WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Critical Minerals: Estimating Price Elasticity of Supply Using Mine-Level Data

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July 2025, WP #1002

Abstract

As the demand for critical minerals to the energy transition strongly grows, it is crucial to understand whether their supply is able to match it. In this paper, we address this question by estimating the price elasticity of supply for 8 minerals between 2000 and 2019, using mine-level production data with global coverage. We isolate global price variations related to mineral-specific demand shocks using a structural VAR with sign restrictions and study the reaction of mineral production to these price variations in a local projection framework. We find robust evidence of a significantly positive price elasticity of supply, reaching 50% on average in the five years following the shock, largely driven by silver, copper, and nickel. We explore how the location of mines, mine-level characteristics and market-level characteristics shape these elasticities. Among location factors, we find smaller elasticities for mines located close to conflicts. Such effects partly explain a smaller price elasticity of supply in Africa. Turning to mine-level characteristics factors, we find smaller effects for mines with larger proven reserves, a larger number of produced minerals and more than one owner. Finally, regarding market-level characteristics, we find smaller effects when the global production is more concentrated across mines. The magnitude and significance of estimated heterogeneity are stronger immediately after the shock and decrease over time, suggesting that producers adapt to their environment.

Keywords: Critical Minerals, Price Elasticity of Supply, Energy Transition.

JEL classification: C33, O13, Q3

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The authors thank participants to the Banque de France-Ferdi research seminar, as well as Bruno Cabrillac, Laurent Clerc, Vincent Fleuriet, Julien Gourdon, Patrick Guillaumont, Sylviane Guillaumont Jeanneney, and Hervé Le Bihan for useful comments. The ⓡ symbol indicates that the authors' names is random. The order has been drawn using the AEA author randomization tool and can be accessed using confirmation code n° To54RV34_n8, or here.

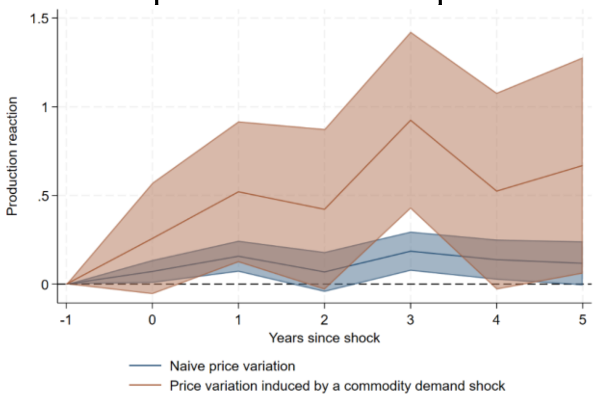
NON-TECHNICAL SUMMARY

The transition to a low-carbon global economy will require a strong increase in the use of critical minerals and metals. Whether the supply will be able to adjust to this increase in demand is an open question, and it is important to understand its determinants. Among them, prices are likely to be crucial. Indeed, an increase in the latter is likely to boost production in the long-run, higher expected returns fostering technological innovations and geological exploration. But it might also increase production in the short-run, through a change in the intensity or production. While it is important to understand the sensitivity of production to prices, especially as increased demand is expected to put upward pressure on the latter, there are few recent estimations of the price elasticity of supply, and they rarely focus on minerals that are critical to the energy transition.

In this paper, we assess this question by leveraging mine-level data from Jasansky et al. (2023), focusing for the period 2000-2019, on the production (in tons) of 8 minerals essential to the energy transition, namely cobalt, copper, lead, molybdenum, nickel, platinum-group metals, silver, and zinc. These minerals represent about 70% of the basket of the IMF's Energy Transition Index, and their production in the dataset, based on the information of 318 mines located in 43 countries, covers more than 20% of global production over the period of interest. We examine whether the production of these minerals, at the mine-level, reacts to shocks on their global prices, on a time window ranging from 0 to 5 years. In order to estimate a proper price elasticity of supply, we focus on the reaction of production to price movements induced by mineral-specific demand shocks.

To do so, we first estimate, for each mineral, a 3-variable structural VAR model with sign restrictions, including global economic activity, global real mineral price, and global production, from 1912 to 2019. We define three types of shocks, that we identify through sign restrictions following Boer et al. (2024), namely aggregate demand shocks (having a positive effect on mineral prices, mineral production and economic activity), mineral-specific supply shock (having a positive effect on mineral production and economic activity, but a negative effect on mineral prices) and mineral-specific demand shock (having a positive effect on mineral production and prices, but a negative effect on economic activity). Based on this methodology, we isolate the variations of mineral prices that are due to a mineral-specific demand shock, and study the reaction of production at the mine-level, using a local-projection approach, and controlling for mine-mineral fixed effects.

Average critical mineral production reaction to price shocks on minerals



Source: USGS, IMF, authors' computation.
Note: the blue line represents the production reaction to a raw price variation occurring between year -1 and year 0. The brown line represents the production reaction to a mineral-demand-shock-induced price variation between year -1 and year 0. The respective confidence intervals are at the 90% levels.

Our baseline estimation indicates a rapid and strong reaction of production to price variations induced by a demand shock, with an elasticity reaching about 50% one year after the shock, which

remains broadly stable up to 5 years. This result is robust to a large number of robustness checks, and appears larger than existing estimates. This difference might come from the fact that, contrarily to existing studies, our elasticities are based on micro-level production.

The estimates are heterogeneous across minerals, as silver, copper, and nickel drive the results. They are also affected by characteristics of the global mineral market, of the mines, and of their location. Regarding the characteristics of the global mineral market, we find that the price elasticity of supply is lower for minerals with a greater concentration of production (measured through a Herfindahl-Hirschmann index on mine-level production), but that the implementation of export restrictions measures does not significantly affect the reaction of production. Regarding the characteristics of mines, we find that the reaction is stronger for the primary mineral they produce (defined either in volume or in value), and that the production of non-primary minerals within a mine is more sensitive to the price of the primary-mineral than to their own price. Mines owned by more than one company, having larger proven reserves and producing more than one mineral also tend to have lower reactions. Finally, regarding the location of the mine, we do not find that local economic activity or proximity to transport infrastructure affects the price elasticity of supply, but we document that greater proximity to conflict reduces the latter. This partly explains a lower price elasticity of supply in Africa, which faces a stronger intensity of conflicts that other continents.

Minerais critiques : une estimation de l'élasticité-prix de l'offre à l'aide de données minières

RÉSUMÉ

Alors que la demande de minerais critiques à la transition énergétique augmente fortement, il est crucial de comprendre si l'offre est capable de s'ajuster pour y répondre. Dans cet article, nous abordons cette question en estimant l'élasticité-prix de l'offre de huit minerais entre 2000 et 2019, à l'aide de données production à l'échelle de la mine, et ayant une couverture mondiale. Nous isolons les variations de prix mondiaux des minerais dues à des chocs spécifiques de demande, grâce à un VAR structurel à restrictions de signe, et étudions la réaction de la production de minerais à ces variations de prix dans le cadre de projections locales. Pour la plupart des minerais, nous estimons une élasticité-prix de l'offre significativement positive et robuste. En moyenne, elle atteint 50 % au cours des cinq années suivant le choc, avec des effets plus marqués pour l'argent, le cuivre et le nickel. Nous explorons dans quelle mesure ces élasticités sont affectées par la localisation de la mine, ses caractéristiques, et celles du marché des minerais. Parmi les facteurs liés à la localisation, nous documentons des élasticités plus faibles pour les mines localisées à proximité de conflits. Ceci explique en partie des élasticités plus faibles sur le continent africain. S'agissant des caractéristiques de la mine, nous trouvons des élasticités plus faibles pour les mines dont les réserves prouvées sont plus grandes, produisant un plus grand nombre de minerais, et détenues par plus d'une entreprise. Enfin, s'agissant des caractéristiques du marché, nous trouvons des élasticités plus faibles lorsque la production mondiale est plus concentrée. L'ampleur et la significativité de ces hétérogénéités sont plus fortes immédiatement après le choc, et décroissent au cours du temps, suggérant que les producteurs s'adaptent à leur environnement.

Mots-clés : minerais critiques, élasticité-prix de l'offre, transition énergétique.

1.Introduction

The transition to a low-carbon global economy goes hand in hand with a sharp increase in the use of minerals and metals (Miller et al., 2023; Boer et al., 2024). Clean energy technologies - from wind turbines and solar panels to electric vehicles and battery storage - require a wide range of minerals. For example, electric vehicles use six times more minerals than a conventional car (IEA, 2021). According to the IEA's 2021 projections, the scenario of limiting global warming to 2°C implies a fourfold increase in demand for critical minerals by 2040.

Increasing the supply of minerals critical to the energy transition is therefore of paramount importance to meet the growing demand in the coming years. Economic factors, especially prices, are crucial to stimulate supply. While in the medium- to long-run, geological discoveries as well as technological innovations are partly driven by expected future returns, in the shorter term, price changes can also influence the intensity of production. An accurate measurement of the price elasticity of supply is essential to better grasp how production adapts to demand shocks and price dynamics in the short-run, and to design credible transition scenarios in a context of expected growing demand and upward pressure on prices (Boer et al., 2024). Yet, recent estimations of price elasticities of mineral supply are scarce, implying that recent general equilibrium models that need to include them as inputs often rely on largely outdated data (see for instance Fally and Sayre, 2018; or Dahl, 2020).

To answer this question, we use mine-level data from Jasansky et al. (2023), focusing on the production of 8 minerals essential to the energy transition: cobalt, copper, lead, molybdenum, nickel, platinum, silver, and zinc[1]. We examine whether mine-level production is sensitive to price movements, focusing on a time window ranging from 0 to 5 years after the price shock. More specifically, we focus on the reaction of output to price movements induced by mineral-specific demand shocks, which can be interpreted as price elasticity of supply. We first use the method of Boer et al (2024) to isolate the component of the price change that is exclusively due to a mineral demand shock. We then estimate the dynamic response of mine-level mineral production in a local projection setting, up to 5 years ahead. Our results, based on the production of 318 mines in 43 countries from 2000 to 2019, show that production reacts immediately after a price variation induced by a mineral-specific-demand shock, and that the elasticity hovers around 50% in the 5 years following the shock. The average elasticity is mainly driven by silver, copper, and nickel, with different reaction lags across minerals. We also document spillover

[1] These 8 minerals represent about 70 % of the basket of the IMF's Energy transition Index.

effects between commodities, leveraging on the fact that most mines produce several minerals. We document that non-primary minerals (i.e. not the most produced within the mines, either in value or in volume) react to the price variations of the primary mineral produced within the mine. Finally, we explore the role of mine-specific factors (location), of other mine-specific factors (number of minerals produced by the mine, reserves) and of market-specific factors (market concentration of the mineral, number of global export restrictions of the mineral) in shaping the price elasticity of supply.

We find substantial heterogeneity, which is however more pronounced immediately after the shock. Regarding location-specific factors, we find that mines located close to a conflict zone and in Africa have lower price elasticities of supply after one year. Once controlling for the interaction effect of conflict, the effect of Africa disappears, suggesting it is mainly driven by the higher-than-average prevalence of conflicts on the continent. In the outer range of the projection horizon (three to five years), we do not find significant heterogeneity. Turning to mine-specific factors, we find that, after one year, mines with larger proven reserves, mines producing numerous minerals, or with more than one owner have smaller elasticities. We also find that mineral-specific price elasticities of supply are lower when the global production of the mineral is more concentrated. However, these interaction effects tend to weaken in the outer range of the projection horizon (three to five years). In addition, we find no significant effect of potentially mitigating factors such as proximity to transport infrastructure, level of local development or export bans.

One of the main limitations of our study is that, even though the mine-level data we use encompass an important share of global production, they under-represent some important players (notably China). The implications are likely to be mixed for our results: on the one hand, omitting some key players may limit the external validity of our findings; on the other hand, this reduces the risk that our sample contains large market makers, which production might have an impact on global prices, thus limiting our identification strategy. Regarding the latter point, we perform several tests in order to ensure that this sample limitation does not alter our conclusions. These tests show that our results are insensitive to the size of sampled mines (suggesting that most of them are price-takers), and to the exclusion of mines from the largest producing, exporting, or importing countries. Likewise, controlling for Chinese imports of the minerals does not affect the results. All in all, even though focusing on a subset of mines limits the external validity of the results, it is unlikely to undermine their internal validity.

Our study contributes to the literature on the price elasticity of supply for energy transition metals by using mine-level data for eight critical minerals. While there was considerable interest in the question of mineral markets and mineral production in the 1970s and 1980s[2], to our knowledge only few papers have examined this supply sensitivity for metals critical to the low-carbon transition recently (Fernandez, 2019; Fu et al., 2019; Boer et al., 2024; Bogmans et al., 2024), and they usually have low or moderate price elasticity of supply. This has resulted in a gap in the literature focusing on the price elasticity of supply for critical minerals that have only recently experienced a surge in global demand (such as cobalt or molybdenum). In addition, all available studies are limited to the use of macroeconomic aggregate time-series data (at the country- or even at the world-level) and have not made use of recently available micro (mine-level) datasets.

Our study advances this literature in several ways. First, our estimated price elasticities of supply from disaggregated mine-level data are in the higher range of existing estimates. This suggests that studies using aggregate production data suffer from aggregation bias, as discussed by Bjørnland et al. (2021) in the context of oil supply, where aggregation can mask local variability and lead to underestimated elasticities. Second, micro-level data allow us to account for heterogeneity at the mine level. This approach is consistent with findings in the literature on the price elasticity of supply for oil, which show considerable variability across countries (Caldara et al., 2019) and within countries (Newell & Prest, 2019; Bjørnland et al., 2021). Specifically, we find that price transmission is shaped by various factors, including conflicts, size of the reserves, ownership of the mine, and market concentration. Third, the use of mine-level data allows us to control for unobserved factors through fixed effects, leading to better identification and more precise elasticity estimates. Finally, our study extends the scope of research by including critical but previously understudied minerals - such as platinum, molybdenum and cobalt - that are essential to the energy transition.

The remainder of the paper is structured as follows. Section 2 presents the data we use and descriptive statistics. Section 3 presents the estimation framework. Section 4 presents the results. Section 5 discusses the results in light of the literature. Section 6 concludes.

[2] Several studies find low price elasticity of supply in the 1990s for a wide range of different minerals: bauxite-aluminium (Hojman, 1981; Fisher an Owen, 1981), copper (Fisher et al., 1972; Suan Tan, 1987), tin (Chhabra et al., 1979), tungsten (Suan Tan, 1977), uranium (Trieu et al., 1994; Amavilah, 1995), zinc (Gupta, 1982). Empirical literature on the price elasticity of supply for mining products has largely declined since then. Furthermore, according to Dahl (2020), the number of estimates of price elasticities of supply in the literature is more than ten times lower than the number of estimates of the price elasticity of demand.

2.Data and descriptive statistics

2.1 Mine-level production data

We use the data set data from Jasansky et al. (2023) which covers 1,171 individual mines for 80 different minerals between 2000 and 2020. Since mines may produce different minerals at the same time, each observation is defined at the mine-mineral-year level. Additionally, the sample is not perfectly balanced, as some mines have opened after 2000 or have closed before 2020. Based on this, the full raw dataset of mineral production between 2000 and 2020 comprises 9,423 observations. The dataset reports the volume, in tons, of the *valuable content* of minerals produced from different metal ores and non-metallic minerals. In the remainder of the paper, we refer to this quantity as *mineral production.*

To interpret this variable, it should be kept in mind that the *valuable content* represents only a subset of the extracted metal ores and non-metallic minerals, with varying proportions depending on ores and mines. Within a given ore can coexist several types of valuable minerals, with different levels of concentration (head grade), and of recovery rates. The share of extracted ores transformed into valuable materials is likely to be mainly affected by geological or long-run technological factors. Furthermore, the extracted raw metal ores and non-metallic minerals every year are not necessarily fully processed immediately to extract its valuable content: part of them might be stockpiled to be processed during following years. Therefore, our main variable of interest excludes extracted material that is stockpiled during the year but may include destocked ore (processed in the current year). Information on yearly stocked and destocked quantities of mineral would be useful, given our focus on a rather short-run production reaction, and likely reactions of stockpiling to economic fluctuations, but it is only partially available. However, additional information data from the dataset of metal ores and non-metallic minerals[3] give insights on the extent of stockpiling. When comparing the tons of *mined* and of *processed* minerals, we observe that, on average, across 5,339 year-mine-ore observations, 76 % entail similar values of extracted and processed minerals. When the two values differ, their median absolute deviation is of 8.7 %, suggesting stockpiling is unlikely to strongly affect our results.

Focusing on this mineral production variable, we proceed to several sample selections (see Appendix A). First, we exclude year 2020, the starting year of Covid-19, which accounts for

[3] This dataset is called "*minerals*", while the dataset on valuable content is called "*commodities*".

only 50 observations. Second, we keep only minerals (i) present in at least one of the selected lists of strategic raw materials (World Bank (2020) and IEA (2021)) and (ii) with more than 50 observations in the dataset. Additionally, we impose that the production of mines covered by Jasansky et al. (2023) are representative enough of global production and represent at least 20 % of the latter on average between 2000 and 2018, according to the representativeness information provided with the data set (Jasansky et al., 2023).

Table 1– Yearly production variations within mines for 9 selected minerals over 2000-2019 (final dataset)

	Average yearly variation within mines	
	Mean	SD
Copper/Copper cathode	0.021	0.772
Silver	0.032	0.612
Zinc	0.014	0.564
Lead	0.028	0.530
Nickel	0.025	0.515
Molybdenum	0.035	0.386
Cobalt	0.079	0.374
Platinum et al.	0.038	0.178

Using these criteria, our final dataset contains 6,068 observations for the following 8 minerals[4]: copper and copper cathode[5] (34.3 % of observations), silver (23.2 %), zinc (13.9 %), lead (10.2 %), nickel (8.1 %), molybdenum (4.4 %), platinum group metals[6] (4.1 %) and cobalt (1.7 %). Table A.1 in Appendix shows the full sample selection process. Most of the deleted observations come from the exclusion of gold, which represented 27.8 % of the raw sample[7]. Table 1 represents the average yearly variations of production within mines for each mineral over the sample. We observe significant heterogeneity of both the average variation and the volatility of selected minerals' outputs. Most minerals show positive yearly average variations, with most values ranging between +1.5 % and +4 %, with a particularly strong surge for cobalt

[4] Note that iron is also considered as critical mineral according to our selected lists of strategic raw materials, and has 228 observations in Jasansky et al. (2023). However, the latter represent only 3.3 % of global production between 2000 and 2018 according to Jasansky et al. (2023) (see Table A.1 in Appendix). We therefore exclude iron from the baseline analysis, but include it in a robustness check.

[5] We keep observations of copper cathode production and consider it as copper production if there is no copper production in the same mine and year.

[6] Platinum Group Metals (PGM) include platinum, palladium, ruthenium, rhodium, osmium, and iridium. However, while some mines report detailed production of each PGM produced, other mines report only the aggregate production of all PGM produced (under the name "pgm"). Therefore, we sum all values for each PGM produced and values for aggregated PGM to obtain total PGM production. It must also be noticed that a few mines also include gold in PGM production. As we cannot retrieve the specific value of gold production, we keep it in our data.

[7] However, in an additional exercise, we test whether the production response of gold-producing mines differ from others.

(average yearly increase of +7.9 %). Standard deviations of productions are also heterogeneous, ranging from 0.18 (platinum and platinum group minerals) to 0.77 (copper).

The final dataset covers 318 mines in 43 countries from 2000 to 2019. Observations are however unevenly distributed, with a majority coming from a few countries in South America, North America and Oceania. Eight countries alone represent over 75 % of observations: 16.3 % of observations come from Peru, 11.7 % from Canada, 9.7 % in Mexico, 9.3 % from Chile, 8.7 % from Australia, 6.2 % from Kazakhstan, 6.1 % from the US and 5.6 % from South Africa (Africa representing 9.3 % of observations). Analyzing the data at the country and mineral level (Table A.2 in Appendix), we find that, unsurprisingly, the largest productions are located in South America, North America and Australia for most minerals (all excluding cobalt and platinum). African countries are lead producers of cobalt (Democratic Republic of Congo) and platinum (South Africa). Yearly reported production is particularly uniform for copper (average yearly Herfindahl-Hirschman Index (HHI) of 434), silver (760), and zinc (914), while it is quite concentrated for platinum (HHI higher than 4,500 for all categories of PGM) and cobalt (HHI of 5,787). Other minerals have HHI ranging between 1212 and 1438.

We document that most mines produce several types of minerals[8]. In Table A.3 in Appendix, we show the most represented combinations among the selected minerals[9]. Among all observations, 21 % of mines produce only one mineral and respectively 25 %, 35 % and 19 % of mines produce 2, 3 and at least 4 minerals. Most represented combinations involve copper, silver, or zinc. However, most combinations of minerals are asymmetric in that they are often characterized by a "main" mineral and one or more "by-products" (minerals that are co-produced in mines where they are not the main mineral). In Table A.4, we indicate for every observed pair of minerals, the main extracted mineral (both in value and in volume) and the "by-product". In our dataset, cobalt, lead, molybdenum, and silver are mostly extracted as by-products of other major minerals when focusing on volumes extracted. This finding is less clear-cut for silver when using data in value. Conversely, copper, nickel, and zinc are often the major mineral of their respective mines. This classification is consistent with the literature on the subject (see for instance Afflerbach et al., 2014).

[8] This analysis is based on the data we selected. The dataset also provides information about the produced mineral among all possible minerals reported in the data. Such an analysis yields broadly similar results, the main difference being a large presence of gold in the results.

[9] Which means that mines producing only one mineral in our sample may in reality produce more than one mineral if the other minerals are not those we are interested in.

In terms of sample coverage, Jasansky et al. (2023) show that the raw data cover generally from 20 % to 40 % of global production, with a larger coverage for copper (65 %). A main issue with these data is the small coverage of Chinese production. Furthermore, in Table A.5, we identify countries representing at least 25 % of global production, imports and exports: we use this information later in the paper to exclude the main market-making countries from the sample. We control for Chinese production in alternative specifications.

2.2 Global series

To identify mineral-specific demand shocks, we gather several global series between 1912 and 2019. For each of the 8 selected minerals, we gather global production data from USGS, and real global prices from USGS and Officer (2025), where nominal prices from USGS are deflated by US CPI data provided by Officer (2025)[10]. We gather real global GDP by combining data from Jacks and Stuermer (2020) from 1912 to 1979 and from the IMF from 1980 onwards. In a robustness check, we also control for real cotton prices, whose variations are likely to capture effects from aggregate commodity demand shocks, but not from mineral-specific shocks: it therefore further helps capturing part of the aggregate demand shocks. To do so, we use directly data from Jacks and Stuermer (2020) from 1912 to 2014, and by combining IMF PCPS nominal cotton prices with US CPI from Officer (2025) from 2015 to 2019. All series are normalized to 100 in 1912.

3. Empirical framework

The aim of this paper is to estimate the price elasticity of supply, i.e. the percent variation of supply to a 1% variation of prices. In our context, we observe $Q_{i,j,t}$ the production of mineral *j* in mine *i* during year *t*, as well as $P_{j,t}$ the real international price of mineral *j* during year *t*. Following Boehm et al. (2023), we denote Δ_h the difference in a variable between year *t- 1* and *t+h*, such that $\Delta_h\, y_t = y_{t+h} - y_{t-1}$. In this setting, we start by estimating the reaction of produced quantities between *t-1* and *t*, to a price variation occurring between *t-1* and t. This quantity can be expressed as the following elasticity:

$$\varepsilon_h = \frac{\Delta_h\, ln\, Q_{i,j,t}}{\Delta_0\, ln\, P_{j,t}} \qquad (1)$$

[10] This approach follows that of Jacks and Stuermer (2020). Using the same methodology, we also compute the real price of gold in a robustness check. For copper, USGS price data are missing for years 2019 and 2020. The nominal prices for these years are imputed from the IMF PCPS dataset (after checking that, on historical values, USGS and PCPS nominal prices are virtually identical). The resulting nominal series is then transformed in a real price series as described above.

This elasticity can be estimated through the following "naive" regression, using the local projection framework of Jordà (2005):

$$\Delta_h \ ln \ Q_{i,j,t} = \alpha_h + \pi_h \Delta_0 \ ln \ P_{j,t} \rho_t + \mu_{i,j} + \omega_{i,j,t} \quad (2)$$

We include mine-mineral fixed effects $\mu_{i,j}$[11], which aim at estimating effects within each mine and mineral across years. We also include year fixed effects ρ_t to capture shocks that are common to all minerals and all mines each year, such as shocks on the global business cycle (aggregate demand or aggregate supply shocks). Interaction of mineral and year fixed effects are impossible, since the price variation for a given mineral in a given year is common to all mines. In the baseline analysis, we estimate this local projection up to h=5.

Following the interpretation of Boehm et al. (2023), we interpret $\widehat{\pi_h}$ as the estimated value of ε_h. However, this quantity cannot be interpreted as a *price elasticity of supply*. Indeed, the joint movements of prices and quantities can result from movements of both the supply and demand shocks. Estimating the price elasticity of supply using production and price data therefore requires estimating the production response to the part of price variation arising from a mineral-specific demand shock.

To isolate the contribution of mineral-specific demand shocks to aggregate prices, we build a structural VAR with sign restrictions following the baseline methodology of Boer et al. (2024). For each of the 8 minerals, we build a 3-variables VAR including real global activity, global mineral production and real global mineral prices, between 1912 and 2019, all taken in log values. We include three shocks identified through sign restrictions (see Table B.1 in Appendix): 1) an aggregate demand shock (AD) with positive effects on prices, economic activity and production; 2) a mineral-specific supply shock (MS) with positive effects on economic activity and production but negative effects on prices; 3) a mineral-specific demand shock (MD) with positive effects on prices and production but a negative effect on economic activity. As in Boer et al. (2024), our baseline model includes dummies for the two world wars (starting at the beginning and ending three years after the end of the war) and we control for time trends and for the real price of cotton. The rationale for time trends is that mineral-specific long run factors (for instance geological or technological) might affect their global production

[11] Note that, regarding copper/copper cathode and minerals of the platinum group, we link the reactions of the production to the price of the main related mineral. Namely, the production of copper/copper cathode is compared to shocks on the price of copper, and the production of platinum group metals to the price of platinum. However, we maintain separate fixed effects for copper/cathode and each mineral of the platinum group, in order to capture potential heterogeneity at the finest level possible. Introducing a single fixed-effect (namely a "copper" fixed effect and a "platinum" fixed effect) have very marginal effects on the results.

and prices. The rationale for controlling for the price of cotton is that, in the setting of our VAR, its variations are likely to capture effects from aggregate commodity demand shocks, but not from mineral-specific shocks. Cotton is a globally traded commodity, whose prices are likely to be affected by aggregate demand shocks in the same way as mineral prices. As cotton is not a substitute to critical minerals, its prices are unlikely to be affected by mineral-specific shocks. Including such a variable in the analysis therefore further helps capturing part of the aggregate demand shocks. Details of these estimations are presented in Appendix B.

Using this setting, we can decompose $ln\ P_{j,t}$ as such:

$$ln\ P_{j,t} = ad_{j,t}^{P} + ms_{j,t}^{P} + md_{j,t}^{P} + r_{j,t}^{P} \qquad (3)$$

Where $ad_{j,t}^{P}$ is the contribution of the aggregate demand shock to the log-level of the real price of mineral j in year t, $ms_{j,t}^{P}$ is the contribution of the mineral-specific supply shock, $md_{j,t}^{P}$ is the contribution of the mineral-demand shock and $r_{j,t}^{P}$ is a residual.

Table 2 – Raw price variations vs price variations induced by mineral-specific demand shocks

	Raw price variations – 2000/2019		**Price variations induced by mineral demand shocks – 2000/2019**	
Mineral	Mean	SD	Mean	SD
Copper	0.043	0.222	0.001	0.031
Silver	0.034	0.215	-0.016	0.050
Zinc	0.021	0.276	-0.001	0.044
Lead	0.020	0.165	0.003	0.042
Nickel	0.013	0.315	-0.001	0.033
Molybdenum	0.054	0.426	0.008	0.067
Cobalt	-0.016	0.363	-0.003	0.006
Platinum	0.048	0.410	0.006	0.061

Table 2 presents descriptive statistics on raw price variations and demand shocks: the latter are on average from 2 to 10 times lower than the former, and are of opposite signs for silver, zinc and nickel. Overall, aggregate demand shocks mainly drive price variations and mineral-specific demand shocks tend to represent the smallest contributions. Furthermore, in Figure C.1 in Appendix, we document the autocorrelation of the price variations induced by mineral-specific demand shocks, which may affect interpretation (discussed later). We show that, for a given variation of prices induced by a mineral-demand shock between t-1 and t, only part of it remains in horizons t+h[12]. On average, a 1-% increase in prices due to a mineral demand shock between t-1 and t is associated with an increase of about 0.8/0.9 at horizon h=1 and of about 0.4 to 0.6 at horizons greater than 2. After two years, only about half of the initial price variations induced by a mineral specific-demand shock permanently remains in mineral prices.

Using this decomposition, our baseline equation for the price elasticity of supply is therefore:

$$\Delta_h \ ln \ Q_{i,j,t} = \beta_h + \theta_h \Delta_0 \ md_{j,t}^P + \rho_t + \mu_{i,j} + \varepsilon_{i,j,t} \qquad (4)$$

The estimated parameter of interest is $\widehat{\theta_h}$, which captures the average percent change of production between *t-1* and *t+h* for a 1 % increase in prices due to a *one-time* mineral-specific demand shock between *t-1* and *t*. The fact that the shocks on prices between *t-1* and *t* only partially persist in subsequent years implies that our production reaction estimates at horizons *h* are likely conservative. We document this by estimating *h*-horizon production reactions in the spirit of Boehm et al. (2023). By contrast to the reaction to a one-time price variation that we estimate in the baseline equation (4), the *h*-horizon production reaction estimates the reaction of production at horizon h induced by the *cumulated* variation of variation of prices induced my mineral-specific demand shock over this horizon h. We estimate it through the following specification:

$$\Delta_h \ ln \ Q_{i,j,t} = \beta_h + \widetilde{\theta_h} \Delta_h \ md_{j,t}^P + \rho_t + \mu_{i,j} + \varepsilon_{i,j,t} \qquad (5)$$

In which $\Delta_h \ md_{j,t}^P$ is instrumented by $\Delta_0 \ md_{j,t}^P$. As documented by Boehm et al. (2023), the estimated value of $\widetilde{\theta_h}$ in this instrumental variable setting corresponds to *h*-horizon elasticity.

We also compare our baseline to an approach generally used in this literature. The latter uses aggregate macroeconomic series and the price elasticity of supply is generally defined, following Kilian and Murphy (2014), as the aggregate mineral production response to the mineral demand shock, divided by the price response to the mineral demand shock. In our case, the production data is disaggregated at the mine level and we cannot use this approach. One way of bridging this gap is to estimate equation (2), by instrumenting the raw price variation $\Delta_0 \ ln \ P_{j,t}$ by the median mineral-specific demand shock derived from the VAR. We show that our baseline results are broadly comparable to results using such an approach.

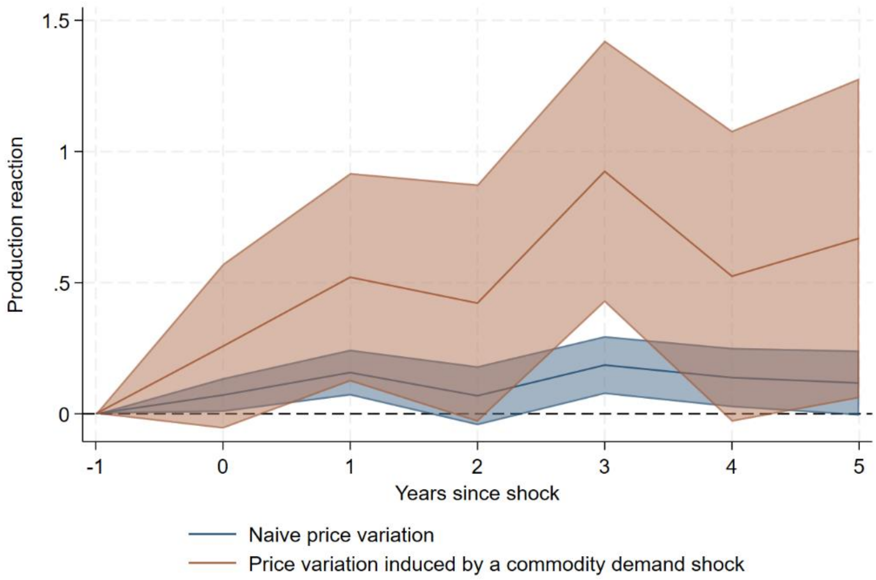
[12] Namely, we instrument the cumulated variation of prices induced by mineral-specific demand shock ("md price variations") over horizon h by the one-time md price variation between t-1 and t in a yearly panel of global prices ("unweighted" panel). The "weighted" panel represents the same analysis, but within the framework of the first stage of the *h*-horizon price elasticity of supply, that we document in the next section.

4.Main results

4.1 Baseline local projection

In this section, we present our main results. Figure 1 presents the results of the baseline local projection. The coefficients associated to this figure are reported in Table C.1 in the Appendix.

Figure 1 – Average production reaction to price shocks on minerals



Note: the blue line represents the production reaction to a raw price variation between occurring between year -1 and year 0 (Equation 2). The brown line represents the production reaction to a mineral-demand-shock-induced price variation between year -1 and year 0 (Equation 4). The respective confidence intervals are at the 90 % levels.

Three main results emerge. First, the production response to the simple price variation ("naive shock") is positive and overall significant, but of low magnitude (from 5 % to 20 %). Second, the production response to the mineral-specific demand shock on prices are much larger, averaging about 50 %, and with values ranging between 20 % and 100 %. Third, the effect of demand shocks to production seems rather fast: it reaches 52 % at $h=1$ and then fluctuates around 60 % from horizon $h=2$ to horizon $h=5$. These estimates represent an upper bound of the existing estimates of price elasticities of supply for energy transition minerals.

4.2 Robustness analysis

In this section, we discuss various robustness tests on the aggregate effect. Table 3 presents a set of alternative specifications, in which we control for different combinations of fixed effects (columns (2) and (3)). In column (2), we control separately for mineral, mine and year fixed effects, without any interaction between mineral and mine fixed effects. The results are very close to the baseline presented in column (1), with a slightly smaller magnitude. In column (3), we do not include mine fixed effects but interact mineral and year fixed effects with a country fixed effect. The rationale for country fixed effects is that country-level strategies may favor mining industries, varying both across minerals and over time, and affect the reaction of producers to global prices[13]. The interaction of country and year fixed effects aims at capturing any time-varying policies at the country level that may affect the development of all mineral productions altogether. The interaction of country and mineral fixed effects aims at capturing the country-specific policies, invariant over time, which might differ across minerals. In this specification, the effects are broadly comparable to the baseline, albeit a little smaller both in terms of magnitude and significance. In column (4), we maintain the interaction of year and country fixed effects but combine it with the mine-mineral fixed effects from the baseline. The results are comparable to the baseline, and if anything, slightly higher.

Other columns of Table 3 present additional robustness checks based on the baseline specification, but with alternative controls. In column (5), we add iron to the baseline specification: the results remain close to the baseline. We then test different price variations induced by mineral demand shocks, derived from VARs controlling for the real price of cotton (column (6)) or for trends (column (7)). In column (8), we control for price variations induced by mineral-specific supply shocks[14]. In column (9), we control for two lags of the contribution of the mineral-specific demand shock to the price level, and in column (10), we control for two lags of mineral production. In column (11), we control for both these sets of covariates. The limit of two lags in column (10) is dictated by the small time span of production series: including larger number of lags drastically reduces the sample size. We apply the same number of lags to the specification of column (9) for comparability of the results.

We also present specifications with only mines having at least 5 years of observations (column (12)) and controlling for an interaction between the real price of gold and a dummy indicating whether the mine produces gold (column (13)). In column (14), we drop the main market-making countries (based on the information from Table A.5 in Appendix). In column (15), we drop mines located in China, and in column (16), we control for Chinese imports of each mineral. Finally, in column (18), we check that our analysis is not driven entirely by large

[13] This strategy is especially relevant for price-taking countries or firms, which are unlikely to affect global prices. For those countries or mines that are market-making, such country strategies might also affect global prices, and we deal with these issues in separate regressions in Table 3.
[14] Note that controlling for price variations induced by aggregate demand shocks is not relevant here, since we already control for year fixed effects.

swings on global markets, by excluding the main booms and busts of mineral prices, i.e. observations of the top decile of absolute real price variations (i.e. 42 % in absolute value).

The results are largely robust to these alternative specifications, and the results from the baseline appear to be in the range of all the alternative specifications. For instance, at h=1, results from the alternative specifications range between 33 % and 88 %, while the baseline is equal to 52 %. At h=3, results from the alternative specifications range between 50 % and 131 % while the baseline is equal to 92 %. At h=5, results from the alternative specification range between 13 % and 102 %, while the baseline is equal to 67 %.

In Table C.1 in Appendix, we also present results from two alternative specifications. First, we estimate h-horizon price elasticities of supply, estimating equation (5). These h-horizon price elasticities of supply estimate the reaction of production at horizon h to the *cumulated* variation of prices induced my mineral-specific demand shock over this horizon h[15]. As expected, we find that the h-horizon price elasticity of supply is greater than the baseline elasticity reaching a maximum value of 157 % at h=5 (though not significantly different from the baseline estimate). Two takeaways can be derived from this result.

First, because we focus on a rather short-term horizon, estimating elasticities of one-time shocks rather than of cumulated shocks has limited implications on the results. However, for studies focusing on longer-run elasticities, the autocorrelation of price shocks should be taken into account, as the long run value of a price shock conditional on an initial price shock might vary more substantially. In particular, as price trends are expected to differ substantially from those observed until now (Boer et al., 2024), the autocorrelation of prices might be affected and should be carefully into account to accurately evaluate price elasticities of supply. Second, this suggests that our baseline estimate is likely to be a lower bound, which stacks the deck against our interpretation that we estimate stronger short-run price elasticities of supply than previously estimated in the literature.

[15] Following Boehm et al. (2023), to recover these elasticities, we instrument the cumulated variation of prices induced by mineral-specific demand shock ("md price variations") over horizon h by the one-time md price variation between t-1 and t. Results from this first-stage regression are presented in Figure C.1 ("weighted" panel). The results are very close to the local projection of h-horizon md price variation on one-time md price variations between t-1 and t, estimated in a yearly panel of global prices ("unweighted" panel in the same figure).

Table 3 – Robustness of the reaction of production to a mineral-specific demand shock

	Baseline	Alternative fixed effects			With iron	Control for cotton in VAR	Control for trends in VAR	Control for mineral supply shock	Control for 2 lags of the contrib. of mineral demand shock	Control for 2 lags of mineral prod.	(9) + (10)	>=5 years of obs.	Control for gold	Drop main market making countries	Drop China	Control for log China imports	Drop booms and busts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
h=0	**0.258**	0.263	0.260	0.278	0.314*	0.150	0.199	0.222	0.553**	0.146	0.283	0.630**	0.246	0.424*	0.251	0.234	0.342
	(0.191)	(0.186)	(0.226)	(0.216)	(0.188)	(0.186)	(0.184)	(0.204)	(0.222)	(0.161)	(0.185)	(0.286)	(0.191)	(0.255)	(0.192)	(0.191)	(0.268)
h=1	**0.521****	0.500**	0.524*	0.550**	0.503**	0.649***	0.493**	0.458*	0.878***	0.328	0.508**	0.813**	0.513**	0.667**	0.509**	0.494**	0.408
	(0.242)	(0.240)	(0.291)	(0.268)	(0.236)	(0.243)	(0.239)	(0.250)	(0.279)	(0.201)	(0.233)	(0.338)	(0.242)	(0.316)	(0.244)	(0.244)	(0.300)
h=2	**0.422**	0.331	0.500	0.575*	0.366	0.247	0.389	0.446	0.752**	0.090	0.214	0.533	0.426	0.435	0.406	0.385	0.302
	(0.276)	(0.275)	(0.350)	(0.302)	(0.267)	(0.264)	(0.270)	(0.280)	(0.321)	(0.200)	(0.226)	(0.342)	(0.276)	(0.339)	(0.278)	(0.274)	(0.329)
h=3	**0.924*****	0.741**	0.814**	0.982***	0.794***	0.703**	0.938***	0.897***	1.306***	0.501**	0.630***	1.002***	0.922***	1.094***	0.909***	0.878**	1.076***
	(0.304)	(0.305)	(0.382)	(0.331)	(0.297)	(0.296)	(0.301)	(0.307)	(0.351)	(0.217)	(0.239)	(0.352)	(0.304)	(0.366)	(0.307)	(0.306)	(0.384)
h=4	**0.525**	0.330	0.246	0.541	0.461	0.524	0.597*	0.496	0.833**	-0.015	0.064	0.449	0.524	0.642	0.490	0.483	0.808*
	(0.338)	(0.340)	(0.447)	(0.375)	(0.334)	(0.331)	(0.329)	(0.346)	(0.391)	(0.227)	(0.264)	(0.362)	(0.338)	(0.424)	(0.340)	(0.340)	(0.428)
h=5	**0.669***	0.472	0.620	0.907**	0.615*	0.641*	0.759**	0.649*	1.016**	0.126	0.260	0.669*	0.669*	0.738*	0.636*	0.628	0.951*
	(0.371)	(0.374)	(0.481)	(0.386)	(0.365)	(0.389)	(0.368)	(0.379)	(0.430)	(0.227)	(0.271)	(0.371)	(0.372)	(0.447)	(0.373)	(0.371)	(0.492)
Fixed effects																	
Year	**X**	X			X	X	X	X	X	X	X	X	X	X	X	X	X
Mine		X															
Mineral		X															
Mine##mineral	**X**			X	X	X	X	X	X	X	X	X	X	X	X	X	X
Country##Year			X	X													
Country##mineral			X														

Note: Robust standard in parentheses. * p<0.10, ** p<0.05, *** p<0.

Finally, we provide estimates using an instrumental-variable approach, where we estimate the naive equation (2), instrumenting the raw price variation with the median mineral-specific demand shock derived from the structural VAR with sign restrictions. We find broadly comparable effects, with effects ranging from 60 % to 130 %, though less accurately estimated. This confirms the robustness of our baseline analysis.

5.Heterogeneity

5.1 Mineral-Specific Estimations

In this section, we discuss the heterogeneity of our baseline results across minerals. To do so, we fully interact the price variation induced by mineral-specific demand shocks with a dummy indicating which mineral is affected by the shock. We report the average production reaction to price shocks over time for each mineral in Table 4.

Table 4 – Coefficients of the baseline local projection

	Cobalt	**Copper**	**Lead**	**Molyb.**	**Nickel**	**Plat.**	**Silver**	**Zinc**
h=0	0.067	1.298*	-0.788	0.502	-0.109	-0.447*	0.782*	0.242
	(0.469)	(0.697)	(0.603)	(0.405)	(0.637)	(0.239)	(0.467)	(0.487)
h=1	-0.198	0.750	-0.799	0.413	0.893	-0.190	1.398***	0.554
	(0.849)	(0.855)	(0.820)	(0.536)	(0.846)	(0.301)	(0.535)	(0.557)
h=2	0.857	0.300	-0.934	0.360	1.331	0.212	1.080*	0.151
	(1.271)	(0.779)	(0.835)	(0.590)	(1.096)	(0.527)	(0.585)	(0.644)
h=3	3.458*	1.785**	-0.824	0.575	2.150**	0.333	1.431**	0.691
	(1.956)	(0.826)	(0.869)	(0.630)	(1.012)	(0.607)	(0.663)	(0.633)
h=4	2.864	-0.010	-1.184	0.408	3.461***	-0.438	0.988	0.538
	(2.122)	(1.039)	(0.989)	(0.590)	(1.062)	(0.563)	(0.834)	(0.668)
h=5	2.155	1.669*	-1.175	0.332	2.837**	-0.252	1.303	0.219
	(2.036)	(0.894)	(1.198)	(0.707)	(1.258)	(0.508)	(0.851)	(0.742)
Fixed effects								
Year	X	X	X	X	X	X	X	X
Mine##Mineral	X	X	X	X	X	X	X	X
Share of obs.	2%	34%	10%	4%	8%	4%	23%	14%
Number of obs.	105	2,084	616	270	494	250	1,405	844

Note: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

We can classify minerals in different categories based on their production reaction. In the first group, copper, nickel, and silver present clearly positive production reactions to exogenous demand shocks, in that they all have a significant positive coefficient (at 10%) for at least three time-horizons out of six. Among them, copper and silver have fast reaction (with significant coefficients at h=0), although this reaction seems to fade away for silver in the outer range of the projection horizon (the coefficient becoming insignificant yet still positive after 4 years). The reaction of nickel is only significant only after 3 years, but becomes then highly positive, with a peak of 3.461 (significant at 1%) at h=4.

Coefficients for lead, molybdenum, and zinc are never significant at any time-horizons, making these minerals difficult to analyze. In the case of cobalt, only one coefficient (at h=3) is significantly different from 0 (at only 10%), even though its medium-run coefficients are quite high in magnitude (ranging between 2 and 3.5). This low level of significance could however be attributed to the very small number of observations (105) for this specific mineral. Platinum group metals also display one significant (at only 10%) but surprisingly negative coefficient immediately after the shock (h=0), which seems to suggest an unexpected negative production reaction to platinum demand shocks. However, the coefficients associated with the other time-horizons are never significant and vary over time between positive and negative values.

This heterogeneity across minerals is in line with previous literature but we find on average higher elasticities for minerals with positive price elasticities of supply. Using annual time-horizons from shock-year to 5 years onwards, Bogmans et al. (2024) also find an absence of significant price elasticity of supply for lead or zinc for any time-horizons but a highly significant positive price elasticity of supply for copper after one year and up to five years (though with lower values than ours). Boer et al. (2024) also find, from shock-year to 5 years onward, a higher short-run price elasticity of supply for copper than for cobalt, and an even higher for nickel (and the highest elasticity for lithium), but their estimates at these horizons are overall smaller than ours.

These results confirm that different minerals tend to react differently to exogenous shocks, geological factors and production specificities. It is likely that "by-product" minerals (almost exclusively co-produced with other minerals in mines where they are not the primary mineral) are less sensitive to global shocks for their respective demand. For example, since cobalt is often a by-product of copper or nickel, as suggested in the literature (Afflerbach et al., 2014; Nassar et al., 2015), it is likely that the extraction of minerals in cobalt-producing mines will be mainly driven by shocks on the global markets for copper and zinc, cobalt being a "residual" of these minerals. The three products that were described as mainly "by-products" in section 2 (cobalt, lead, and molybdenum) are mainly associated with non-significant coefficients.

In Table C.2 in the Appendix, we assess more systematically whether secondary minerals react differently from the main one. In a first exercise, we focus on minerals that are identified as non-primary in each mine, whether in value or in volume. We then regress simultaneously the production variation of these minerals on their own price variation induced by a demand shock, and on the price variation (induced by a demand shock) of the primary mineral produced in the mine. We find that the production of these minerals reacts significantly only for the price shock on the primary mineral. In a second exercise, we focus on the primary minerals identified in each mine. We then regress simultaneously the production variation of these minerals on their own price variation induced by a demand shock, and on the price variation (induced by a demand shock) of the main non-primary mineral produced in the mine. In this case, we find that the production of the primary minerals reacts significantly only to their own price shock (and not to those on the main non-primary minerals). These results confirm that our baseline results are mostly driven by the reaction of the primary minerals produced in the mine, and that, for the non-primary minerals, the price shocks of the main mineral of the mine are a stronger determinant of their production than their own price shocks.

Finally, the heterogeneity across minerals could reflect a possible heterogeneity across countries of production, thereby affecting estimated price elasticity of supply. For example, 7 mines of cobalt out of 12 and 7 mines of platinum out of 9 are located in Africa (primarily in the Democratic Republic of Congo for cobalt and in South Africa for platinum), while African mines represent only 11% of all our mines. 40% of observations for nickel are located in Canada.

Given the limited number of observations for some minerals, especially regarding cobalt (105 observations), platinum (250) and molybdenum (270), some caution is warranted when interpreting these coefficients. Yet these results clearly suggest that supply responses to global demand shocks are highly heterogeneous across minerals in terms of sign, magnitude, and time-horizon. In the next section, we discuss other sources of non-mineral-specific heterogeneity, such as other economic, contextual or geographical factors.

5.2 Location of the mine, mine-characteristics and mineral markets

In this section, we test for heterogeneity as a function of characteristics based on the geographic location of the mine, the characteristics of the mine itself, and the market for the mineral produced. To assess heterogeneity in price elasticities of supply, we adjust the baseline model by interacting the log of the mineral price with the moderator of interest.

5.2.1 Characteristics of the location of the mine

First, we examine whether the price elasticity is affected by the characteristics of the area in which the mine operates. To do this, we collect variables available at a granular level (longitude and latitude) and match them to mine-level data using the exact location of the mine. We consider the following list of moderators: (i) proximity to a conflict, (ii) availability of transportation infrastructure, and (iii) local levels of income and economic activity. First, for each year and mine, we compute the distance between the mine and the nearest conflict that occurred during the year using the UCDP Georeferenced Event Dataset Global version v24.1 (Davies et al., 2024; Sundberg and Melander, 2013). Second, we compute the distance between the mine and the nearest transportation infrastructure using UNECE LOCODE data: this dataset provides a list of transportation infrastructure, including airports, railway stations, seaports, and road terminals, for each country at the time of download. For each mine, we calculate the distance to the closest infrastructure among these four groups. Third, we use local annual GDP from Kummu et al. (2018), which is available between 2000 and 2015: for each year, we match the mine to the closest grid cell from Kummu et al. (2018) and assign the mine the GDP level of that grid cell. To account for economic activity, we use the variation in local GDP over the previous five years. Finally, we also use a dummy equal to one if the mine is located in Africa. Columns (1) to (5) of Table 5 present the results at horizon $h=1$ and results for other horizons are displayed in Tables C.3 and C.4 in the Appendix (for h=3 and h=5, respectively). The three main findings are the following: (i) mines located farther from conflicts tend to have a higher price elasticities of supply (column 1), (ii) mines in Africa are less sensitive to price variations (column 5) and (iii) neither the proximity to infrastructure (column 2) nor the level of local activity affects the level of price elasticity (columns 3-4).

Specifically, we document that shortly after the shock (h=1) the price elasticity increases with distance to the nearest conflict in the first column. This result is consistent with existing contributions documenting depressed investment in mines close to conflicts (Blair et al., 2022). However, the results in Tables C.3 and C.4 show that the effect of conflict proximity weakens over time. One possible explanation is that when the price rises, a mine close to a conflict may find it difficult to increase its production (e.g., difficult access to the mine for workers) or to sell its production in the short term (road cutters). However, some of these difficulties might be temporary, as mining companies might adapt quickly by hiring private security companies, negotiating with the parties to the conflict, or finding new routes to sell their production.

Table 5 – Heterogeneity at horizon *h*=1

	Location					**Mine characteristics**							**Market**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Interaction variable	Km to closest conflict in t-1	Log GDP in t-1	GDP variation in 5 previous years	Km to closest transport infra.	Mine is in Africa	Mine is producing only one mineral	Mine is producing one or two minerals	Considered mineral is the primary produced by the mine (volume)	Considered mineral is the primary produced by the mine (value)	The mine is held by a single company	High mineral reserve	Small producers	HHI	New global restrictions on mineral exports (t-1)
Shock	-0.401	2.521*	0.828**	0.514*	0.696**	1.533**	1.149**	0.149	0.073	-0.204	1.389**	0.617*	0.859**	0.422
	(0.367)	(1.350)	(0.416)	(0.305)	(0.274)	(0.775)	(0.516)	(0.256)	(0.280)	(0.367)	(0.569)	(0.345)	(0.334)	(0.391)
Interaction variable	-0.00006**	-0.191	0.053										0.00000	-0.002*
	(0.00002)	(0.121)	(0.110)										(0.00002)	(0.001)
Shock x interaction variable	0.0007***	-0.115	-0.356	0.0001	-1.305**	-1.179	-0.958*	1.041**	1.051**	1.221*	-1.507**	-0.187	-0.0002**	-0.023
	(0.0003)	(0.082)	(1.858)	(0.002)	(0.584)	(0.807)	(0.564)	(0.509)	(0.478)	(0.618)	(0.677)	(0.481)	(0.0001)	(0.015)
Characteristics of interaction var.														
Type	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Continuous	Continuous
Time-varying	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	Yes	Yes
Mean value	1,305.62	14.75	0.11	103.49	0.09	0.21	0.46	0.51	0.531	0.55	0.50	0.52	918.74	23.28
Fixed effects														
Year	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Mine ## Mineral	X	X	X	X	X	X	X	X	X	X	X	X	X	X
N	4,676	3,703	3,703	4,676	4,747	4,747	4,747	4,747	4,747	3,107	2,467	4,747	4,747	3,072
Adjusted R^2	0.079	0.076	0.074	0.076	0.075	0.076	0.076	0.076	0.076	0.031	0.065	0.075	0.075	0.091

Note: Shock refers to CD-induced price variation. Estimations of columns (2) and (3) end in 2015. The number of produced minerals per mine (columns 6 and 7) and the identification of the primary mineral within each mine is computed based on selected minerals. Whether reserves are above or below median is computed at the mineral level, among mines that are matched with the ETM data (column 11). HHI is computed yearly based on mining data. Estimation of column (14) starts in 2009. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The result in column (5) of Table 5 shows a significant effect for Africa shortly after the shock (h=1), suggesting that price elasticity of supply is lower in this continent. Additional results presented in Appendix Table C.5 suggest that when we test for the joint heterogeneity of conflicts and the Africa dummy, the effect of the former remains significant while that of the latter becomes insignificant. This suggests that the heterogeneity with respect to Africa is at least partly driven by the occurrence of conflicts on the continent. Conflicts are more prevalent in Africa than in other regions during the reference period (Fang et al., 2020), and they are particularly strong near mines (Berman et al., 2017), especially where informal/artisanal mining occurs alongside industrial mining (Rigterink et al., 2025). However, these effects of conflict and Africa are only observed shortly after the shock. Testing these interactions at h=3 (Table C.3) and h=5 (Table C.4), we find no significant interaction effects for conflict (although the sign and magnitude of the coefficient remain comparable to those estimated at h=1) and for Africa (where the interaction coefficient has an unstable sign over time).

Finally, we find no effect of income (measured by GDP, either in level or in variation) or of transport infrastructure (measured by road density or distance to the nearest airport, railway station, port or road), whatever horizon we consider (as documented in Tables C.3 and C.4 in the Appendix). One possible explanation is that mining companies adapt to the environment in which they operate. For example, if the area is far from the main transportation infrastructure, mining companies will build roads to open up the area. Similarly, in the absence of a skilled local workforce, mines will resort to hiring workers from outside the area. As a result, environmental factors such as distance from infrastructure or local economic dynamics have little impact on their production levels and ability to adapt to price variations, confirming their often-used description as economic enclaves.

5.2.2 Mine-level characteristics

The second category of moderators examined relates to mine characteristics. We consider six mine-level characteristics, all represented by a dummy that takes the value one if (i) the mine produces only one mineral; (ii) the mine produces less than two minerals; (iii) the mineral of interest is the primary mineral produced in the mine (whether in volume or in value); (iv) the mine is owned by only one company; (v) the mine has high reserves (above the median); and (vi) the producer is a small one (the level of mineral production of the mine is below the median of all producers). The dummies are constructed using variables available in the main datasets, except for reserves, for which data are extracted from Energy Transition Minerals (ETM) dataset of Owen et al. (2022)[16]. We consider a mine from Jasansky et al. (2023) and an ETM mine to be identical if either i) their centroids are less than 1 km apart, or ii) they are less than 2 km apart and the nearest other mine is more than 10 km away[17]. A summary of all the data sources used is presented in Table A.6 in Appendix.

The results of the influence of mine characteristics are displayed in columns (6) to (12) of Table 5 (horizon *h=1*) and of Tables C.3 and C.4 (for *h=3* and *h=5*, respectively). Higher price elasticity are found, shortly after the shock, for: (i) mines producing multiple minerals (columns 6-7), (ii) primary minerals produced within the mines (columns 8-9), (iii) mines owned by a single company (column 10), and (iii) mines with small reserves (column 11). However, we do not find that smaller mines have a significantly different price elasticity of supply, confirming that possible endogeneity related to the presence of potential market-makers among mines is unlikely to drive our results. Here again, these heterogeneities are overall more significant shortly after the shock: at *h*=3, the heterogeneity with respect to mineral reserves is not significant anymore, and at *h*=5, both the heterogeneities with respect to both mineral reserves and ownership structure are not significant anymore.

The effect of the number of minerals produced on price elasticity is theoretically unknown. On the one hand, producers of a single mineral may be highly sensitive to changes in the price of that mineral and may seek to increase their production when its price rises. On the other hand, these producers may also be constrained by their production capacity and their ability to increase it rapidly. Companies that produce a large number of ores can arbitrage between these different productions and reallocate resources accordingly. This makes it easier for them to respond to price increases. The results in columns (6) and (7) support the second argument. The presence of multiple minerals allows producers to quickly adjust their production levels to take advantage of higher prices. Relatedly, the stronger reaction for primary mineral within the mine (columns 8-9) appears in line with the results on Table C.2 in the Appendix.

The ownership structure of the mine also plays a role in the production response to a price change. Indeed, as indicated in column (10), the fact of being the sole owner of the mine facilitates the decision-making process and thus the ability to make a decision to intensify production following a price increase.

16 We obtain mineral-level reserves for 156 mines (49% of the mines in the final dataset), corresponding to 3,110 observations (51% of the total observations in the final dataset), by matching mine-level production data with mine-level reserve data from the Energy Transition Minerals (ETM) dataset.

[17] An alternative could be to use directly the reserves data from Jasansky et al. (2023). However, the main issue with these data is that, in most cases, they are constant across minerals produced in a given mine.

A possible explanation for the smaller response of mines with large reserves may be that these producers take a long-term view and manage their resources over a long period of time. As a result, they are less sensitive to short-term price variations.

5.2.3 Market-level characteristics

Finally, we consider two market-level variables. We compute the Herfindahl-Hirschman Index (HHI) of production concentration. HHI is computed annually based on mining data. We also use global mineral export restrictions. Annual export restrictions are derived from the OECD national restrictions on industrial commodities from 2009 onward: for each mineral and each year, we compute the number of new restrictions implemented across countries (where an export restriction can be either the introduction, the reintroduction, the extension, or the increase of export restrictions[18]).

The results presented in column (13) shows that the price elasticity is stronger when production is less concentrated (HHI tends to zero). This interaction effect is significant at $h=1$ and $h=5$, but not at $h=3$. Export restrictions overall have a non-significant effect on the price elasticity of supply, with signs of interaction effects varying depending on horizons. In Table C.6 in the Appendix, we test separately the effect of different types of export restrictions, distinguishing export bans, export taxes and licensing requirements: overall, we do not find that these indicators significantly and meaningfully affect the price elasticity of supply[19].

The stronger elasticities observed in less concentrated markets (lower HHI) are in line with expectations. In less concentrated markets, firms behave in a more competitive, flexible, and responsive manner, leading to a higher price elasticity of supply. In contrast, dominant firms in concentrated markets may restrict supply adjustments due to strategic considerations, higher fixed costs, or long-term optimization. The absence of moderating effects of export restrictions could be explained by the joint development of local value chains when price increase, the increase in domestic opportunities offsetting the decrease in exporting opportunities.

[18] Most of the export restrictions in the dataset licensing requirements, export taxes and export prohibitions.

[19] The only exception is for horizon $h=5$, where we find export taxes and licensing requirements to respectively have positive and negative significant interaction effects. The fact that these coefficients are significant only at $h=5$, while export restrictions overall have a non-significant effect at this horizon as well as at previous ones, makes them hard to interpret. Furthermore, they are overall not robust to alternative specifications regarding fixed effects.

6.Conclusion

In this paper, we estimate the price elasticity of supply for 8 minerals critical to the energy transition, up to 5 years ahead. For this, we first implement a structural VAR model to isolate price variations due to mineral-specific demand shocks, and then apply a local projection approach to assess the impact of these shocks on mineral production between 2000 and 2019. Using mine-level data for 318 mines located in 43 countries, we find higher elasticities of supply than previous studies, suggesting that estimations based on macroeconomic aggregates may have suffered from an aggregation bias, leading to an underestimation of the supply response. The results also reveal a large heterogeneity across minerals in their supply responses, with nickel, silver, and copper having particularly high price elasticities of supply. The price elasticity of supply is stronger for primary minerals, and the production of non-primary minerals is more affected by shocks on the prices of primary minerals than by their own price shocks. This highlights the importance of considering each mineral's specificities in further analyses, especially in the case of new critical minerals neglected so far by the economic literature. The results suggest heterogeneity in the time horizon: the supply response seems to be almost immediate for silver or copper but becomes significant only after 3 years for nickel. Our results are robust to several robustness checks and alternative specifications.

Finally, even though we are able to provide estimates up to five years after a shock, this time horizon remains relatively short in an industry where lead times from discovery to production can reach ten to twenty years. From this standpoint, our estimates are likely to be mostly informative about the intensive margins of the price elasticity of supply. Yet, it is also crucial to understand the drivers of longer run production reaction, whose drivers may differ from that of the short run (e.g. Stuermer, 2022), because of factors such as technological change or decreasing concentration of ores in active mines over time. Likewise, and even though we focus on a large number of minerals, several crucial minerals for the transition are excluded due to the lack of data, such as lithium. More complete data on large countries (e. g. China) is crucial to improve transparency and assess (or dispel myths), on the role of large countries in price determination in different critical minerals' markets. Improving geological mapping of mineral resources in low-income countries and Africa would help assess the potential (and the risks) of these resources for sustainable development. A key condition to gain a better understanding of mine-level long-term price elasticity of supply of minerals that matter for the energy transition will be to produce longer series of production at the mine-level for a wider range of mineral.

7.References

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APPENDIX

Appendix A – Sample selection and descriptive statistics

We start from the raw dataset *commodities*, containing 9,423 observations between 2000 and 2020. We first drop all observations from 2020 (50 observations). We then keep only minerals i) present in selected lists of strategic raw materials (World Bank (2020) or IEA (2021), following Espagne and Lapeyronie (2023)) and ii) with more than 50 observations in the dataset. Additionally, we keep only minerals whose coverage of global production is greater than 20 % in Jasansky et al. (2023). Selected minerals are in blue in Table A.1. Copper cathode production is included as copper production only if, in the same year and in the same mine, there is no simultaneous production. This corresponds to 139 observations. In mines producing copper and copper cathode simultaneously, we exclude copper cathode records from the analysis (152 observations) to avoid double counting. Largely represented in the dataset, gold is not considered a critical raw material in existing classifications. Iron is classified as a strategic raw material and has more than 50 observations in the dataset, but the dataset covers only 3.3 % of global production, and we thus exclude it from the analysis. Among the 13 remaining minerals (2.3 % of the dataset), only 4 are considered critical to the energy transition in the World Bank or IEA lists (manganese, alumina, tin and lithium). The final sample is constructed by aggregating some duplicate production observations in a single mine and year to obtain a panel at the mine-year level.

Table A.1 – Selection criteria of metals in the dataset of mines, based on raw data from 2000 to 2019

Mineral	Freq.	Percent	Present in WB list*	Present in IEA list*	Average coverage of global production between 2000 and 2018 in raw dataset (according to Jasansky et al., 2023), if present in WB or IEA lists.
Gold	2,608	27.82	NO	NO	
Copper or copper cathode	2,136	22.79	YES	YES	65.9 %
Copper	*1,997*	*21.31*	*YES*	*YES*	
Copper cathode in mine with no copper prod.	*139*	*1,48*	*YES*	*YES*	
Silver	1,441	15.37	YES	YES	29.1 %
Zinc	847	9.04	YES	YES	30.5 %
Lead	622	6.64	YES	YES	23.3 %
Nickel	496	5.29	YES	YES	37.1 %
Molybdenum	270	2.88	YES	YES	40.1 %
Platinum or related	250	2.67	NO	YES	35.1 % (PGM)
PGM	*60*	*0.64*	*NO*	*YES*	
Platinum	*57*	*0.61*	*NO*	*YES*	
Palladium	*49*	*0.52*	*NO*	*YES*	
Rhodium	*34*	*0.36*	*NO*	*YES*	
Iridium	*25*	*0.27*	*NO*	*YES*	
Ruthenium	*25*	*0.27*	*NO*	*YES*	
Iron	228	2.43	YES	NO	3.3 %
Copper cathode in mine with copper prod.	152	1.62	YES	YES	
Cobalt	107	1.14	YES	YES	17.4 %
Diamonds	59	0.63	NO	NO	
Triuranium octoxide	51	0.54	NO	NO	
Manganese	30	0.32	YES	YES	
Alumina	25	0.27	YES	NO	
Tin	18	0.19	NO	YES	
Niobium	8	0.09	NO	NO	
Tellurium	7	0.07	NO	NO	
Fluorspar	5	0.05	NO	NO	
Lithium oxide	5	0.05	YES	YES	
Antimony	3	0.03	NO	NO	
Phosphate and phosphorus oxides	2	0.02	NO	NO	
Sodium compounds n.e.c.	2	0.02	NO	NO	
Tantalum pentoxide	1	0.01	NO	NO	
Total	9,373	100			
Total preselected	6,169	65.82			

* As documented in World Bank (2020) and IEA (2021).

Table A.2 - Observations by mineral and country (final dataset)

Mineral	**Obs.**	**Number of mines**	**Countries with more than 5 % of obs. (share of observations, in %)**	**Average yearly HHI index**
Copper	2,084	195	Chile (18.2 %) Canada (13.2 %) Peru (11.1 %) US (9.2 %) Australia (8.6 %) Kazakhstan (7.2 %)	Copper=434.4 Copper cathode=2426.9
Silver	1,405	163	Peru (24.2 %) Mexico (14.7 %) Kazakhstan (10.4 %) Australia (9.9 %) Chile (7.6 %) Canada (6.9 %) Sweden (5.4 %)	760.0
Zinc	844	90	Peru (20.1 %) Mexico (14.4 %) Australia (10.1 %) Canada (9.9 %) Kazakhstan (8.8 %) Sweden (7.2 %) India (5.7 %)	913.9
Lead	616	65	Peru (27.9%) Mexico (19.6 %) Australia (13.0%) Sweden (9.2 %) India (7.8 %) Ireland (6.7 %)	1437.7
Nickel	494	45	Canada (40.3 %) Russian Federation (10.5 %) South Africa (8.7 %) Brazil (7.7 %) Australia (6.7 %)	1392.9
Molybdenum	270	21	Chile (36.7%) Peru (27.4 %) USA (21.9 %) Mexico (7.8 %) Canada (6.3 %)	1212.3
Platinum et al.	250	16	South Africa (71.2 %) Russia (11.2 %) Canada (7.2 %) Finland (5.6 %)	Platinum=4661.9 Iridium=5508.2 Palladium=4961.2 PGM=8262.6 Rhodium=5448.7 Ruthenium=5512.1
Cobalt	105	12	DRC (36.2 %) Cuba (19.1 %) South Africa (14.3 %) Australia (9.5 %) Canada (7.6 %) Madagascar (7.6 %)	5787.5
Total	6,068	318		

Table A.3 - Descriptive statistics, mine level (final dataset)

Number of minerals (among selected minerals)	Obs.	Most represented combinations (>5 %)	Share of each combination (in %)
1	1,271	- Copper - Silver - Nickel	47.6 29.7 15.8
2	1,536	- Silver, Copper - Copper, Nickel - Lead, Zinc - Copper, Molybdenum - Cobalt, Copper	42.5 21.1 13.9 8.4 5.9
3	2,122	- Silver, Lead, Zinc - Silver, Copper, Molybdenum - Silver, Copper, Zinc - Copper, Nickel, Platinum - Copper, Lead, Zinc	30.7 24.3 20.1 12.9 5.6
4+	1,139	- Silver, Copper, Lead, Zinc - Cobalt, Copper, Nickel, Platinum	86.3 7.9

Table A.4 - List of combinations of minerals differencing between main mineral and by-products (total production of the mine over 2000-2019)

Using data in volume										
Main Mineral	**By-Product**	**Cobalt**	**Copper**	**Lead**	**Molybdenum**	**Nickel**	**Platinum**	**Silver**	**Zinc**	**# Pairs as main mineral**
Cobalt			0	0	0	0	0	0	0	**0**
Copper		7		3	19	7	1	55	13	**105**
Lead		0	2		0	0	0	4	4	**10**
Molybdenum		0	0	0		0	0	0	0	**0**
Nickel		5	14	0	0		3	1	0	**23**
Platinum		0	0	0	0	0		0	0	**0**
Silver		0	2	0	0	0	0		0	**2**
Zinc		0	37	57	0	0	0	50		**144**
# Pairs as by-product		**12**	**55**	**60**	**19**	**7**	**4**	**110**	**17**	
Using data in value										
Main Mineral	**By-Product**	**Cobalt**	**Copper**	**Lead**	**Molybdenum**	**Nickel**	**Platinum**	**Silver**	**Zinc**	**# Pairs as main mineral**
Cobalt			0	0	0	0	0	0	0	**0**
Copper		6		6	19	1	0	65	25	**122**
Lead		0	1		0	0	0	0	1	**2**
Molybdenum		0	0	0		0	0	0	0	**0**
Nickel		6	18	0	0		2	1	0	**27**
Platinum		0	2	0	0	2		0	0	**4**
Silver		0	7	19	0	0	0		18	**44**
Zinc		0	21	39	0	0	0	25		**85**
# Pairs as by-product		**12**	**49**	**64**	**19**	**3**	**2**	**91**	**44**	

Note: For each combination of minerals, we define the main mineral in volume as the one for which the total volume of production (in tons) is highest. We define the main mineral in value as the one for which the total volume of production (in international US$) is highest. Other minerals are defined as by-products. If a combination includes more than 2 minerals, it is included several times in this table (one time for each by-product, the main mineral being always the same for a given mine). For instance, a mine producing copper, cobalt and zinc with copper as the main mineral appears twice: one time with copper as main and cobalt as by-product, and one time with copper as main and zinc as by-product.

Table A.5 – Main producers, exporters and importers of each mineral

Mineral	Production (USGS)	Exports (BACI)	Imports (BACI)
Silver		Mexico Peru	China
Cobalt	Congo Dem Rep	Congo Dem Rep	China Zambia
Copper	Chile		China
Molybdenum		Chile	
Nickel		Indonesia Philippines	China
Lead	China		China
PGM	South Africa Russia		
Zinc	China		

Note: This table lists countries which produce/export/import more than 25% of each product between 2012 and 2019

Table A.6 – List of data sources

Variable	**Source**
Mineral production at the mine level	Jasansky et al. (2023)
Global mineral production	USGS
Real global mineral prices	USGS, Officer (2025); PCPS for copper prices in 2019
Global GDP	Jacks and Stuermer (2020), IMF (World Economic Outlook)
Real cotton prices	Jacks and Stuermer (2020), IMF (PCPS)
Reserves	Energy and Transition Minerals dataset (Owen et al. 2022)
Geolocalized conflict	UCDP Georeferenced Event Dataset Global version v24.1 (Davies et al., 2024; Sundberg and Melander, 2013).
Gridded GDP data	Kummu et al. (2018)
Geolocalized transport infrastructure	UNECE-LOCODE
Export restrictions	OECD industrial raw materials restrictions

Appendix B –Estimating demand shocks for critical materials

We present the methodology used to isolate the demand-shock component of price. We combine our global series to estimate mineral-specific demand shocks. To do so, we follow the baseline approach of Boer et al. (2024) and estimate a structural VAR with sign restrictions, for each mineral.

More specifically, we follow the framework of Boer et al. (2024), by estimating the following VAR model for each of the 8 minerals between 1912 and 2019:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + c + u_t$$

where y_t=(gdp_t, q_t,p_t), where gdp_t represent the world GDP in year *t*, q_t represent the world production of the mineral in year *t*, and p_t represents the real price of the mineral in year *t*, all taken in log values (of their index equal to 100 in 1912). We set $p=4$, and A_i represent reduced form VAR coefficients, c is a constant and u_t are the reduced-form forecast errors. The structural form of this equation can be written as:

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + d + \varepsilon_t$$

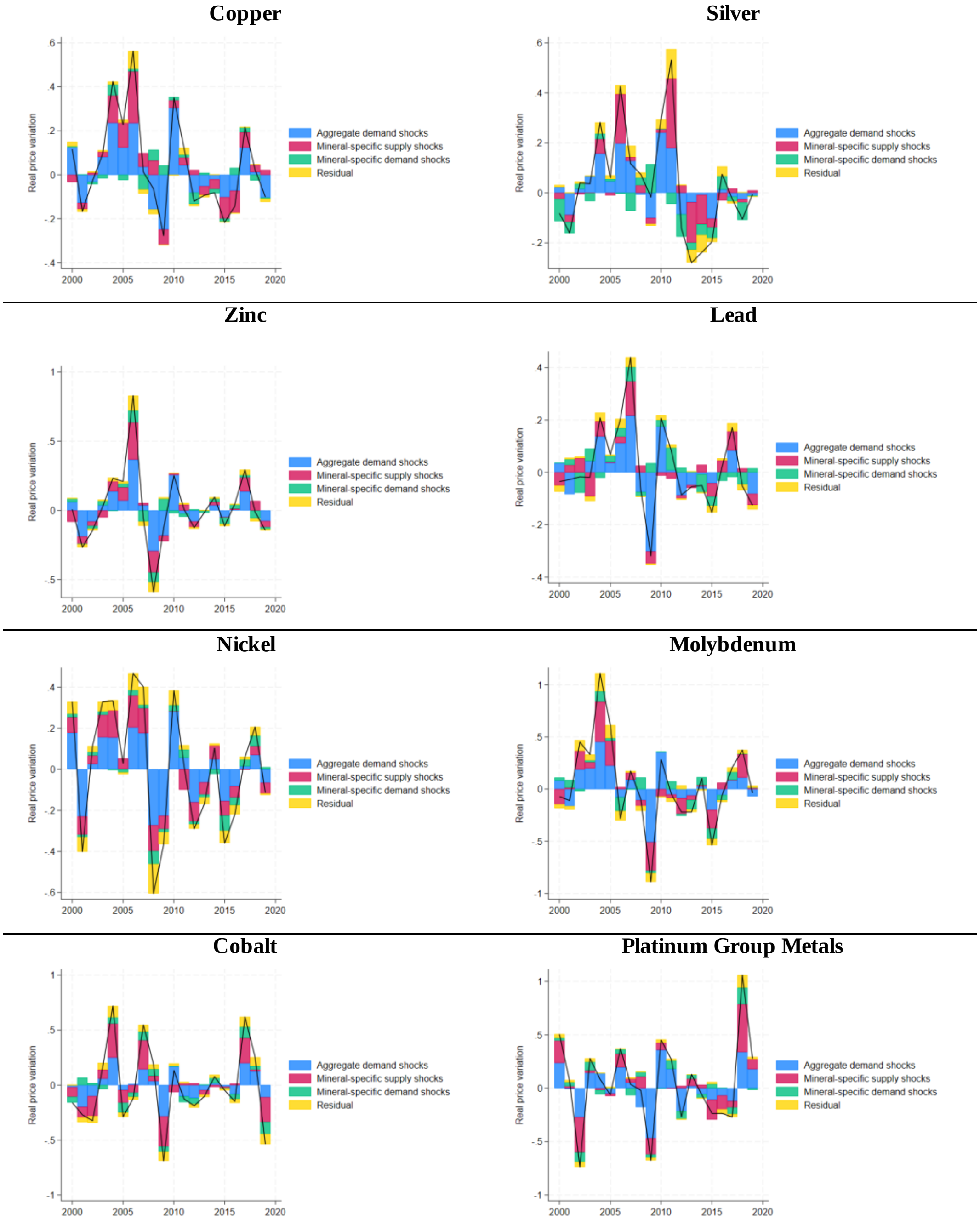
Where ε_t=$B_0^{-1} u_t$ is a set of structural shocks, and B_0^{-1} gives information about the impact of structural shocks on y_t. In order to identify B_0^{-1}, we apply the three types of shock, as in Boer et al. (2024).

Table B.1 – Sign restrictions and their impact

	Global GDP	**Global mineral production**	**Real mineral price**
Aggregate demand shock (AS)	+	+	+
Mineral-specific supply shock (MS)	+	+	-
Mineral-specific demand shock (MD)	-	+	+

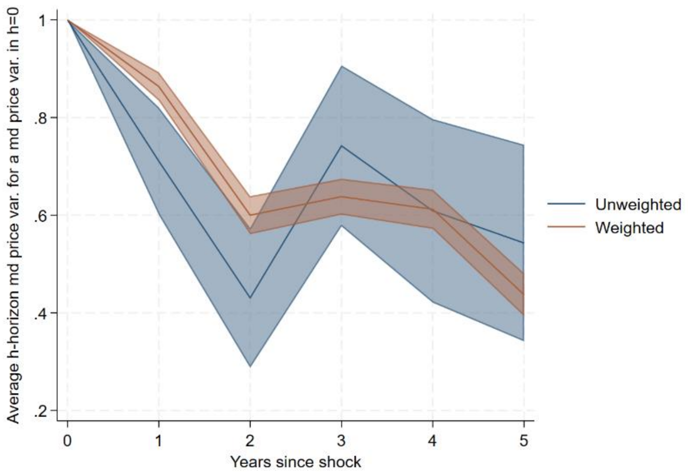
The first shock is a global demand shock, for instance related to the global business cycle: it entails positive effects on GDP, positive effects on mineral production, and positive effects on their real prices. The second shock is a global supply shock, for instance related to strikes, or mine openings/closure: it entails positive effects on GDP and mineral production, but negative effects on real mineral prices. Finally, the last shock is our shock of interest, and is a mineral-specific: in line with Boer et al. (2024), we assume that it entails negative effects on global economic activity, but positive effects on global mineral production and real prices. This shock captures idiosyncratic shifts in demand for a specific metal, which drives up the production of the latter, but also shifts prices upward, thereby reducing global economic activity (as documented in Kilian, 2009, or Baumeister and Peersman, 2013). The model is estimated on yearly data from 1912 to 2019, using the *var_nr* package in Stata.

Figure B.1 – Decomposition of the real price variation, 2000-2019



Appendix C – Additional results

Figure C.1 – Autocorrelation of price variations induced by mineral-specific demand shocks, in a local projection setting



Note: the figure presents results from a local projection of the price variation induced by mineral-specific demand-shock-induced price variation ("md price variation") on its own variation between t-1 and t. In blue ("unweighted" regression), the estimate is based on a yearly panel of md price variations for the 8 minerals. In orange ("weighted" regression), the estimate is based on the first stage of the *h*-horizon instrumental variable strategy, where we regress the *h*-horizon production variation on the *h*-horizon md price variation, and instrument the latter on the md price variation between t-1 and t. The orange curve can be interpreted as a weighted version of the blue curve, where, for each mineral-year, the weight corresponds to the yearly number of mines producing each mineral. Confidence intervals are at the 10 % level.

Table C.1 - Baseline model and alternative specifications

	Naive regression	**Baseline**	**Horizon-h projection**	**IV**
h=0	0.071*	0.258	0.258	0.072
	(0.039)	(0.191)	(0.192)	(0.177)
h=1	0.157***	0.521**	0.595**	0.567*
	(0.053)	(0.242)	(0.277)	(0.297)
h=2	0.069	0.422	0.716	0.618*
	(0.060)	(0.276)	(0.470)	(0.362)
h=3	0.186***	0.924***	1.450***	1.322*
	(0.067)	(0.304)	(0.484)	(0.676)
h=4	0.138**	0.525	0.848	1.317
	(0.069)	(0.338)	(0.552)	(1.014)
h=5	0.117	0.669*	1.571*	1.234
	(0.075)	(0.371)	(0.886)	(1.347)
Fixed effects				
Year	X	X	X	X
Mine##Mineral	X	X	X	X

Note: the first column corresponds to the naïve estimation by local projection, in which we regress the variation of mine production of a mineral between t-1 and t+h on the variation of its global price between t-1 and t. The second column corresponds to the baseline, where we replace the global price variation of minerals between t-1 and t by their price variation induced by a mineral-specific demand shock ("md price variation") between t-1 and t. In the third column, we regress the variation of production between t-1 and t+h on the cumulated md price variation between t-1 and t+h, instrumenting the latter with the md price variation between t-1 and t. Finally, the last column corresponds to the naive regression, but instrumenting the price variation with the median mineral-specific demand shock estimated in the VAR. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table C.2 – Cross-elasticities of primary and non-primary minerals

	Primary and non-primary defined in volume				Primary and non-primary defined in value			
	Regression 1: sample of non-primary minerals		**Regression 2:** sample of primary minerals		**Regression 3:** sample of non-primary minerals		**Regression 4:** sample of primary minerals	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Own price variation due to md-shock	**Price variation of primary mineral due to a md-shock**	**Own price variation due to md-shock**	**Price variation of the main non-primary mineral due to a md-shock**	**Own price variation due to md-shock**	**Price variation of primary mineral due to a md-shock**	**Own price variation due to md-shock**	**Price variation of the main non-primary mineral due to a md-shock**
h=0	0.221	-0.065	0.218	0.354	0.207	-0.070	0.103	0.435
	(0.216)	(0.395)	(0.462)	(0.301)	(0.234)	(0.343)	(0.341)	(0.273)
h=1	0.072	0.643	0.742	0.031	0.116	0.430	0.559	0.169
	(0.280)	(0.480)	(0.462)	(0.333)	(0.297)	(0.423)	(0.363)	(0.308)
h=2	0.313	0.930*	0.493	-0.005	0.415	0.207	0.287	0.235
	(0.319)	(0.533)	(0.547)	(0.360)	(0.337)	(0.505)	(0.488)	(0.345)
h=3	0.506	1.447**	1.399**	-0.134	0.484	0.528***	1.422***	0.045
	(0.351)	(0.605)	(0.597)	(0.368)	(0.370)	(0.543)	(0.529)	(0.373)
h=4	0.131	1.400**	1.006	0.046	0.228	0.981*	0.799	0.214
	(0.380)	(0.592)	(0.614)	(0.370)	(0.400)	(0.559)	(0.522)	(0.407)
h=5	0.121	1.475**	1.278**	-0.092	0.045	0.543	1.218	0.210
	(0.429)	(0.615)	(0.630)	(0.395)	(0.453)	(0.582)	(0.559)	(0.459)
Fixed effects								
Year	X		X		X		X	
Mine##Mineral	X		X		X		X	

Note: this table presents the results of four regressions. In the first two regressions, primary and non-primary minerals are based on production in volume, while in the last two regressions, they are based on production in value. In the first regression (columns 1 and 2), we focus on the sample of minerals that are identified as non-primary in a given mine (where primary minerals are those with the highest total production in tons in a given mine). Coefficients from columns 1 and 2 are estimated jointly at each horizon *h:* those from column 1 correspond to the own mineral price variation due to a demand shock on the latter, while those from column 2 correspond to price variations of the primary mineral produced in the mine induced by a demand shock on the latter. In the first regressions (columns 3 and 4), we focus on the sample of minerals that are identified as primary in a given mine. Coefficients from columns 3 and 4 are estimated jointly at each horizon *h*. Those from column 3 correspond to the own mineral price variation due to a demand shock on the latter, while those from column 4 correspond to price variations of the price variation of the main non-primary mineral produced in the mine induced by a demand shock on the latter. Coefficients from regression 3 (columns 5 and 6) are estimated in the way as those from regression 1 (columns 1 and 2), but the primary and non-primary are defined in value. Coefficients from regression 4 (columns 7 and 8) are estimated in the way as those from regression 2 (columns 3 and 4), but the primary and non-primary are defined in value.

Table C.3 – Heterogeneity at horizon *h*=3

	Location					**Mine characteristics**							**Market**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Interaction variable	Km to closest conflict in t-1	Log GDP in t-1	GDP variation in 5 previous years	Km to closest transport infra.	Mine is in Africa	Mine is producing only one mineral	Mine is producing one or two minerals	Considered mineral is the primary produced by the mine (volume)	Considered mineral is the primary produced by the mine (value)	The mine is held by a single company	High mineral reserve	Small producers	HHI	New global restrictions on mineral exports (t-1)
Shock	0.408	2.052	1.401**	0.778**	0.868***	2.209**	1.963***	0.512	0.419	0.405	1.535**	0.814**	1.092***	0.739
	(0.451)	(1.425)	(0.451)	(0.367)	(0.319)	(0.971)	(0.516)	(0.326)	(0.343)	(0.485)	(0.655)	(0.395)	(0.388)	(0.645)
Interaction variable	-0.00008**	0.020	0.145										0.00004	-0.002*
	(0.00003)	(0.137)	(0.127)										(0.00003)	(0.001)
Shock x interaction variable	0.0004	-0.069	-3.013	0.002	0.640	-1.501	-1.579**	1.084*	1.257**	1.329*	-1.001	0.229	-0.0001	-0.009
	(0.0003)	(0.087)	(2.255)	(0.002)	(0.954)	(0.992)	(0.624)	(0.589)	(0.571)	(0.690)	(0.702)	(0.548)	(0.0001)	(0.020)
Characteristics of interaction var.														
Type	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Continuous	Continuous
Time-varying	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	Yes	Yes
Mean value	1,305.62	14.75	0.11	103.49	0.09	0.21	0.46	0.51	0.53	0.55	0.50	0.52	918.74	23.28
Fixed effects														
Year	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Mine ## Mineral	X	X	X	X	X	X	X	X	X	X	X	X	X	X
N	3,617	3,385	3,385	3.617	3,662	3,662	3,662	3,662	3,662	2,432	1,950	3,662	3,662	2,063
Adjusted R^2	0.241	0.250	0.251	0.240	0.240	0.241	0.242	0.241	0.241	0.187	0.161	0.240	0.240	0.341

Note: Shock refers to CD-induced price variation. Estimations of columns (2) and (3) end in 2015. The number of produced minerals per mine (columns 6 and 7) and the identification of the primary mineral within each mine is computed based on selected minerals. Whether reserves are above or below median is computed at the mineral level, among mines that are matched with the ETM data (column 11). HHI is computed yearly based on mining data. Estimation of column (14) starts in 2009. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table C.4 – Heterogeneity at horizon *h*=5

	Location					Mine characteristics							Market	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Interaction variable	Km to closest conflict in t-1	Log GDP in t-1	GDP variation in 5 previous years	Km to closest transport infra.	Mine is in Africa	Mine is producing only one mineral	Mine is producing one or two minerals	Considered mineral is the primary produced by the mine (volume)	Considere d mineral is the primary produced by the mine (value)	The mine is held by a single company	High mineral reserve	Small producers	HHI	New global restrictions on mineral exports (t-1)
Shock	-0.107	1.224	0.865*	0.691	0.758*	1.585	1.728**	0.147	-0.009	-0.0137	0.815	0.274	1.063**	-0.249
	(0.558)	(1.661)	(0.512)	(0.440)	(0.392)	(1.270)	(0.738)	(0.388)	(0.413)	(0.555)	(0.802)	(0.505)	(0.462)	(0.787)
Interaction variable	-0.00001***	0.012	-0.093										0.0001***	-0.001
	(0.00003)	(0.174)	(0.141)										(0.00003)	(0.002)
Shock x interaction variable	0.0006*	-0.037	-1.481	-0.0002	-0.951	-1.058	-1.588**	1.363*	1.656**	1.085	-0.344	0.869	-0.0003**	0.045
	(0.0004)	(0.101)	(2.534)	(0.003)	(1.096)	(1.286)	(0.777)	(0.716)	(0.680)	(0.821)	(0.871)	(0.658)	(0.0001)	(0.030)
Characteristics of interaction var.														
Type	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Continuous	Continuous
Time-varying	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	Yes	Yes
Mean value	1,305.62	14.75	0.11	103.49	0.09	0.21	0.46	0.51	0.53	0.55	0.50	0.52	918.74	23.28
Fixed effects														
Year	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Mine ## Mineral	X	X	X	X	X	X	X	X	X	X	X	X	X	X
N	2,699	2,699	2,699	2,699	2,717	2,717	2,717	2,717	2,717	1,847	1,488	2,717	2,717	1,249
Adjusted R^2	0.359	0.356	0.356	0.356	0.356	0.356	0.357	0.357	0.358	0.298	0.257	0.356	0.358	0.552

Note: Shock refers to CD-induced price variation. Estimations of columns (2) and (3) end in 2015. The number of produced minerals per mine (columns 6 and 7) and the identification of the primary mineral within each mine is computed based on selected minerals. Whether reserves are above or below median is computed at the mineral level, among mines that are matched with the ETM data (column 11). HHI is computed yearly based on mining data. Estimation of column (14) starts in 2009. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table C.5 – Joint heterogeneity of distance to conflict and of Africa dummy

	h=1	*h*=3	*h*=5
Shock (MD-induced price variation)	-0.233	0.321	0.006
	(0.408)	(0.470)	(0.584)
Shock x Africa	-0.892	0.718	-0.873
	(0.585)	(0.967)	(1.116)
Distance to closest conflict in t-1	-0.00006**	-0.00007***	-0.0001***
	(0.00002)	(0.00003)	(0.0003)
Shock x distance to closest conflict in t-1	0.0007**	0.0004	0.0006
	(0.0003)	(0.0003)	(0.0004)
Fixed effects			
Year	X	X	X
Mine ## Mineral	X	X	X
N	4,676	3,617	2,699
Adjusted R^2	0.079	0.241	0.359

Note: Robust standard in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table C.6 – Detailed effect of export restrictions

	Interaction variable: New global mineral export prohibitions (t-1)			**Interaction variable:** New global mineral export taxes (t-1)			**Interaction variable:** New global mineral licensing requirements (t-1)		
	h=1	*h*=3	*h*=5	*h*=1	*h*=3	*h*=5	*h*=1	*h*=3	*h*=5
Shock (MD-induced price variation)	0.095	0.534	1.166*	-0.296	0.340	0.215	0.112	0.336	1.408**
	(0.307)	(0.510)	(0.679)	(0.358)	(0.505)	(0.647)	(0.316)	(0.500)	(0.700)
Interaction variable	-0.009	-0.024**	-0.018**	0.002	0.001	0.003	-0.002	-0.007**	-0.016**
	(0.009)	(0.010)	(0.011)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.007)
Shock x interaction variable	-0.091	0.038	-0.044	0.056	0.036	0.143**	-0.054	0.064	-0.229*
	(0.152)	(0.155)	(0.183)	(0.043)	(0.065)	(0.072)	(0.054)	(0.071)	(0.135)
Fixed effects									
Year	X	X	X	X	X	X	X	X	X
Mine ## Mineral	X	X	X	X	X	X	X	X	X
N	3,072	2,063	1,249	3,072	2,063	1,249	3,072	2,063	1,249
Adjusted R^2	0.091	0.341	0.550	0.091	0.340	0.554	0.237	0.342	0.551

Note: Robust standard in parentheses. * p<0.10, ** p<0.05, *** p<0.01