation (*SD*), the percentage of elasticities greater than 1 in absolute value ($|x| > 1$), zero estimates (% = 0), the percentage of positive and negative elasticities (% > 0 and % < 0), the number of elasticities reported (N), and the name of the coefficient in $\mathbf{A}$ associated with this type of elasticity (*Coef*).

Table 1 – Summary statistics of elasticity estimates from the literature

Type of elasticity	Mean	SD	% $\|x\| > 1$	% $= 0$	% > 0	% < 0	N	Coef.
Price of demand	-0.148	0.279	1.71	61.9	0.381	37.7	525	
Income of demand	0.487	0.495	23.9	34.1	64.9	1.09	276	
Demand of price	-0.120	0.342	0	44.4	11.1	44.4	9	γ_y
Price of supply	0.330	0.461	6.59	29.7	70.3	0	182	α_p
Production of price	-0.631	0.291	0	10	0	90	30	γ_q
Income of supply	0	0	0	100	0	0	6	α_y

Note: Mean and SD denote the sample mean and standard deviation of reported elasticities. % $|x| > 1$ is the share of estimates larger than one in absolute value, and % $= 0$ corresponds to estimates not statistically different from zero at the 5% level. % > 0 and % < 0 denote the proportions of positive and negative estimates. N is the number of observations. The last column indicates the corresponding coefficient in matrix A when applicable.

Elasticities related to "price of demand" and "income of demand" are not used, as our specification does not include a direct measure of mineral consumption. Moreover, the "demand of price" elasticity appears to rely on a proxy closer to production than to demand, and is therefore discarded.

For each coefficient, we specify a truncated Student-t distribution with three degrees of freedom, following Baumeister and Hamilton (2019). The distribution is truncated to reflect the theoretical sign assumptions. The location parameter is set equal to the empirical mean when available and to zero otherwise. The scale parameter is calibrated so that the theoretical probability of observing values larger than one in absolute value matches the empirical frequency ("Target" in Equation (11)). For negative elasticities, this corresponds to:[3]

$$\frac{\mathbb{P}(X < -1)}{\mathbb{P}(X < 0)} = \text{Target} \tag{11}$$

When no empirical frequency of elasticities exceeding one in absolute value is available, or when such occurrences are not observed in the data, we calibrate the target probability based on economic considerations. For α_y, no empirical estimates exceed one in absolute value, and we therefore set the target probability to 1%. For β_q and β_p, in the absence of direct empirical evidence, we consider it unlikely that production or mineral prices have effects on global economic activity exceeding unity, and similarly set the target probability to 1%. For γ_y, while large effects are still considered unlikely, they appear more plausible than for the other coefficients. We therefore set a higher target probability of 5%.

The scale parameter is obtained by numerical optimization, and the resulting prior distributions are:[4]

- $\alpha_y \sim$ Student$(0, 0.171, 3)$, truncated to be positive,
- $\alpha_p \sim$ Student$(0.33, 0.296, 3)$, truncated to be positive,
- $\beta_q \sim$ Student$(0, 0.171, 3)$, truncated to be positive,
- $\beta_p \sim$ Student$(0, 0.171, 3)$, truncated to be negative,
- $\gamma_q \sim$ Student$(-0.631, 0.221, 3)$, truncated to be negative,
- $\gamma_y \sim$ Student$(0, 0.314, 3)$, truncated to be positive.

3.4. Priors for det(A)

To encourage consistency with the expected sign patterns of the contemporaneous responses encoded in $\mathbf{A}^{-1}$, we introduce a prior favoring positive values of $\det(\mathbf{A})$. We simulate 100,000 draws of $\det(\mathbf{A})$ based on the priors on $\mathbf{A}$, yielding an empirical distribution with mean 0.7145, a 2.614% probability of negative values, and a 0.038% probability of exceeding one (see Figure A.2 in Appendix).

We approximate this distribution using a non-central Student-t distribution. The location parameter is fixed at the empirical mean, while the scale and non-centrality parameters are chosen to match the empirical tail probabilities. In the parameterization below, the four arguments correspond, respectively, to the location parameter, the standard deviation, the degrees of freedom, and the non-centrality parameter. This yields:

$$\det(\mathbf{A}) \sim \text{NC-Student}(0.7145, 0.0882, 3, -1.8097). \tag{12}$$

3.5. Priors for H

Finally, we impose priors on selected elements of the contemporaneous impact matrix $\mathbf{H} = \mathbf{A}^{-1}$ whose signs are not implied by the structure of $\mathbf{A}$. For these coefficients, we

[3]The standard deviation, which is the only unknown parameter of the Student-t distribution, is estimated by minimizing the absolute difference between the theoretical probability implied by the distribution and the observed probability.

[4]See Figure A.1 in Appendix.

use truncated Student-t distributions with three degrees of freedom, centered at zero and consistent with the theoretical sign assumption. The scale parameter is calibrated so that the probability of observing values larger than one in absolute value is 20%. Since no coefficient-specific empirical information is available for these elements, we adopt a common prior structure across coefficients. This ensures a consistent degree of dispersion while remaining agnostic about their relative magnitudes:

- $h_{1,3} \sim$ Student$(0, 0.611, 3)$, truncated to be positive,
- $h_{2,3} \sim$ Student$(0, 0.611, 3)$, truncated to be negative,
- $h_{3,1} \sim$ Student$(0, 0.611, 3)$, truncated to be negative,
- $h_{3,2} \sim$ Student$(0, 0.611, 3)$, truncated to be positive,
- $h_{3,3} \sim$ Student$(0, 0.611, 3)$, truncated to be positive.

3.6. Computation of elasticities

Following Kilian and Murphy (2014) and the methodology used in Boer et al. (2024) and Miller and Martinez (2025), elasticities are defined as the response of one variable relative to the response of the shocked variable itself.

They are computed from the estimated structural impulse response functions implied by the SVAR model. Let $\mathbf{\Theta}_h$ denote the $(n \times n)$ matrix of structural impulse responses at horizon h, defined as:

$$\mathbf{\Theta}_h = \mathbf{\Phi}_h \mathbf{A}^{-1} \tag{13}$$

where $\mathbf{\Phi}_0 = \mathbf{I}_n$ and the matrices $\mathbf{\Phi}_h$ are recursively obtained from the reduced-form coefficients of the VAR model (Lütkepohl, 2005).

We consider three types of elasticities. First, we compute the elasticity of prices with respect to supply shocks, which measures the relative response of prices to a shock in world mineral production. Second, we compute the elasticity of prices with respect to aggregate demand shocks. Finally, we compute the elasticity of supply with respect to mineral-specific demand shocks.

The impact elasticity of variable A with respect to a shock in variable B is defined as:

$$\eta_{A,B,0} = \frac{(\Theta_0)_{A,B}}{(\Theta_0)_{B,B}} \tag{14}$$

At longer horizons, elasticities are computed using cumulative impulse responses. The elasticity of variable A with respect to a shock in variable B at horizon h is given by:

$$\eta_{A,B,h} = \frac{\sum_{i=0}^{h} (\Theta_i)_{A,B}}{\sum_{i=0}^{h} (\Theta_i)_{B,B}} \tag{15}$$

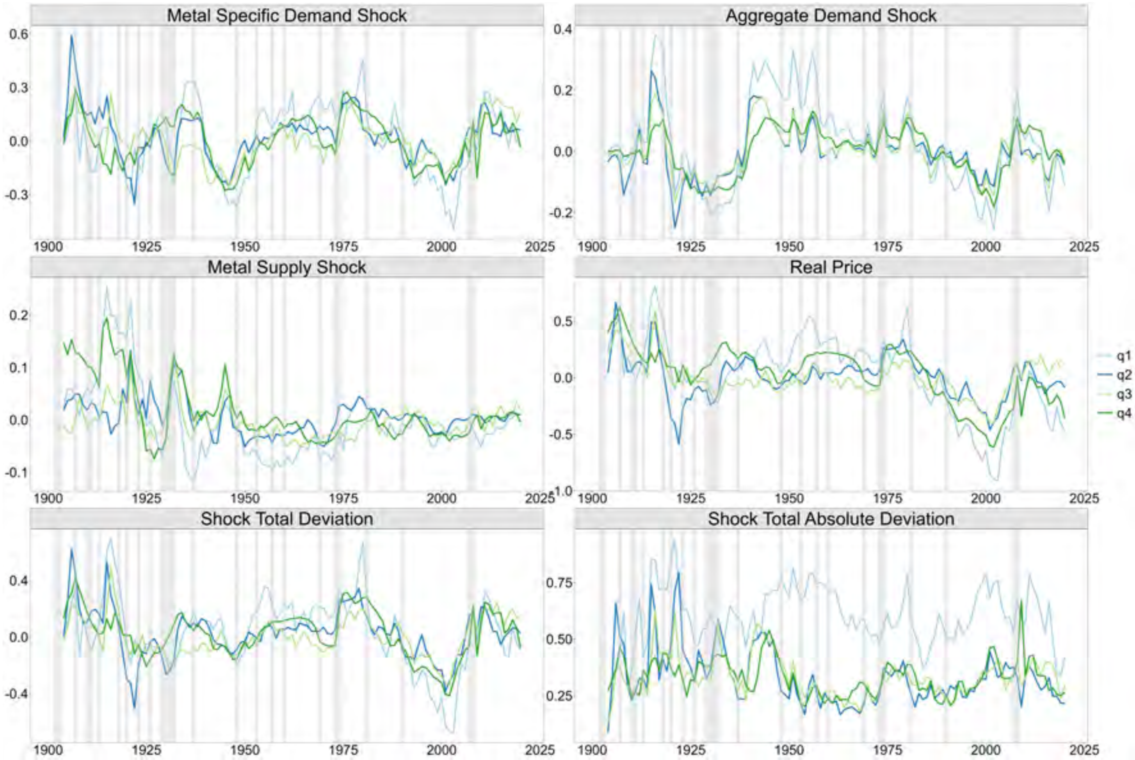
4. Results

4.1. Demand-driven price dynamics: Evidence from historical decomposition

We begin by analyzing the historical decomposition of real mineral commodity prices in order to identify the main drivers of price fluctuations over time.[5] Figure 1 reports the

[5] These historical decompositions can be interpreted as the contribution of each structural shock to the observed price dynamics, providing a counterfactual decomposition of prices into distinct driving forces.

Figure 1 – Historical decomposition of real commodity prices by production quartiles



Note: The figure reports the historical decomposition of real commodity prices aggregated by quartiles of production levels. Real prices are expressed as deviations from their long-term mean. Each panel shows the contribution of metal-specific demand shocks, aggregate demand shocks, and supply shocks, as well as their sum. The panel *total_deviation* corresponds to the sum of shock contributions. The panel *total_deviation_abs* reports the absolute sum of shock contributions, capturing the overall intensity of shocks. Shaded areas indicate global recession periods.

historical decomposition aggregated by quartiles of production levels.

A first stylized fact emerges from the evolution of real prices. Across production groups, real prices tend to display a declining pattern in recent years and remain generally below their long-term mean. This pattern does not support the hypothesis of a sustained upward trend in prices that would be consistent with increasing resource scarcity (e.g., Krautkraemer, 2005; Svedberg and Tilton, 2006).

The decomposition highlights the central role of demand-side forces. Metal-specific demand shocks constitute the main driver of price fluctuations relative to other shocks across periods and production groups. Their contribution follows a broad U-shaped pattern over time: they are dominant at the beginning of the sample, decline around the First World War and subsequent periods, and increase again in more recent decades. Aggregate demand shocks also contribute significantly, although their importance does not follow a clear long-term trend and appears to increase during recent decades marked by repeated global instability. The similarity in the dynamics of metal-specific and aggregate demand shocks is particularly pronounced during crisis periods, where both shocks display closely aligned fluctuations. This pattern may reflect changes in the structure of demand over time. In the early part of the sample, demand was closely tied to specific industrial uses, making prices highly sensitive to sectoral shocks. The decline around the

Table 2 – Contribution of shocks to real metal price variation across periods

Periods	Metal-specific demand shocks	Aggregate demand shocks	Supply shocks
1900-1913	61.98	17.11	20.91
1914-1918	41.34	32.26	26.41
1919-1938	48.65	29.37	21.97
1939-1947	52.29	28.92	18.79
1948-1970	53.23	25.99	20.78
1971-1997	58.44	23.08	18.48
1998-2020	57.38	26.96	15.66

Note: Each column reports the share (in percent) of each shock in the total absolute variation of real prices induced by shocks. Periods are defined following Jacks and Stuermer (2020), isolating the First and Second World Wars, while the final period begins after the Kyoto Protocol.

First World War coincides with major economic disruptions and changes in market conditions that may have altered the relative importance of demand shocks. The renewed importance of global demand shocks in recent decades likely reflects the expansion of global economic activity and increased market integration.

In contrast, and consistent with the dominance of demand-side forces, supply shocks play a more limited role. Their contribution is relatively high at the beginning of the sample and peaks around the First World War (or shortly thereafter), but declines from the mid-20th century onwards and stabilizes at a lower level. This pattern may reflect structural changes in commodity markets over time. In the early part of the sample, production was more geographically concentrated and markets were less integrated, making prices more sensitive to supply disruptions. The peak around the First World War is consistent with major disruptions in production and trade. From the mid-20th century onwards, the decline in the importance of supply shocks may reflect increased market integration, the expansion and diversification of production capacity, and the development of inventories and storage mechanisms that help smooth supply fluctuations. At the same time, the growing role of global demand may have reduced the relative importance of supply-side disturbances in price formation.

The decomposition further reveals substantial heterogeneity across production groups. Metals with lower production volumes exhibit higher volatility in response to shocks, suggesting greater exposure to external shocks. While general trends are similar across production quartiles, volatility is more pronounced for smaller producers.

Tables 2 and 3 quantify these patterns by reporting the relative contribution of each shock across periods and production groups. Several patterns emerge.

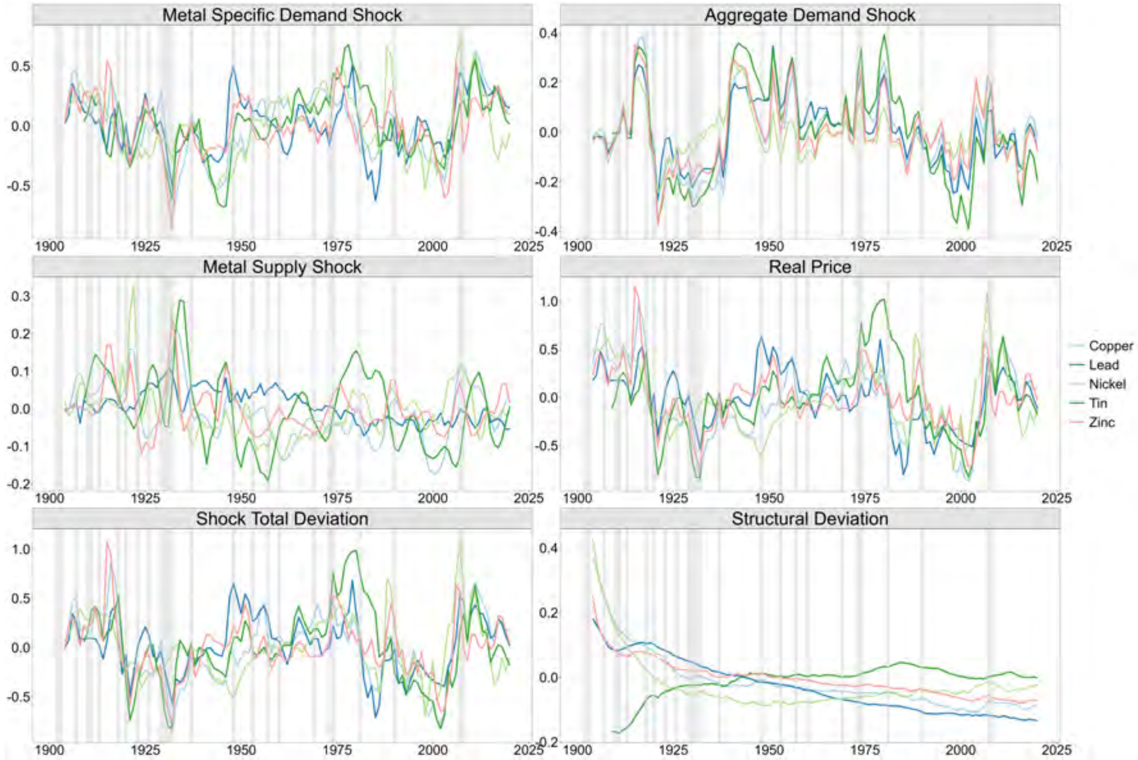
First, metal-specific demand shocks consistently account for the largest share of price fluctuations across all periods. Their contribution remains above 40% in all subperiods and exceeds 50% in most cases, confirming their dominant role. Second, aggregate demand shocks represent the second most important source of variation. Their contribution increases markedly during major disruption periods, such as 1914–1918 where they account for around 30% of total price variation. This suggests that global economic conditions play a role during periods of macroeconomic instability. Third, the

Table 3 – Contribution of shocks to real metal price variation by production quartiles and periods

Quartile	Period	Metal-specific demand shocks	Aggregate demand shocks	Supply shocks
q1	1900-1913	63.39	14.69	21.92
q1	1914-1918	29.76	36.59	33.65
q1	1919-1938	49.06	27.75	23.19
q1	1939-1947	49.20	33.09	17.71
q1	1948-1970	52.99	27.70	19.32
q1	1971-1997	57.12	25.22	17.66
q1	1998-2020	62.49	24.49	13.01
q2	1900-1913	63.45	19.58	16.97
q2	1914-1918	49.21	35.02	15.76
q2	1919-1938	54.47	25.06	20.47
q2	1939-1947	55.12	28.28	16.60
q2	1948-1970	57.20	22.13	20.67
q2	1971-1997	63.43	18.10	18.48
q2	1998-2020	59.19	24.94	15.87
q3	1900-1913	60.43	21.06	18.51
q3	1914-1918	47.36	33.44	19.20
q3	1919-1938	47.51	32.95	19.54
q3	1939-1947	51.94	31.79	16.27
q3	1948-1970	49.68	28.04	22.28
q3	1971-1997	55.55	25.54	18.90
q3	1998-2020	54.30	29.91	15.78
q4	1900-1913	61.88	12.09	26.03
q4	1914-1918	39.75	22.24	38.01
q4	1919-1938	45.36	28.40	26.24
q4	1939-1947	53.97	20.55	25.47
q4	1948-1970	53.96	25.31	20.73
q4	1971-1997	57.87	23.17	18.96
q4	1998-2020	52.88	28.75	18.37

Note: Each column reports the share (in percent) of each shock in the total absolute variation of real prices induced by shocks, for each production quartile. Periods are defined following Jacks and Stuermer (2020), isolating the First and Second World Wars, while the final period begins after the Kyoto Protocol. Values sum to 100 within each quartile-period.

Figure 2 – Historical decomposition of real prices for LME metals



Note: The figure reports the historical decomposition of real prices for LME metals. Real prices are expressed as deviations from their long-term mean. Each panel shows the contribution of metal-specific demand shocks, aggregate demand shocks, and supply shocks, as well as their sum. The panel *total_deviation* corresponds to the sum of shock contributions. The *structural* component corresponds to the price path implied by initial conditions and the propagation mechanism of the model, net of identified shock contributions. Shaded areas indicate global recession periods.

contribution of supply shocks is systematically lower and tends to decline over time. While supply shocks account for around 20–26% of price variation in the early part of the sample, their importance falls to around 15–18% in the most recent period. Finally, the quartile-based decomposition confirms that these patterns are broadly shared across production groups. While differences in magnitudes exist, the ranking of shocks—metal-specific demand first, aggregate demand second, and supply shocks last—remains globally unchanged across quartiles.

The analysis of LME metals provides additional insights into the structure of price dynamics. Figure 2 shows that, while real prices display a strong degree of co-movement across metals, the underlying decomposition reveals important differences across shocks.

A first notable feature is the similarity in the contribution of demand shocks across LME metals. Both metal-specific and aggregate demand shocks generate closely aligned dynamics, particularly during periods of global economic stress. This suggests that these markets are exposed to common demand factors, consistent with a high degree of market integration and the central role of global industrial activity in driving metal demand.

However, Table 4 highlights important differences across metals in the relative importance of each shock. Metal-specific demand shocks remain dominant across all metals and periods, but their magnitude varies. For instance, their contribution is particularly

Table 4 – Contribution of shocks to real price variation for LME metals across periods

Metal	Period	Metal-specific demand shocks	Aggregate demand shocks	Supply shocks
copper	1900-1913	68.05	16.88	15.07
copper	1914-1918	32.79	49.24	17.97
copper	1919-1938	40.81	43.06	16.13
copper	1939-1947	60.51	31.72	7.77
copper	1948-1970	59.35	21.86	18.79
copper	1971-1997	51.86	31.03	17.11
copper	1998-2020	65.33	19.41	15.26
lead	1900-1913	67.33	25.68	6.99
lead	1914-1918	41.45	52.91	5.65
lead	1919-1938	38.63	45.07	16.30
lead	1939-1947	54.39	31.87	13.74
lead	1948-1970	43.38	41.18	15.44
lead	1971-1997	61.32	27.09	11.58
lead	1998-2020	64.21	26.05	9.74
nickel	1900-1913	83.87	7.66	8.46
nickel	1914-1918	41.39	53.01	5.59
nickel	1919-1938	42.33	27.31	30.36
nickel	1939-1947	62.60	29.28	8.12
nickel	1948-1970	51.97	16.63	31.40
nickel	1971-1997	68.68	19.55	11.77
nickel	1998-2020	66.42	21.46	12.12
tin	1900-1913	57.68	7.70	34.62
tin	1914-1918	28.79	47.01	24.21
tin	1919-1938	34.15	47.56	18.29
tin	1939-1947	51.88	35.35	12.77
tin	1948-1970	37.76	32.91	29.33
tin	1971-1997	53.36	27.89	18.75
tin	1998-2020	43.46	35.49	21.05
zinc	1900-1913	77.78	19.26	2.96
zinc	1914-1918	31.00	43.97	25.03
zinc	1919-1938	43.50	39.50	16.99
zinc	1939-1947	47.92	38.83	13.25
zinc	1948-1970	45.22	28.89	25.89
zinc	1971-1997	48.03	36.99	14.99
zinc	1998-2020	59.84	28.44	11.72

Note: Each column reports the share (in percent) of each shock in the total absolute variation of real prices induced by shocks, for each LME metal and period. Periods are defined following Jacks and Stuermer (2020), isolating the First and Second World Wars, while the final period begins after the Kyoto Protocol. Values sum to 100 within each metal-period.

high for nickel and copper in most periods, often exceeding 60%, while it is generally lower and more variable for tin. These differences may reflect the nature of industrial uses across metals: copper and nickel are key inputs in core industrial sectors such as construction, energy, and manufacturing, making their demand closely tied to global economic conditions. In contrast, tin is associated with more specialized uses and a smaller market size, which may result in more volatile and less systematic demand patterns.

Aggregate demand shocks also exhibit substantial variation across metals and periods. They become particularly important during disruption periods, such as 1914–1918, where they account for a large share of price variation for all metals (e.g., 49.24% for copper, 52.91% for lead, and 53.01% for nickel). This pattern is consistent with the presence of large-scale macroeconomic disturbances affecting all commodity markets simultaneously, leading to synchronized price movements across metals.

In contrast, supply shocks display the greatest heterogeneity across metals. Their contribution is generally limited but can become substantial for specific metals and periods. For example, tin exhibits a relatively high contribution of supply shocks in the early period (34.62% in 1900–1913), while nickel displays large fluctuations over time, with peaks above 30% in some periods. For zinc and lead, supply shocks remain comparatively small in most periods, although they increase during certain episodes. This heterogeneity likely reflects differences in production structures across metals, including the degree of geographical concentration, the flexibility of production, and the presence of capacity constraints. Metals with more concentrated or constrained supply conditions may be more exposed to supply disruptions, while more diversified production structures tend to dampen their impact on prices.

Overall, these results indicate that metal price fluctuations are primarily driven by demand shocks—both specific and aggregate—while supply conditions remain strongly metal-specific. Prices tend to move together in response to global demand shocks, while supply shocks introduce divergence across metals.

4.2. Elasticities and adjustment mechanisms

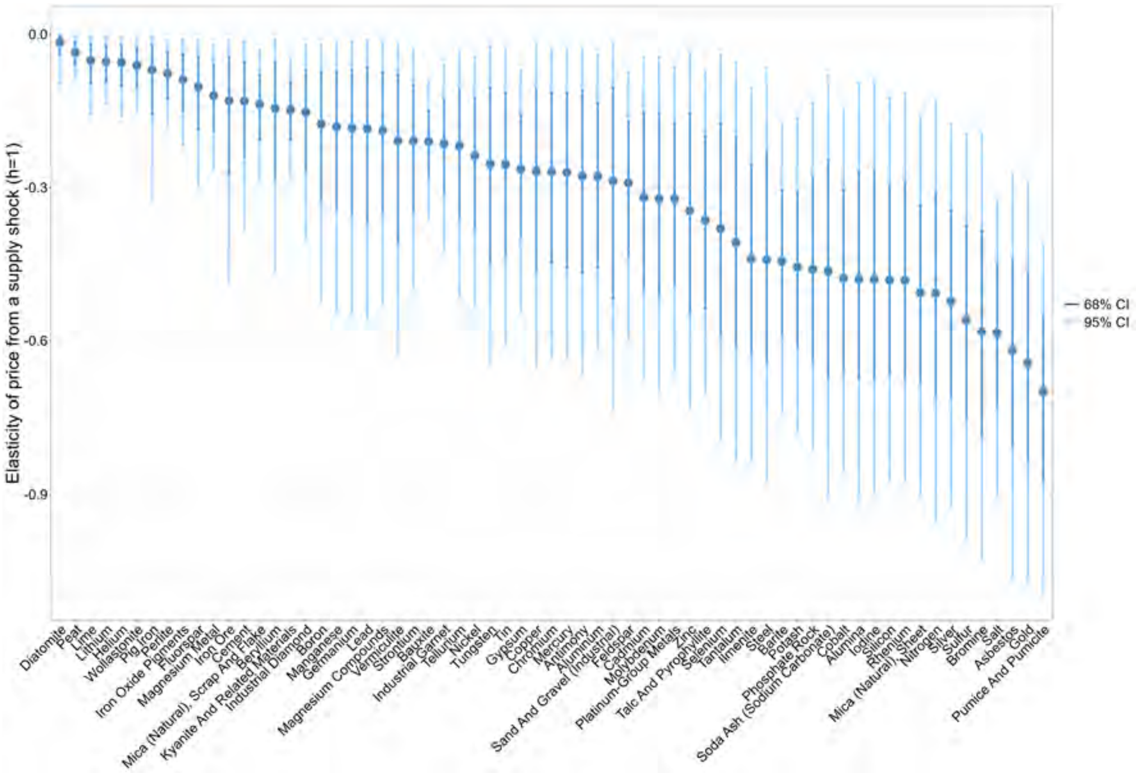
We now turn to the analysis of elasticities to better understand the mechanisms underlying the price dynamics identified in the historical decomposition.

4.2.1. Price responses to supply and demand shocks

Figure 3 shows that price responses to supply shocks are systematically negative across metals, as expected. However, there is substantial heterogeneity in the magnitude of these elasticities. While all responses share the same sign, their dispersion is large and credible intervals are often wide, indicating a significant degree of uncertainty. Elasticities also exhibit a clear cross-sectional gradient across metals, with some displaying large and precisely estimated responses, while others remain small or imprecisely estimated.

The evolution of these elasticities across horizons, reported in Figure 4, highlights their instability. A large share of elasticities becomes statistically insignificant when moving from the 68% to the 95% credible interval. Moreover, significance is unevenly distributed across metals and across horizons. Price responses to supply shocks are short-lived for some metals, with significant responses concentrated at specific horizons, whereas others

Figure 3 – Price responses to supply shocks at impact

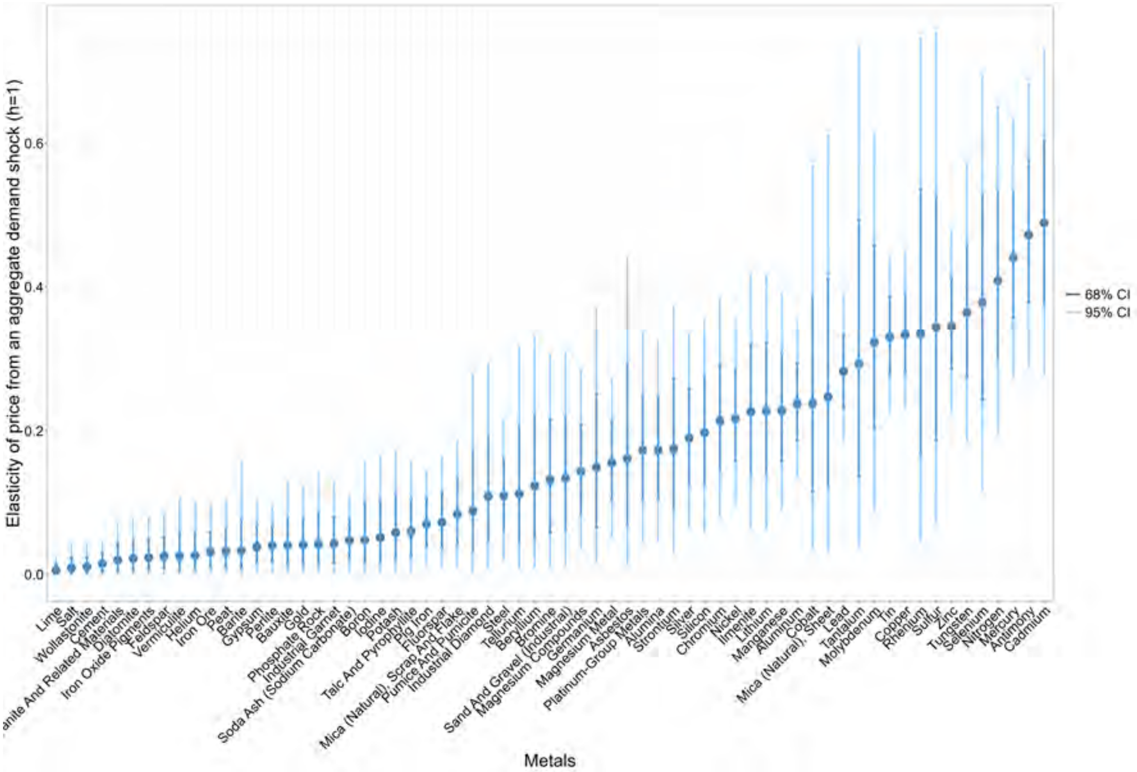


Note: The figure reports the impact elasticities of real prices to supply shocks across metals. Points correspond to median estimates, while vertical bars represent 68% and 95% credible intervals.

Figure 4 – Elasticities of prices to supply shocks across horizons

Note: The figure reports price elasticities to supply shocks across horizons for different metals. Elasticities are set to zero when not statistically significant. The left panel corresponds to the 68% credible interval and the right panel to the 95% credible interval.

Figure 5 – Price responses to aggregate demand shocks at impact



Note: The figure reports the impact elasticities of real prices to aggregate demand shocks across metals. Points correspond to median estimates, while vertical bars represent 68% and 95% credible intervals.

display more persistent adjustment patterns. This suggests that the impact of supply shocks on prices is heterogeneous across metals and horizons.

In contrast, Figure 5 shows that median price responses to demand shocks are positive across all metals. Although there is again substantial dispersion in magnitude, positive responses are generally more robust than supply responses. The corresponding heatmap (Figure 6) indicates that demand-driven price responses are more persistent and more frequently significant over long horizons. Compared to supply shocks, demand elasticities display more continuous and stable patterns, particularly under the 68% credible interval.

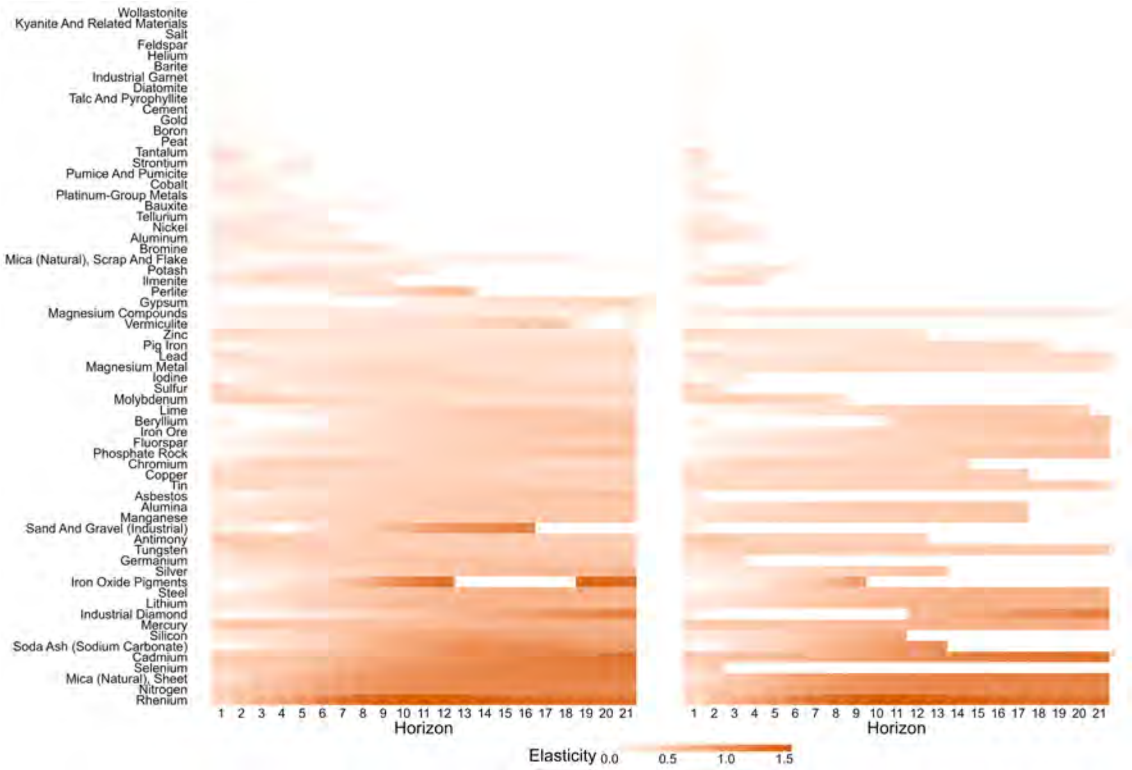
Taken together, these results indicate that prices respond more strongly and more systematically to demand shocks than to supply shocks, providing complementary evidence for the demand dominance observed in the historical decomposition.

4.2.2. Supply responses to price shocks

Figure 7 shows that supply responses to price shocks are positive and statistically significant at impact for all metals. However, their magnitude remains generally limited, suggesting that production is only weakly responsive to price signals in the short run. The substantial dispersion of estimates and the width of credible intervals further indicate considerable heterogeneity and uncertainty across metals.

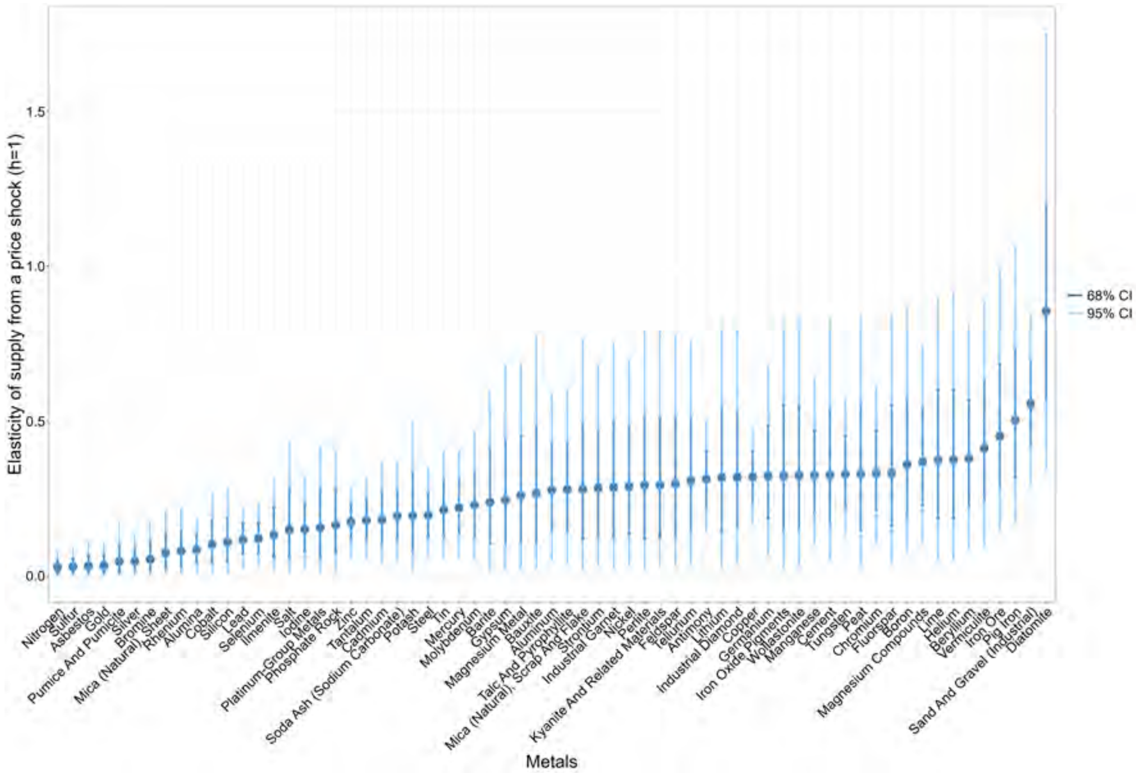
The evolution of these elasticities across horizons (Figure 8) suggests that supply responsiveness tends to increase with horizon in some cases, although this pattern is not uniform and often lacks statistical significance at the 95% level. In addition, signifi-

Figure 6 – Elasticities of prices to aggregate demand shocks across horizons



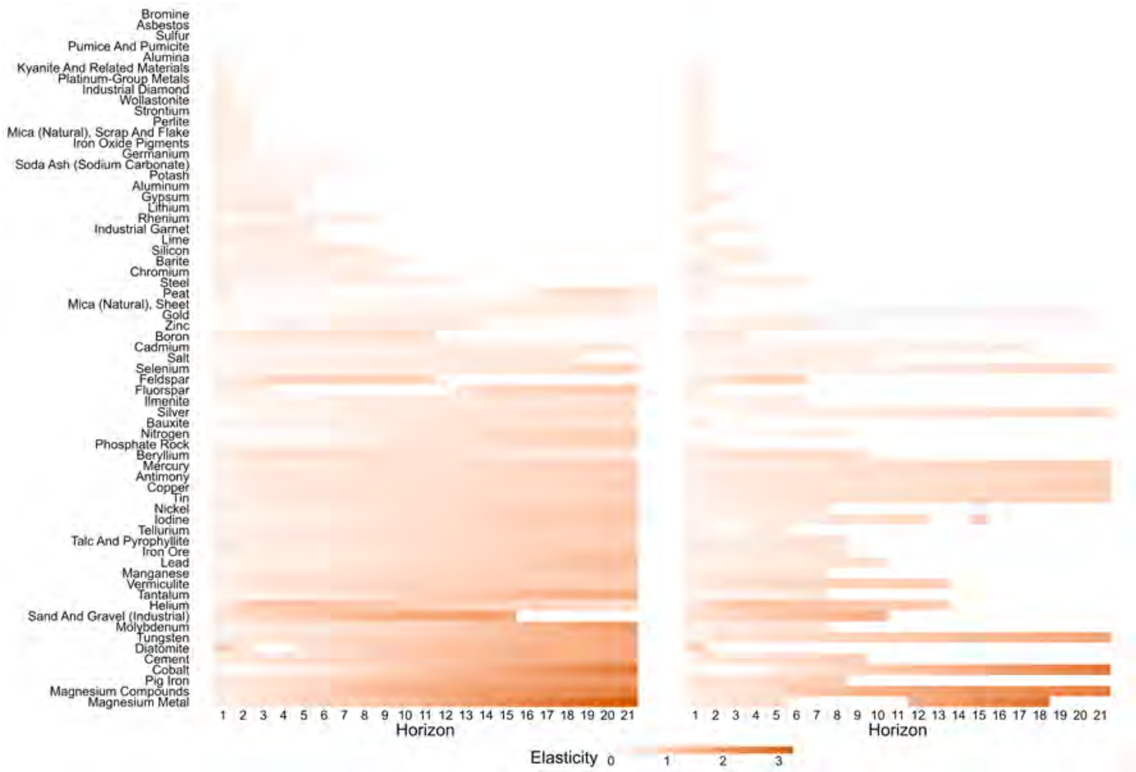
Note: The figure reports price elasticities to aggregate demand shocks across horizons for different metals. Elasticities are set to zero when not statistically significant. The left panel corresponds to the 68% credible interval and the right panel to the 95% credible interval.

Figure 7 – Supply responses to price shocks at impact



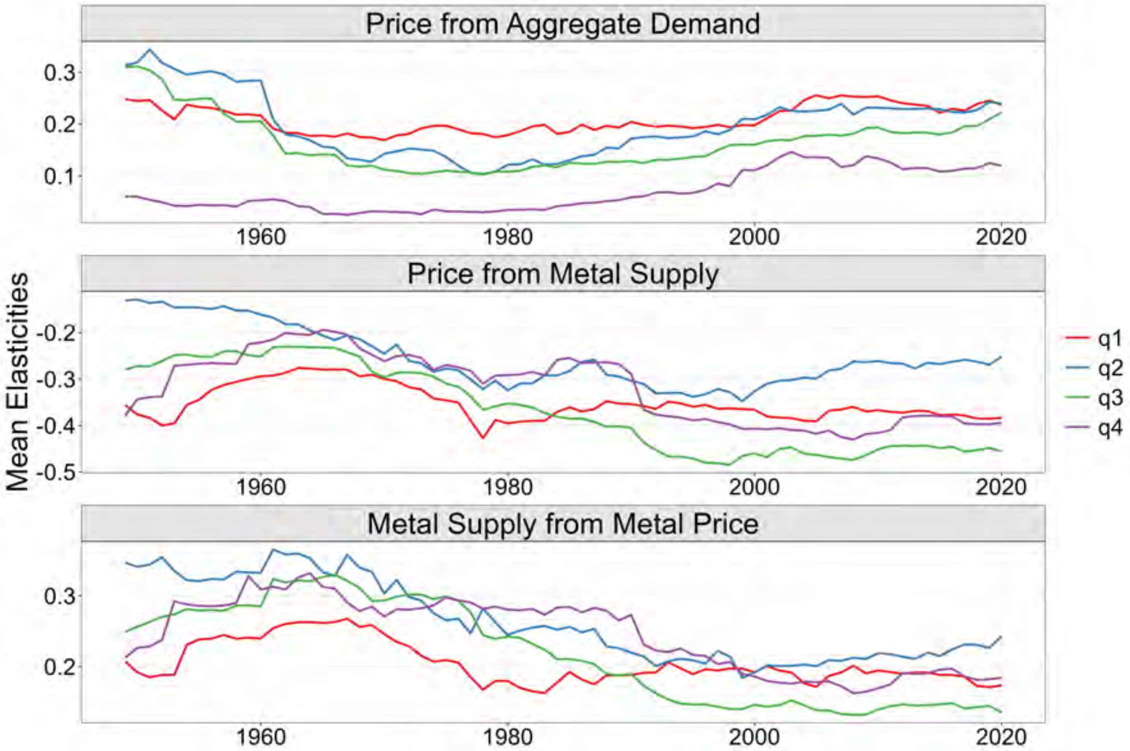
Note: The figure reports the impact elasticities of supply to price shocks across metals. Points correspond to median estimates, while vertical bars represent 68% and 95% credible intervals.

Figure 8 – Supply elasticities to price shocks across horizons



Note: The figure reports supply elasticities to price shocks across horizons for different metals. Elasticities are set to zero when not statistically significant. The left panel corresponds to the 68% credible interval and the right panel to the 95% credible interval.

Figure 9 – Rolling elasticities by production quartiles (window size = 50)



Note: The figure reports rolling median elasticities computed over a moving window of size 50, aggregated by production quartiles. Diatomite is excluded due to extreme values affecting graphical readability.

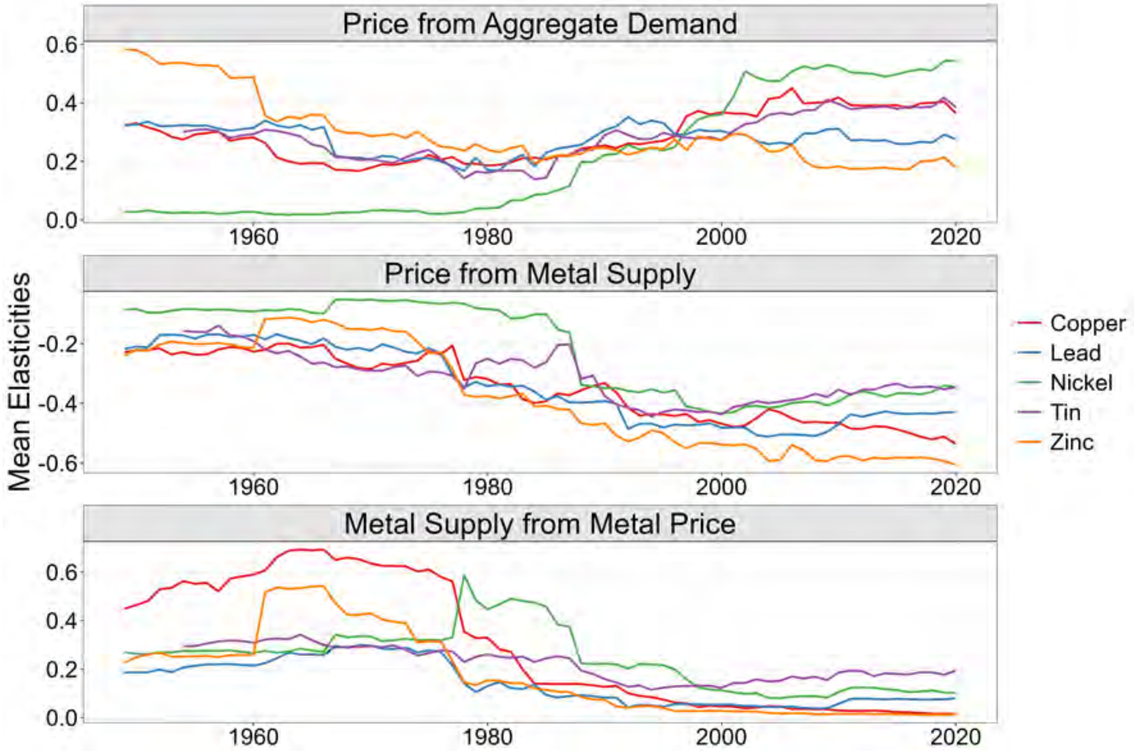
cant responses are typically confined to specific horizons rather than being persistently different from zero.

These findings indicate that supply adjustments are limited in the short run and vary considerably across metals. At longer horizons, responses also remain heterogeneous, both in magnitude and persistence.

4.2.3. Time variation and rolling estimates

Rolling estimates provide further insight into the evolution of elasticities over time. Figures 9 and 10 show that supply responses to price shocks tend to decline over time across production groups. This pattern is consistent with previous findings for other commodity markets (e.g., Baumeister and Peersman, 2013). One possible interpretation is that production may have become increasingly constrained in the short run, possibly reflecting technological, geological, or institutional rigidities that limit the ability of producers to adjust output rapidly in response to price signals. In resource-based industries, investment decisions are typically characterized by long lead times and high adjustment costs, which may reduce short-run supply elasticities. This pattern may also reflect the cyclical nature of mining investment, which is characterized by substantial uncertainty, long project horizons, and large irreversible costs. In addition, the growing complexity of global supply chains and the concentration of production in specific regions may further restrict the flexibility of supply. Taken together, these mechanisms suggest that supply has become less responsive to price fluctuations over time, reinforcing the role of demand shocks in driving price dynamics.

Figure 10 – Rolling elasticities for LME metals (window size = 50)



Note: The figure reports rolling median elasticities computed over a moving window of size 50 for LME metals (copper, lead, nickel, tin, and zinc).

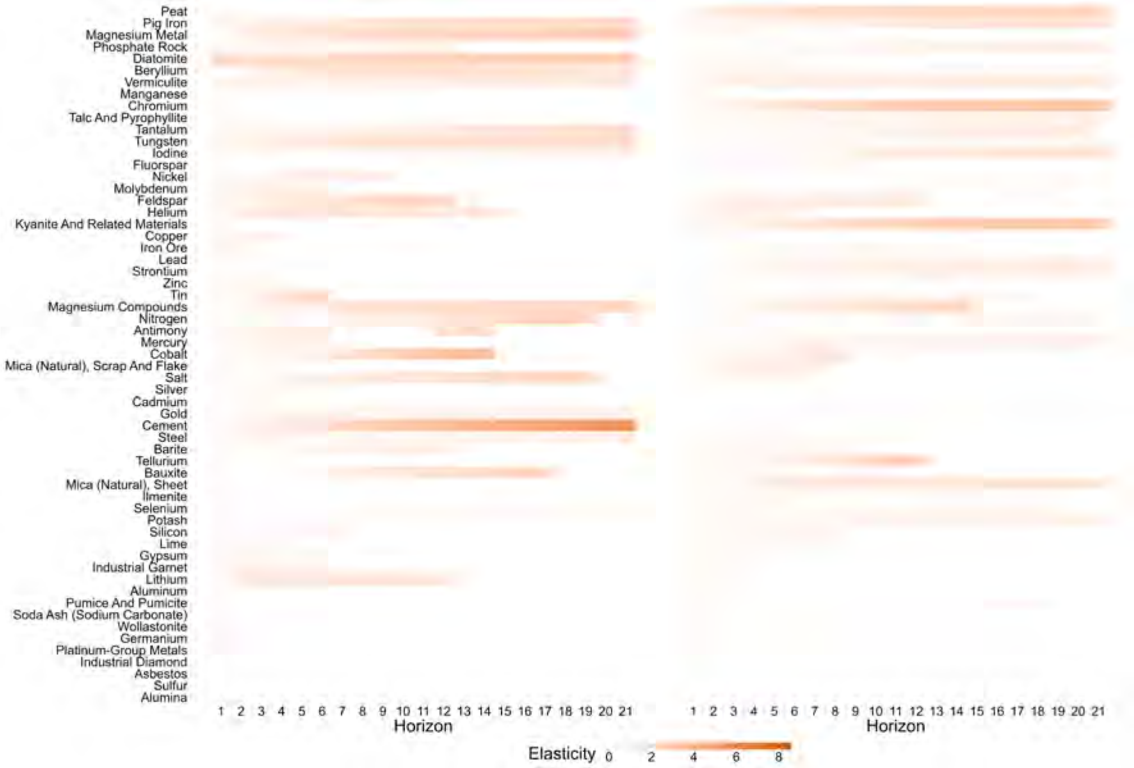
In contrast, price elasticities—both in response to supply and demand shocks—tend to increase in absolute value over time, indicating that prices have become more sensitive to shocks. One possible interpretation is that the reduced responsiveness of supply, documented above, has led to steeper short-run supply conditions, implying that price adjustments must absorb a larger share of market imbalances. This mechanism is consistent with standard commodity market dynamics, where lower supply elasticities translate into larger price responses to shocks. Our results could also reflect the growing financialization of the metals markets with the introduction of new financial tools (funds, commodity ETFs) and the growing importance of non-physical-players in the market. However, this trend is not uniform across metals or groups, and important deviations from aggregate patterns remain.

Another notable feature concerns the persistence of supply responses. While their magnitude tends to decrease, their effects appear to last longer in more recent periods, suggesting weaker but more persistent adjustments of production to price signals. This pattern is consistent with the presence of adjustment frictions in production, whereby supply reacts only gradually to price changes. These patterns are also in line with the heatmap evidence, which shows substantial dispersion across metals and horizons.

Finally, the comparison between early and late subsamples (Figure 11) confirms substantial changes in both the magnitude and the significance of elasticities over time.

Overall, the elasticity results reveal a clear asymmetry in adjustment mechanisms. Prices respond more strongly and more systematically to demand shocks than to supply shocks, while production responses to price signals remain limited in the short run. Although some evidence of increasing responsiveness over time emerges, these patterns are not

Figure 11 – Elasticities at different horizons: early versus late sample



Note: The figure compares elasticities estimated at different horizons. The left panel is based on early-sample estimates, while the right panel is based on estimates using the most recent data.

uniform and often lack support at conventional credible levels.

These findings reinforce the demand-driven interpretation obtained from the historical decomposition. At the same time, they highlight the presence of substantial heterogeneity across metals and over time, both in the magnitude and persistence of elasticities. This coexistence of common patterns and metal-specific dynamics underscores the importance of accounting for both aggregate forces and heterogeneous adjustment mechanisms in the analysis of metal price formation.

5. Robustness checks

This section presents several robustness checks to assess the sensitivity of our findings to alternative specifications. In particular, we examine the choice of the proxy for global economic activity, the specification of prior distributions, and the length of the rolling window used in the rolling elasticity analysis.[6]

5.1. Proxy for global economic activity

As a robustness check, we replace the Dry Freight Index used in the baseline specification with world real GDP—extracted from Stuermer (2018) and IMF World Economic Outlook Database—as an alternative proxy for global economic activity. While the Dry

[6]To save space, only the most relevant results are reported in the paper, while additional estimates are available from the authors upon request.

Freight Index captures global demand conditions through developments in international shipping markets, world GDP provides a more direct measure of aggregate economic activity. Overall, the main conclusions remain largely unchanged. In particular, as shown in Table A.2 in Appendix, metal-specific demand shocks continue to represent the dominant source of real price fluctuations across periods.

Using world GDP nevertheless affects the estimated elasticities and the relative contribution of aggregate demand shocks. In particular, price responses to aggregate demand shocks become larger under the GDP specification, especially for metals traded on the London Metal Exchange.[7] This result is economically intuitive. Since LME metals are heavily used in manufacturing, construction, and investment-related activities, their prices appear more sensitive to fluctuations in aggregate economic activity when the latter is measured directly by world GDP. By contrast, the Dry Freight Index is also affected by factors specific to maritime transport, including changes in freight costs, shipping capacity constraints, and temporary disruptions in trade flows.

Despite these larger elasticities, the contribution of aggregate demand shocks to overall price fluctuations does not increase proportionally. Historical decompositions depend not only on the magnitude of impulse responses but also on the statistical properties of the identified shocks. Since the Dry Freight Index exhibits substantially greater volatility than world GDP, replacing it with a less volatile measure of global activity modifies the allocation of price variation across shocks. In the alternative specification, aggregate demand shocks account for a somewhat smaller fraction of total price variation, while supply shocks explain a relatively larger share. Nevertheless, our main result, namely the dominance of metal-specific demand shocks in explaining mineral price dynamics, remains unaffected by the choice of the proxy used for global economic activity.

5.2. Sensitivity to prior distributions

We next investigate the sensitivity of our results to the specification of prior distributions. In particular, we progressively relax the informational content of the baseline priors. In a first alternative specification, informative priors on the elements of $\mathbf{A}$ and $\mathbf{H} = \mathbf{A}^{-1}$ are replaced by weakly informative Student-t distributions with 100 degrees of freedom, centered at zero with unit variance and truncated according to the theoretical sign assumptions. For $\det(\mathbf{A})$, we follow the same calibration strategy as in the baseline specification by approximating the distribution implied by these weakly informative priors on $\mathbf{A}$ with a non-central Student-t distribution. In a second specification, we retain the informative priors on $\mathbf{A}$ and $\det(\mathbf{A})$ while removing those imposed on $\mathbf{H}$. Finally, in a third specification, only the informative priors on $\mathbf{A}$ are maintained.

Table A.3 in Appendix reports the contribution of shocks to real metal price variation across periods under these alternative prior specifications. Overall, the results remain qualitatively very similar to those obtained in the baseline model. Metal-specific demand shocks continue to account for the largest share of price fluctuations, aggregate demand shocks remain the second most important source of variation, and supply shocks continue to play a comparatively smaller role. Although the precise magnitudes vary somewhat across specifications, the overall ranking of shocks and the main conclusions of the paper are preserved. These findings indicate that the dominance of demand-side forces does

[7] The detailed results are available upon request to the authors.

not depend on the particular choice of informative priors.

5.3. Sensitivity to the rolling window length

We also assess the sensitivity of the rolling elasticity estimates to the choice of window length. While the baseline analysis relies on a 50-year rolling window, Figure A.3 in Appendix reports the corresponding estimates obtained using 40-year and 70-year windows.

Overall, the main patterns identified in the baseline specification remain largely unchanged. In particular, the broad time evolution of elasticities is preserved across window lengths, and the differences observed across production quartiles remain qualitatively similar. Although alternative window lengths naturally affect the smoothness of the estimated series, the main conclusions regarding the evolution of adjustment mechanisms over time are robust to the choice of the rolling window. These results indicate that the observed trends are not driven by a particular choice of window length.

6. Conclusion

This paper investigates the historical determinants of real mineral commodity prices using a structurally identified VAR framework with incomplete identification. By combining historical decomposition and elasticity analysis, we provide a comprehensive assessment of the respective roles of supply and demand forces in shaping price dynamics over the long run.

Our results point to a clear and robust pattern: metal price fluctuations are predominantly driven by demand shocks. Both metal-specific and aggregate demand shocks play a central role across periods and metals, whereas the contribution of supply shocks is more limited and tends to decline over time. This demand-driven interpretation is supported by both the historical decomposition and the elasticity analysis.

The elasticity analysis further sheds light on the underlying adjustment mechanisms. Prices respond more strongly and more systematically to demand shocks than to supply shocks, while supply responses to price signals are generally weak and often short-lived. These findings suggest that production often adjusts only slowly to changing economic conditions, reinforcing the dominant role of demand in driving price fluctuations.

At the same time, the results reveal substantial heterogeneity across metals and over time. While common patterns emerge at the aggregate level, the magnitude, persistence, and statistical significance of elasticities vary considerably across markets. In particular, supply conditions appear to remain strongly metal-specific, even in the presence of shared demand dynamics.

These results do not provide evidence of a persistent increase in prices consistent with rising resource scarcity. Instead, price dynamics appear to be primarily driven by demand fluctuations rather than by tightening supply constraints. This suggests that, over the period considered, mineral commodity prices reflect cyclical demand conditions more than long-term scarcity pressures.

Taken together, our findings contribute to the literature on commodity price formation by providing new evidence on the relative importance of demand and supply forces in metal markets. More broadly, they suggest that analyses of resource price dynamics should account not only for aggregate demand conditions, but also for heterogeneous adjustment mechanisms across commodities. Our findings also have implications for policy debates on critical minerals, suggesting that price dynamics are more sensitive to global demand conditions than to short-run supply disturbances.

Several avenues for future research remain open. In particular, further work could explore the role of financial factors, technological change, and policy developments in shaping both demand and supply responses, as well as the implications of these dynamics for long-term resource availability and price formation.

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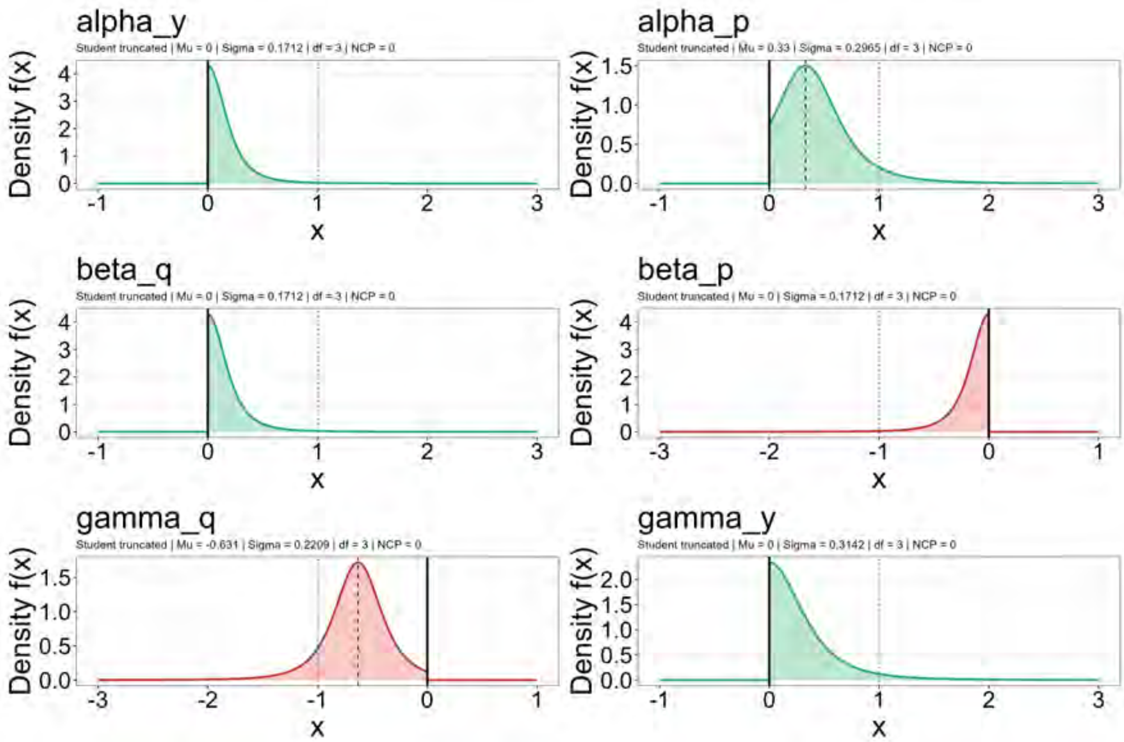
Appendix

Table A.1 – Mineral commodities included in the analysis

Alumina	Industrial Diamond	Platinum-Group Metals
Aluminum	Industrial Garnet	Potash
Antimony	Iodine	Pumice and Pumicite
Asbestos	Iron Ore	Rhenium
Barite	Iron Oxide Pigments	Salt
Bauxite	Kyanite and Related Materials	Sand and Gravel (Industrial)
Beryllium	Lead	Selenium
Boron	Lime	Silicon
Bromine	Lithium	Silver
Cadmium	Magnesium Compounds	Soda Ash (Sodium Carbonate)
Cement	Magnesium Metal	Steel
Chromium	Manganese	Strontium
Cobalt	Mercury	Sulfur
Copper	Mica (Natural), Scrap and Flake	Talc and Pyrophyllite
Diatomite	Mica (Natural), Sheet	Tantalum
Feldspar	Molybdenum	Tellurium
Fluorspar	Nickel	Tin
Germanium	Nitrogen	Tungsten
Gold	Peat	Vermiculite
Gypsum	Perlite	Wollastonite
Helium	Phosphate Rock	Zinc
Ilmenite	Pig Iron	

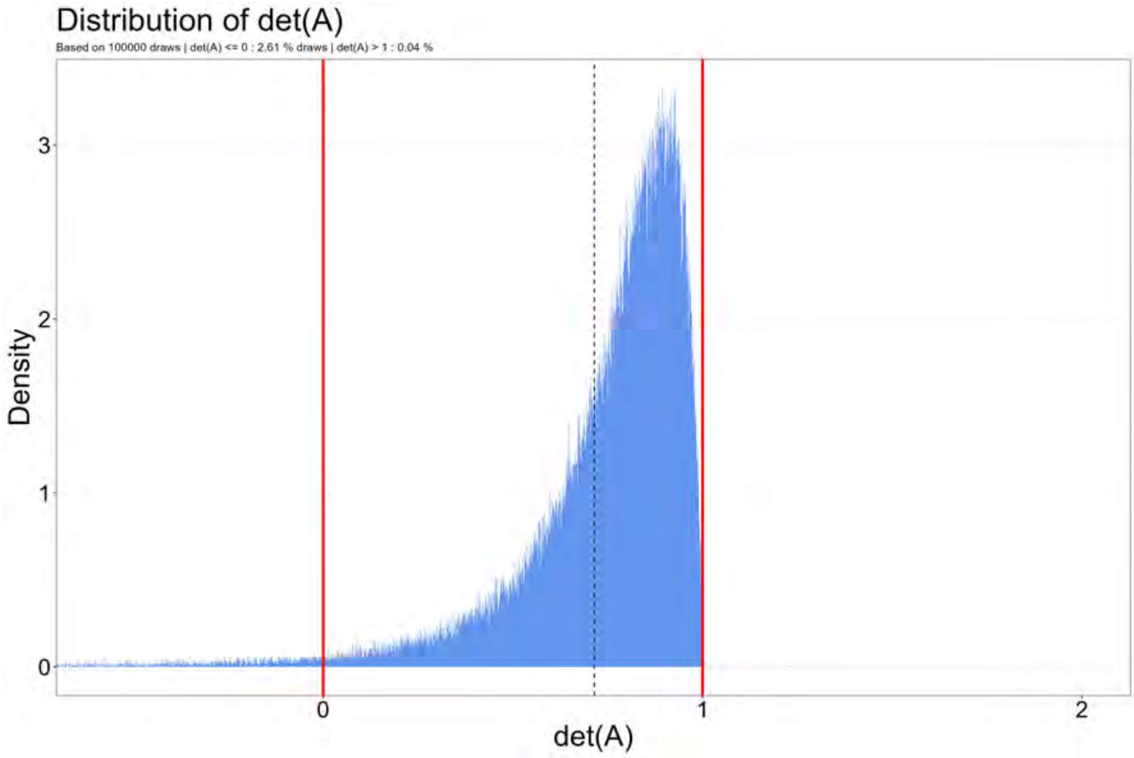
Note: This table lists the 65 mineral commodities included in the analysis.

Figure A.1 – Priors for the contemporaneous coefficients in $\mathbf{A}$



Note: The figure displays the prior distributions of the contemporaneous coefficients in matrix $\mathbf{A}$. Each prior is specified as a Student-t distribution with three degrees of freedom, truncated to satisfy the imposed sign restrictions. The location parameter is set to the empirical mean of the corresponding elasticity when available, and to zero otherwise. The scale parameter is calibrated so that the probability of observing values larger than one in absolute value matches the empirical frequency reported in the literature.

Figure A.2 – Distribution of $\det(\mathbf{A})$ implied by the prior on $\mathbf{A}$



Note: The figure reports the empirical distribution of $\det(\mathbf{A})$ obtained from 100,000 draws of the structural parameters using the prior distributions specified for matrix $\mathbf{A}$. Vertical lines indicate zero and one. The distribution is used to calibrate the prior on $\det(\mathbf{A})$ by matching the probability of negative values and the probability of values exceeding one.

Table A.2 – Contribution of shocks to real metal price variation across periods using world real GDP as a proxy for global economic activity

Periods	Metal-specific demand shocks	Aggregate demand shocks	Supply shocks
1900-1913	67.67	12.15	20.18
1914-1918	67.23	11.06	21.71
1919-1938	58.15	15.51	26.34
1939-1947	52.74	19.99	27.26
1948-1970	53.67	22.19	24.14
1971-1997	61.89	15.09	23.02
1998-2020	64.03	15.20	20.77

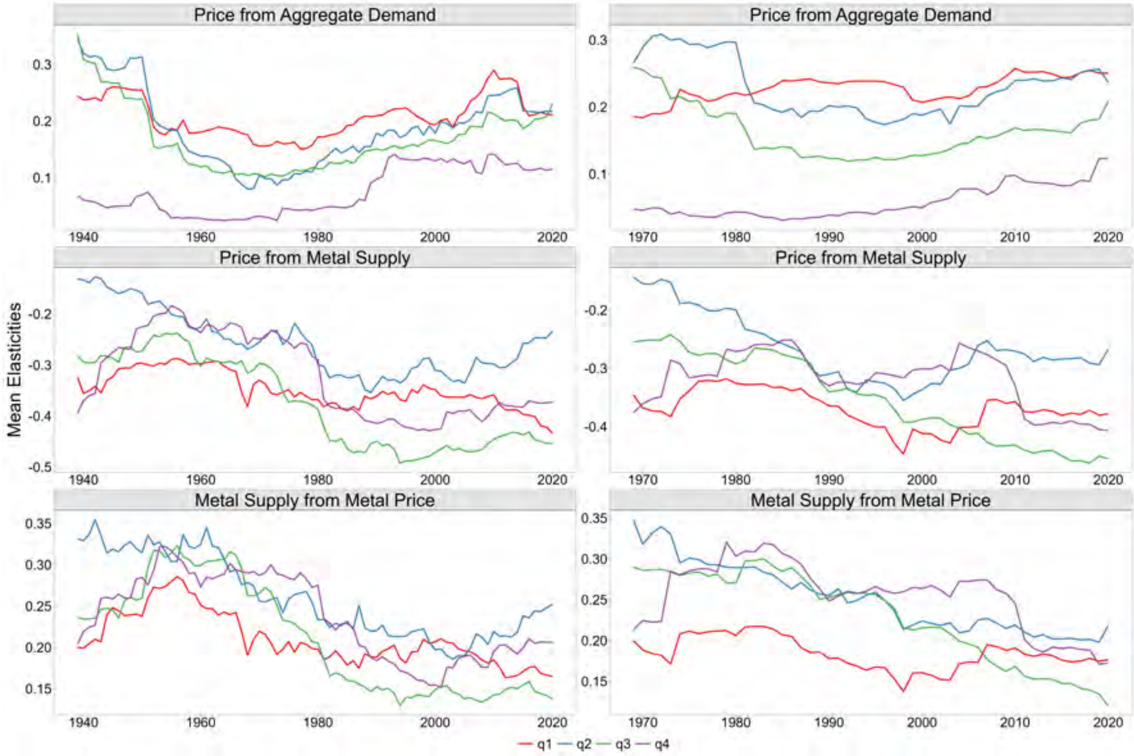
Note: Each column reports the share (in percent) of each shock in the total absolute variation of real prices induced by shocks. Periods are defined following Jacks and Stuermer (2020), isolating the First and Second World Wars, while the final period begins after the Kyoto Protocol.

Table A.3 – Contribution of shocks to real metal price variation across periods - Robustness to the specification of prior distributions

Periods	Metal-specific demand shocks	Aggregate demand shocks	Supply shocks
Case 1: Non meaningful priors on $\mathbf{A}$ and $\mathbf{H}$			
1900-1913	59.32	21.65	19.02
1914-1918	37.40	38.88	23.72
1919-1938	45.15	33.50	21.35
1939-1947	51.21	30.35	18.43
1948-1970	49.62	29.53	20.85
1971-1997	53.31	28.15	18.54
1998-2020	52.30	32.18	15.52
Case 2: Non meaningful priors on $\mathbf{H}$			
1900-1913	59.32	21.65	19.02
1914-1918	37.40	38.88	23.72
1919-1938	45.15	33.50	21.35
1939-1947	51.21	30.35	18.43
1948-1970	49.62	29.53	20.85
1971-1997	53.31	28.15	18.54
1998-2020	52.30	32.18	15.52
Case 3: Non meaningful priors on $\det(\mathbf{A})$ and $\mathbf{H}$			
1900-1913	58.05	15.59	26.37
1914-1918	38.82	29.99	31.19
1919-1938	44.97	27.74	27.29
1939-1947	48.86	28.01	23.13
1948-1970	49.05	25.30	25.64
1971-1997	54.32	22.48	23.21
1998-2020	53.79	26.14	20.07

Note: Each column reports the share (in percent) of each shock in the total absolute variation of real prices induced by shocks. Periods are defined following Jacks and Stuermer (2020), isolating the First and Second World Wars, while the final period begins after the Kyoto Protocol. Case 1: informative priors on the elements of $\mathbf{A}$ and $\mathbf{H} = \mathbf{A}^{-1}$ are replaced by weakly informative Student-t distributions with 100 degrees of freedom, centered at zero with unit variance and truncated according to the theoretical sign assumptions. Case 2: informative priors on $\mathbf{A}$ and $\det(\mathbf{A})$ are maintained, those imposed on $\mathbf{H}$ are removed. Case 3: only the informative priors on $\mathbf{A}$ are maintained.

Figure A.3 – Rolling elasticities by production quartiles (window sizes = 40 and 70)



Note: The figure reports rolling median elasticities computed over a moving window of size 40 (left panel) and 70 (right panel), aggregated by production quartiles. Diatomite is excluded due to extreme values affecting graphical readability.