Grantham Research Institute on Climate Change and the Environment

The changing dynamics in global metal markets: how the energy transition and geofragmentation may disrupt commodity prices

Hugh Miller and Juan Pablo Martínez

January 2026

Grantham Research Institute on
Climate Change and the Environment
Working Paper No. 439

ISSN 2515-5717 (Online)

Grantham Foundation
for the Protection of the Environment

The London School of Economics and Political Science

The Grantham Research Institute on Climate Change and the Environment was established by the London School of Economics and Political Science in 2008 to bring together international expertise on economics, finance, geography, the environment, international development and political economy to create a world-leading centre for policy-relevant research and training. The Institute is funded by the Grantham Foundation for the Protection of the Environment and a number of other sources. It has five broad research areas:

1. Climate change impacts and resilience
2. Cutting emissions
3. Financing a better future
4. Global action
5. Protecting the environment

More information about the Grantham Research Institute is available at: www.lse.ac.uk/GranthamInstitute

Suggested citation:
Miller H and Martínez JP (2026) *The changing dynamics in global metal markets: how the energy transition and geofragmentation may disrupt commodity prices*. Grantham Research Institute on Climate Change and the Environment Working Paper 439. London: London School of Economics and Political Science

Co-author Hugh Miller was previously employed by the OECD and a version of this paper has also been published as an OECD working paper.

OECD ENVIRONMENT WORKING PAPERS

OECD Working Papers should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and arguments employed are those of the author(s).

Working Papers describe preliminary results or research in progress by the author(s) and are published to stimulate discussion on a broad range of issues on which the OECD works. Comments on Working Papers are welcomed, and may be sent to:

OECD Environment Directorate

2 rue André-Pascal, 75775 Paris Cedex 16, France

or by email: env.contact@oecd.org

OECD Environment Working Papers are published on

OECD Environment Working Papers | OECD

The changing dynamics in global metal markets: How the energy transition and geofragmentation may disrupt commodity prices*

Hugh Miller† Juan-Pablo Martínez‡

January 2026

Abstract

The energy transition and the increase in trade restrictions driven by geofragmentation present significant risks to critical mineral markets. This paper examines a subset of essential transition-critical minerals - aluminium, cobalt, copper, lithium, and nickel - to assess how metal commodity markets may be impacted by shifting global economic dynamics. The study explores the key long-term drivers of commodity price formation, the medium-term effects of trade interventions on price expectations, and the short-term volatility triggered by trade announcements. The results indicate that metal commodity markets are primarily influenced by demand-related shocks, with copper and aluminium prices being primarily driven by aggregate demand, whereas nickel prices are influenced by a more diverse set of shocks. Similarly, in the short-term, nickel, cobalt, and lithium prices are more sensitive to trade announcements compared to copper and aluminium. The findings and discussion focus on the risks to the energy transition and financial markets.

*We are grateful to Dr Simon Dietz, Mr Robert Patalano, colleagues from the OECD and the London School of Economics, and the Working Party on Finance and Investment for Environmental Goal (WPFIEG) at the OECD for their useful feedback. Corresponding author - Martínez j.martinez8@lse.ac.uk

†Centre for Economic Transition Expertise (CETEx) and formerly OECD. h.d.miller@lse.ac.uk

‡Centre for Economic Transition Expertise (CETEx). j.martinez8@lse.ac.uk

1 Introduction

The transition to a low-carbon economy is expected to drive a significant increase in demand for critical minerals, which play a central role in the deployment of clean energy technologies (Deetman et al., 2021; Hund et al., 2023; Carrara et al., 2020; Watari et al., 2019). For example, under a Net Zero by 2050 scenario, metals such as copper, cobalt, nickel, and lithium are expected to experience between a twofold to tenfold increase in demand (IEA, 2024). The production of clean technologies is considerably more resource-intensive than their fossil fuel-based counterparts, making the future supply and demand dynamics of minerals a key factor in the feasibility of a Paris-aligned energy transition (IEA, 2021).The cost share of these raw materials in the production of these technologies varies but is between 50 to 70 per cent of total battery costs for electric vehicles, for example (Ibid).

The shift from fossil fuel-based energy systems to clean energy infrastructure alters the very structure of the global markets, moving from a flow-based system, reliant on oil, coal, and gas, to a stock-based system, driven by the extraction and accumulation of materials and clean energy infrastructure. This shift signals unprecedented levels of demand for critical minerals, creating both opportunities and risks for the global economy. Both the upfront financial and material requirements are comparatively greater in the deployment of renewable technologies, whereas traditional energy sources have greater operational costs.

The concept of critical minerals originally emerged in the context of national security, reflecting concerns about supply risks arising from import dependencies and economic importance (Coulomb et al., 2015; NRC, 2008). Over time, the term has evolved and is now widely used in discussions on the energy transition, sometimes referred to as transition-critical minerals[1](TCMs) (Miller et al., 2023).The growing emphasis on achieving net zero emissions has renewed interest in the supply and demand of these minerals, adding new dimensions to the debate. For the subset of TCMs included in this study, aluminium, copper, and nickel are cross-cutting materials used in almost all types of low carbon technologies, whereas lithium and cobalt are primarily used in lithium-ion batteries which are required for electric vehicles and battery storage.

[1]There is no agreed upon list of critical minerals because the definition of 'criticality' is subject to the context of different jurisdictions. The term TCMs refers to critical minerals whose 'criticality' is deemed based on their role in the clean energy transition. TCMs typically include materials such as Aluminium, Chromium, Copper, Cobalt, Graphite, Lithium, Molybdenum, Nickel, and Rare Earth Elements, among others.

As the global energy system transitions towards greater reliance on TCMs[2], there is likely to be a redistribution of economic influence from fossil fuel-rich economies to countries with abundant mineral reserves. However, the extraction and refinement of these minerals remain highly geographically concentrated. For key resources such as cobalt, nickel, and rare earth elements, more than 50 per cent of global supply is controlled by a single country (USGS, 2024). This high concentration presents potential risks to the security and stability of supply chains, which are essential for ensuring a smooth energy transition. These risks are particularly prevalent for metals with low recycling rates, such as lithium, where less than 1 per cent is recovered from lithium-ion batteries worldwide (Bae and Kim, 2021). IEA (2024) estimates the successful scale-up of recycling could reduce demands on primary supply by 25 to 40 per cent by 2050. However, the main focus of this study is on the price dynamics of commodity markets, which are currently dominated by primary supply.

The risks of supply shocks are heightened by the increased geoeconomic fragmentation[3] in recent years (Aiyar et al., 2023; Dadush and Prost, 2023). Global trade flows have been notably affected by geopolitical developments, including Russia's war of aggression against Ukraine. Recent literature highlights the broader economic implications of geofragmentation and the introduction of trade barriers between geopolitical blocs (Aiyar et al., 2023; Bolhuis et al., 2023; Campos et al., 2023; Góes and Bekkers, 2023).

Specifically for TCMs, there has been a five-fold increase in export restrictions in the last decade (Kowalski and Legendre, 2023), which is reflected in the increasingly geofragmented environment for these commodity markets. Hence, for the energy transition, the potential for economic fragmentation may hinder the reliable and affordable supply of these commodities required for low-carbon technological deployment, which in turn may impact the energy transition. However, there has been limited quantitative research that examines the direct impact of trade restrictions on commodity price shocks.

This paper seeks to advance understanding of the structure of metal commodity markets of a subset of TCMs and the key drivers of commodity price shocks – specifically, to examine the role of supply versus demand dynamics in price formation. It

[2]It is worth noting that many TCMs play an important role in other growing sectors of the global economy, such as telecommunications, defence, and information technologies, which means their economic importance will grow beyond just their need for the energy transition. However, demand from these other sectors is beyond the scope of this study.

[3]Geofragmentation refers to policy-driven actions which leads to the reversal of global economic integration.

also explores how geofragmentation, with increase in trade restrictions, and the energy transition may disrupt these markets, posing potential economic risks and challenges to a Paris-aligned transition. To address these questions, the paper undertakes an analysis of the short-, medium-, and long-term structure of commodity prices.

First, drawing upon methodologies commonly applied in oil market research, the paper employs a structural vector autoregression (SVAR) model to examine the role of supply and demand dynamics in historical commodity price shocks and how these affect price formation. The analysis focuses on aluminium, copper, and nickel, given the availability of data and their relative market size compared to other TCMs. The results find demand-related shocks to be the dominant drivers of price formation over the long-term, with aggregate demand shocks accounting for most the price movements in copper and aluminium markets, while nickel is influenced by a broader array of shocks.

Second, using data from the Global Trade Alert Database, the paper investigates the impact of trade interventions on commodity prices in the medium-term. The purpose is to understand the specific contribution of trade interventions on sustained higher commodity prices. In months where restrictive trade policies are announced, price expectations for nickel fluctuate between +8.1 per cent and -6.8 per cent, whereas aluminium and copper markets exhibit smaller revisions, with price movements ranging between +3.0 per cent and -5.0 per cent. These results indicate that nickel markets are more susceptible to policy-induced price volatility.

The third and final analysis provides insights into how import- and export-related trade interventions influence price volatility and short-term expectations. The most significant effects on average are observed in cobalt, lithium, and nickel markets, which suggests short-term prices and volatility is particularly sensitive to changes in expectational demand.

The purpose of the different analyses is to identify the key determinants of commodity price shocks and assess how the energy transition, alongside potential geoeconomic fragmentation, may heighten risks. The scope of the paper concerns global commodity markets, with no specific geographical scope, but it covers a subset of metals that are important for the energy transition and for which sufficient data is available. The first two analyses only consider aluminium, copper, and nickel due to data limitations, whereas the final analysis additionally includes cobalt and lithium.

The rest of the paper is structured as follows. Section 2 offers an overview of the established and emerging literature of commodity markets and the geopolitics of the energy transition. Section 3 outlines the data and methodology used to analyse the historical decomposition of metal commodity price shocks, the effects of trade restrictions, and short-term price volatility in spot markets. Section 4 presents the empirical results, including the findings from the SVAR analysis, the relationship between trade restrictions and commodity price volatility, and the event study analysis. Section 5 discusses the implications of the findings, considering both demand- and supply-side factors and differentiating between short- and long-term impacts. Finally, section 6 concludes the paper.

2 Literature review

The paper compiles three distinct but interlinked strands of literature to understand the role of metal markets, and the potential risks, over the duration of the energy transition. First, the literature on the role of TCMs, and their necessity for the achievement of the energy transition. This literature analyses the future demand and supply of these minerals, as well as the feasibility of different transition scenarios. Second, the emerging literature on economic and political geofragmentation in the global economy. This literature examines the possible reversal of economic integration within the global economy, either based on economic or political objectives. Finally, the existing literature on the price formation of commodity markets, particularly the established research on oil markets[4], as well as the more nascent papers on the price formation of metal markets - e.g., Boer et al. (2024). The focus of the literature is to understand and decompose the various drivers of commodity prices in these markets. Particularly to disentangle the role of demand versus supply in the evolution of commodity prices.

2.1 Transition-critical minerals and the energy transition

Achieving net-zero emissions will require a substantial increase in TCM demand, including materials such as aluminium, copper, nickel, and lithium. This increase will fundamentally alter the structural dynamics of these markets, potentially creating bottlenecks in supply chains. The risks are heightened by the high geographic concentration of TCM supply, with over 50 per cent of global production of several critical materials, such as cobalt, nickel, graphite, and rare earth elements, originating in a single country (Coulomb et al., 2015; IEA, 2021).

[4]See Kilian and Zhou (2023) for an extensive survey.

Several studies examine the future increase in demand for critical minerals from the energy transition (Collins et al., 2024; Miller et al., 2023; Deetman et al., 2021; Watari et al., 2019). The estimates in future demand quantities range significantly between studies and reflect the uncertainty in the pathway and ambition of the energy transition. For example, under the IEA's Net Zero Scenario, lithium demand is projected to rise more than tenfold by 2040 compared to 2023, while annual demand for copper needed for clean technologies is expected to reach nearly 20,000,000 tonnes by 2040 (IEA, 2024). Alternatively, Collins et al. (2024) estimate demand increases ranging from 85.9 to 1,298 per cent, with lithium demand potentially rising thirteenfold under the IEA's Beyond 2 Degrees Scenario by 2050. Similarly, Watari et al. (2019) project mineral flow increases of 200 to 900 per cent in the electricity sector and 350 to 700 per cent in transport, depending on the scenario. Such wide-ranging projections underscore the uncertainty surrounding the pace and ambition of the energy transition.

Several papers examine the supply-demand dynamics of materials over the course of the transition and the potential for bottlenecks in future supply. Miller et al. (2023)) provide further insights by comparing TCM demand under the Net Zero 2050 and Delayed Transition scenarios from the Network for Greening the Financial System (NGFS). Their analysis shows that both the timing and quantity of material demand differ significantly across scenarios, with the annual rate of increase heavily influenced by the narrative underpinning different transition pathways. For example, the Net Zero by 2050 scenario illustrates a linear increase in the deployment of low-carbon technologies, and subsequently material demand. However, a Delayed Transition illustrates only minor deployment of low-carbon technologies prior to 2030, with an abrupt increase post-2030, representing comparatively steeper increases in annual demand for materials. Beyond demand projections, several studies emphasise potential supply bottlenecks, though assessments of severity and which materials may face shortages vary (Miller et al., 2023; IEA, 2021; Valero et al., 2018). However, Collins et al. (2024) argue that efficiency gains, material substitution, and increased production could mitigate the risks of market tightness.

The variation in demand projections reflects not only differing transition scenarios but also disparities in modelling assumptions. For instance, studies by the IEA (2021) and Miller et al. (2023) assume a linear improvement in mineral intensity over time, while Collins et al. (2024) model constant material intensity from 2021 to 2050.

There is significant divergence in the literature in the estimated quantity of materials demanded to achieve the energy transition, mainly due to modelling assumptions and choice of transition scenario; hence substantial uncertainty remains on this front. Consensus exists amongst these papers in the anticipation of significant increase in expected demand for TCMs, with consistent acknowledgement of possible supply bottlenecks over the course of the energy transition. However, in relation to this paper, these studies focus on quantity demanded by the energy transition, and not on the impact of demand on the formation of commodity prices for these markets.

Only one paper, by Boer et al. (2024), provides a quantitative forecast of future cobalt, copper, nickel, and lithium prices, drawing upon IEA estimates of mineral demand under different transition scenarios. Beyond this study, there is limited empirical analysis that directly quantifies the price effects of the energy transition on commodity markets. Other contributions, such as Collins et al. (2024) and Miller et al. (2023), discuss the potential implications of rising demand from the energy transition for commodity prices, but their analyses are conceptual rather than econometric. A related strand of research examines the inverse relationship, assessing how fluctuations in transition-critical mineral prices affect the energy transition and clean energy equity performance, with evidence that such price shocks materially influence both (Attílio, 2025; Sohag et al., 2023).

2.2 Geofragmentation, trade risks, and geopolitical shocks

The second strand of literature investigated in this paper is the reemergence of geopolitics and the possible fragmentation of the global economy. There is a growing body of literature which examines the potential macroeconomic implications of global geofragmentation and increases in trade restrictions. These studies focus on the potential fragmentation of the global economy into politically and/or economically aligned 'blocs', with either limited or no inter-bloc trade (Aiyar et al., 2023; Bolhuis et al., 2023; Campos et al., 2023; Góes and Bekkers, 2023; Fund, 2023). Studies on geofragmentation explore the macroeconomic implications of reduced global integration, with some estimating that trade flows between blocs could decline by up to 57 per cent and global GDP could contract by 1.2 to 7.0 per cent under various fragmentation scenarios (Bolhuis et al., 2023). These shifts are also being linked to the global energy transition, with growing attention to how geopolitical disruptions could exacerbate price volatility and create bottlenecks in critical metal commodity markets (Espagne et al., 2023).

Moreover, geopolitical strategies over the course of the transition from oil-exporting countries may further disrupt the stability of the transition (Americo et al., 2023; Bazilian et al., 2020; Sinn, 2012; Overland, 2015), and by extension these commodity markets. Indeed, there is increasing acknowledgement of the potential geopolitical reshuffle over the course of the energy transition (Overland et al., 2019; Vakulchuk et al., 2020; Van de Graaf, 2018; Scholten et al., 2020). Given the high concentration of production and refining capacity in minerals market, often exceeding that of fossil fuels, their exposure to geopolitical events is acute (IEA, 2021). This risk is exemplified by discussions of the potential weaponisation of energy and mineral exports (Downie, 2022).

Export restrictions on TCMs have already increased fivefold in the past decade, with approximately 10 per cent of global TCM exports subject to at least one restriction (Kowalski and Legendre, 2023). Recent studies have further explored how fragmentation could impact trade flows and commodity prices. For example, Bolhuis et al. (2023); Alvarez et al. (2023) model the effects of geofragmentation using scenario analyses that divide countries into two major blocs: US-Europe+ and China-Russia+. Bolhuis et al. (2023) find that global GDP losses could range from 0.2 to 7.0 per cent, depending on the degree of fragmentation. Alvarez et al. (2023) highlight the specific impact on refined metal commodity prices, estimating price increases of up to 500 per cent in the US-Europe+ bloc. These findings illustrate the vulnerability of metal markets to economic fragmentation and geopolitical tensions. However, the diversification of technologies and the broader range of minerals required for the energy transition, compared with fossil fuels, may partially offset these risks.

The role of geopolitical events in shaping commodity markets is not unprecedented. For example, the formation of OPEC has been widely studied for its effects on global oil markets and broader macroeconomic variables, such as inflation and economic activity (Känzig, 2021; Karabulut et al., 2020; Kilian and Murphy, 2014). Research has also examined the short-term impacts of OPEC announcements on oil spot and futures prices, finding significant market reactions, with effects diminishing over longer maturities. These studies, such as Demirer and Kutan (2010), also note that price responses are often asymmetric, varying by the type of announcement. This body of work provides valuable insights into how trade interventions and market collusion could similarly impact TCM markets during the energy transition.

A more recent body of work explores how rising geopolitical tensions and geoeconomic fragmentation influence transition-critical mineral (TCM) markets. Several studies examine the effects of geopolitical events on metal commodity prices, finding that episodes of heightened geopolitical risk are associated with sharp increases in metal prices and volatility, as well as spillovers to clean energy equity performance (Pham and Hsu, 2025; Huang et al., 2025; Sohag et al., 2023). In a related analysis, Saadaoui et al. (2025) distinguish between geopolitical threats and realised geopolitical actions, showing that perceived threats tend to generate stronger price responses due to elevated uncertainty and shifting market expectations. A subset of these studies also explicitly link geofragmentation and TCM markets to the energy transition (Islam and Sohag, 2024; Pham and Hsu, 2025; Saadaoui et al., 2025). However, existing contributions remain primarily descriptive or based on event correlations. None apply a structural econometric framework to disentangle the supply and demand drivers of price formation in the context of both the energy transition and rising geofragmentation.

2.3 Price formation in commodity markets

Finally, a rich swathe of literature examines the structure and price formation of commodity markets, particularly concerning oil markets (Baumeister and Hamilton, 2024; Baumeister et al., 2024; Caldara et al., 2019; Kilian and Murphy, 2014; Kilian, 2009; Kilian and Zhou, 2020). The most commonly used methodology for studying the supply-demand dynamics in oil price formation is vector autoregression (VAR) models, which have advanced significantly in complexity, incorporating either Bayesian or frequentist approaches (Baumeister and Hamilton, 2024).

The structure of global oil markets evidences the prevailing role of global demand shocks in the formation of oil prices, with supply shocks undertaking a secondary role, albeit with disagreement on its exact importance (Baumeister and Hamilton, 2019; Kilian, 2009). The evidence on the importance and behaviour of different structural shocks – such as expectational demand shocks from geopolitical events – differs between studies (Baumeister and Hamilton, 2019; Kilian and Murphy, 2014; Erbil and Roache, 2010). However, there is less evidence to ascertain whether the same dynamics hold true for metal commodity markets.

In contrast to oil markets, metal markets have received comparatively less attention in terms of price formation and market dynamics. Nonetheless, recent studies have begun applying methodologies from oil market research to analyse the price formation of metal commodities, focusing on supply-demand dynamics (Boer et al., 2024; World Bank Group, 2022; Jacks and Stuermer, 2020). These studies consistently find that demand shocks are the dominant structural factor influencing metal price formation, while supply shocks play a secondary role. This may be due to the acute but short impact of supply shocks compared with the more sustained pressures characterised by structural demand shocks. Beyond price formation, other research has assessed the broader macroeconomic impacts of metal commodity prices. Miranda-Pinto et al. (2024) examines the effects of metal price shocks on inflation, finding that these shocks contribute to both headline and core inflation. Notably, metal price shocks have a more persistent impact on core inflation, suggesting that their inflationary effects, while less immediately visible, may have longer-term implications.

However, there are notable gaps in the literature. For example, Boer et al. (2024) is the only study to explicitly examine the structure of metal commodity markets in the context of the energy transition. Similarly, the World Bank Group (2022) is among the few studies to consider the implications of a changing geopolitical environment on these markets. This highlights the need for further research on how structural shocks, geopolitical dynamics, and the energy transition influence metal commodity markets.

2.4 Further research

Further research is necessary to better understand how metal commodity markets will influence the feasibility of a Paris-aligned energy transition. The impact of geopolitical events on these markets is already evident, as demonstrated by the extreme price volatility in nickel markets following Russia's invasion of Ukraine in 2022. Nickel prices surged by 270 per cent during this period, prompting the suspension of trading (Heilbron, 2024). This event highlights the potential economic and financial risks associated with metal markets and their critical role in the energy transition. Despite this, the current understanding of how these markets will adapt to the evolving structural dynamics of the global economy remains limited.

While some overlap exists between the literature on energy transitions, geofragmentation, and commodity price formation, few studies address these topics in an integrated manner. The paper seeks to fill this gap by providing new insights into the dynamics of metal commodity markets under the dual pressures of the energy transition and increasing geofragmentation of global trade. The analysis contributes to the literature in two ways. First, it uses monthly data to decompose and identify supply- and demand-related price shocks in metal commodity markets with greater precision. Second, it examines the short- and medium-term effects of expectational demand shocks stemming from trade announcements on commodity prices. These contributions aim to deepen the understanding of how structural shocks and policy changes may shape metal markets, offering valuable insights for policymakers and market participants navigating the challenges of the energy transition.

3 Data and Methodology

This section outlines the methodology used to develop the analysis. It describes the data sources and the methodological approach used to undertake the three-fold analysis of commodity price formation and the impact of trade interventions.

3.1 Data

3.1.1 Prices, quantities, and real economic activity data

The S&P Global (2025) database provides daily spot price series for each commodity in the paper. Note, for lithium, a daily spot price series is only available until mid-2021, so the event study analysis on lithium prices is only conducted until this date. In addition to the commodity price series, the S&P Goldman Sachs Commodity Index (GSCI), which is a broad-based commodity market index, is used as a proxy of market returns for the event study analysis. The GSCI, enables the isolation of the impact of trade announcements from general market movements in commodity markets.

For the construction of the surprise index in the second segment of the analysis, futures price data is extracted from Bloomberg Terminals (Bloomberg L.P., 2025). The 3-month futures contract daily prices are extracted for aluminium, copper, and nickel. These time series are used to assess the change in market expectations for future supply and demand conditions, in reaction to the announcement of trade interventions.

For first two sections of the analysis, where the paper examines the determinants of price formation in commodity markets and for the medium-term impact of trade restrictions, the price series are aggregated to provide a monthly average of price changes. These average prices are then deflated using the US's Urban CPI index. For the event study, all commodities prices are transformed to a daily returns series. To facilitate the analysis, the natural logarithm of commodity prices and market index closing prices was computed. These log values serve as the basis for return calculations.

For the first two sections of the analysis, monthly production figures for aluminium, copper, and nickel are extracted from the World Bureau of Metal Statistics via London Stock Exchange Group (LSEG) Database (London Stock Exchange Group, 2024). This provides monthly estimates for global primary production of each metal starting in 1990 (or 1995 for copper) until June 2024. Furthermore, monthly warehouse stocks of each commodity are extracted, which are used in the reduced-form structural VAR model.

The Real Economic Activity measure is the dry cargo ocean freight rates index developed by Kilian (2009) for analysing oil markets. This index captures industrial commodities' demand in global markets by exploiting features of the ocean freight supply. In other words, since the short-run supply is almost vertical because of capacity constraints, the freight rates map to global demand pressures. The index is published by the Federal Reserve Bank of St. Louis and is constructed by averaging across the growth-rates of a representative single-voyage freight rate, accumulating these growth-rates [5], deflating with the US CPI and detrending the resulting series (Kilian, 2009). The Real Economic Activity index offers a proxy for aggregate industrial demand in the global economy within the models used in this paper to capture demand dynamics different from the metal markets.

3.1.2 Global Trade Alert database

The Global Trade Alert (GTA) database gathers detailed information on enacted policies that reflect foreign commercial interests from specific jurisdictions (Evenett and Fritz, 2020). I.e., it considers interventions in the trade of goods and services, financial flows, and labour force migration, with a coverage from 2008 onwards. The database comprises of approximately 1,300,000 entries at the implementing-affected jurisdictions level (one trade policy from an implementing jurisdiction is entered separately for each affected country). Each one of these entries includes information regarding the affected products, affected sectors, an intervention type, and a GTA evaluation of whether the policy liberalises or restricts international trade or associated channels[6].

For instance, intervention *14084* documents an Indonesian export-related non-tariff measure announced in early 2009. Since it affected ten jurisdictions, there are ten different entries in the database because the policy did not necessarily affect the same products across all jurisdictions. This policy was classified by the GTA as negative since it imposed further restrictions on the way the exports of specific

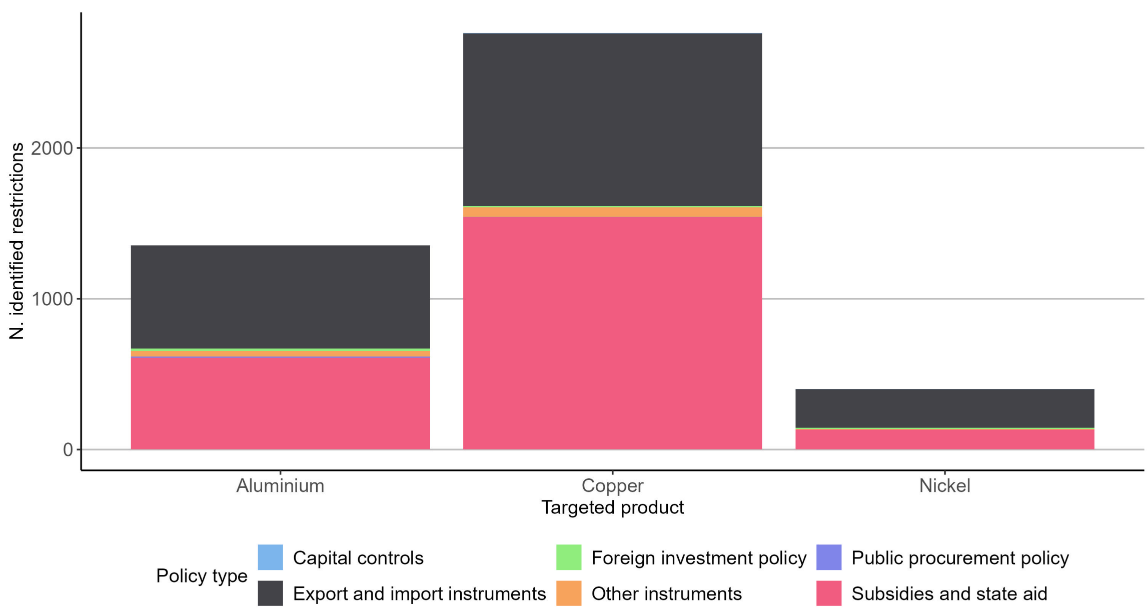
[5] The series is normalised to January 1968.

[6] The policies in the database include: Capital controls and exchange rate policy, export and import policy instruments, foreign investment policy, labour force migration, localisation policy, public procurement policy, subsidies and state aid, trade defence instruments, and other instruments.

products could be funded. The paper focuses on the dates in which restricting policies were enacted, by initially identifying the entries related to aluminium, copper and nickel. Targeted products are encoded at the 6-digit level following the Harmonised System (HS, 2012 version) developed by the World Customs Organisation.

Subsequently, the methodology maps all the products related to these metals and the 6-digit encoding identifies interventions that target the first link of the value chain, namely, the metals' ores. Moreover, interventions that affect downstream products derived from the metals' ores were also identified. The GTA database is combined with the production data for maintaining interventions related to a country that produced at least 5 per cent of the specific metal each year.

Figure 1. Negative restrictions per metal and policy type



Note: This figure displays the number of restrictive trade interventions for each metal, as classified under the Global Trade Alert Database. The figure includes interventions which are applied to the ore materials as well as the refined products.
Source: Author's calculations based on Global Trade Alert Database (2025).

Once the database is refined to identify the most relevant trade restrictions, there are 4,281 implementing-affected jurisdiction pairs, out of which 71.3 per cent are associated with a policy restricting a channel of international trade, 18.3 per cent liberalising trade, and 10.3 per cent are deemed ambiguous. The analysis focuses on the interventions that restrict the free trade of the metals, so only those classified as restrictive by the GTA. Most of the interventions target copper ores (61.1 per cent), followed by aluminium (30 per cent), and the least representative metal is nickel (8.9 per cent).

For the construction of the surprise index, the focus is about the dates in which restrictions were enacted, regardless of the number or related countries. Thus, the dataset identifies 113 intervention days for copper, 113 for aluminium and 74 for nickel[7]. For the event study, a more selective set of trade interventions are chosen, exclusively those which are classified as an Import Tax, Import Tariff, Import Tariff Quota, Import Ban, Export Ban, Export Quota and Export Tax. The rationale of limiting the interventions to export- and import-related policies is to identify interventions which directly constrain the supply or price of metal commodity markets. This leads to 201 interventions for aluminium ores and products, 325 interventions for copper ores and products, 71 interventions for nickel ores and products, 35 interventions for cobalt ores and products, and 82 interventions for lithium products. Additionally, trade interventions related to batteries are also considered for cobalt and lithium, given their role in lithium-ion battery production. 105 trade interventions related to batteries and their production are identified in the dataset.

3.2 Methodological overview

3.2.1 SVAR model for commodity price formation

The initial step of the analysis involves the construction of a structural vector autoregression (SVAR) model to estimate the historical decomposition of commodity price shocks for aluminium, copper, and nickel. This involves the construction of a reduced-form VAR model, as well as additional sign restriction and narrative sign restrictions, to imitate the historical price formation of each metal.

The analysis utilises a dynamic simultaneous equation model comprised of a structural VAR, which is formulated separately for each metal. The model captures the evolution of four key variables: the global real economic activity index REA_t; the percentage change in metal production, denoted by ΔQ_t; the log of the real metal price, P_t; and the change in log inventories, represented by ΔS_t. These variables are stacked into the vector $\mathbf{y}_t$, and the reduced-form VAR(p) model is expressed as:

$$\mathbf{y}_t = \Pi \mathbf{D}_t + A_1 \mathbf{y}_{t-1} + \cdots + A_p \mathbf{y}_{t-p} + \mathbf{u}_t \tag{1}$$

[7]This translates into 78, 92 and 53 intervention months, respectively, in the SVAR analysis.

where $\mathbf{D}_t$ is a matrix of deterministic terms that includes a constant and monthly dummies for the Great Recession, the COVID-19 pandemic, and the Ukraine war[8]. The A_i matrices represent the VAR coefficients. $\mathbf{u}_t$ is the vector of reduced-form innovations, which do not have an immediate economic interpretation. These innovations have a covariance matrix given by:

$$\mathbb{E}(\mathbf{u}_t \mathbf{u}_t') = \Sigma_u \tag{2}$$

A linear mapping between the reduced-form innovations $\mathbf{u}_t$ and the structural shocks $\boldsymbol{\varepsilon}_t$ is defined as:

$$\mathbf{u}_t = B_0^{-1} \boldsymbol{\varepsilon}_t \tag{3}$$

The matrix B_0 captures the contemporaneous impact effects of the structural shocks on the variables in $\mathbf{y}_t$. By normalising the covariance matrix of the structural shocks to the identity matrix, i.e., $\mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') = \mathbb{I}$, the shocks acquire an economic interpretation, as each is orthogonal to the others. Under this assumption, the reduced-form innovations' covariance matrix can be derived as follows:

$$\mathbb{E}(\mathbf{u}_t \mathbf{u}_t') = \mathbb{E}[(B_0^{-1} \boldsymbol{\varepsilon}_t)(B_0^{-1} \boldsymbol{\varepsilon}_t)'] = B_0^{-1} \mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t')(B_0^{-1})' = B_0^{-1}(B_0^{-1})' \Rightarrow \Sigma_u = B_0^{-1}(B_0^{-1})' \tag{4}$$

Notice that identification of B_0^{-1} allows the correlated reduced-form innovations in $\mathbf{u}_t$ to be expressed as weighted averages of the uncorrelated structural shocks, where the entries of B_0^{-1} serve as the respective weights (Kilian and Lütkepohl, 2017). Nevertheless, finding these entries without further information is not possible unless some restrictions are imposed.

The literature has come up with different methodologies to solve this identification problem, either by imposing zero or sign restrictions (Faust, 1998; Uhlig, 2005), both in frequentist and bayesian settings (Arias et al., 2018; Rubio-Ramírez et al., 2010). Moreover, Stock and Watson (2012) and Mertens and Ravn (2019)introduced the "SVAR-IV" method, which leverages exogeneous variation for identifying entries of B_0^{-1}. Both sign restrictions and the SVAR-IV method are employed for analysing structural shocks.

Since it is impossible to identify the entries of B_0^{-1} without further information,

[8] December 2007 through June 2009, January through August of 2020, and March 2022, respectively.

zero and sign restrictions are directly imposed on the matrix' entries, in the spirit of Faust (1998) and Uhlig (2005). In other words, the impacts of structural shocks B_0^{-1} on endogenous variables $\mathbf{y}_t$ are assumed to be either zero, positive or negative, as presented in Table 1. The first shock is hypothesised as an aggregate demand shock in the global economy. It positively affects global economic activity, as well as the production and price of the specific metal.

The second shock corresponds to a positive supply shock, which naturally drives prices down and has no immediate impact on global economic activity. This primarily refers to supply flow shocks related to an increase in production of a commodity. Its effect on inventories is deemed ambiguous, for a decrease in prices could lead to higher inventories. However, this may be counterbalanced by a lower demand for inventories due to lower expected prices in the long run. The shock is thus left unrestricted because it is not clear which effect dominates.

The third shock is a metal-specific contemporaneous demand shock. It positively affects real economic activity, production, and prices, whilst having a negative effect on inventories. A positive shift in demand leads to drawing down inventories as to smooth price shocks in the short run. Moreover, it is noteworthy that, even if the impact response of production is assumed positive, no specific stance is taken on its magnitude. If anything, this increase in production will be quite low and most likely embodies spare capacity in some mines.

Table 1. Sign restrictions on impact responses

	Aggregate demand shock	**Metal flow supply shock**	**Metal-specific contemporaneous demand shock**	**Metal-specific expectational demand shock**
Real economic activity	+	0	+	+
Metal production	+	+	+	+
Metal warehouse stocks	+	−	−	+
Real prices	+	−	+	+

Note: The table provides an overview of the sign restrictions which are enforced on the model. The positive and negative signs refer to the directional movement each type of shock may initially have on each variable. For example, the first positive sign means an aggregate demand shock will initially lead to an increase in real economic activity. The 0 represents a restriction within the model to have no initial reaction of the variable to the shock, whereas empty cells represent an unrestricted variable.
Source: Author's conceptualisation.

It should be noted that the interpretation of price innovation as a metal-specific demand shock hinges upon the assumption that the other variables in the model adequately capture aggregate demand and supply influences. The inclusion of lagged real economic activity, production and inventories, in particular, are intended to control for broader macroeconomic conditions, industry-specific supply innovations and expectations revisions, respectively. Hence, our assumption is that conditioning on the lags of the other variables allows us to isolate the contemporaneous demand shock after pre-multiplying the reduced-form innovations by B_0. However, the extent to which these variables fully capture all these dynamics is unknown, and thus allow us to isolate contemporaneous demand, is a limitation. Finally, the fourth shock is assumed to be a metal-specific expectational demand shock that has positive effects on all variables.

Complementary to the sign-restrictions, Antolín-Díaz and Rubio-Ramírez (2018) developed narrative sign-restrictions that lead to sharper identification. These impose a specific sign to the structural shocks in specific moments of time. Furthermore, the size of the structural shocks in the historical decomposition of the endogenous variables can also be restricted. Given that the data series cover part of the 1990s and ends in mid-2024, restrictions are imposed on the periods which match the Great Recession, the Covid Pandemic, and the Russian invasion of Ukraine.

As presented in Table 2, the great recession was characterised by a rapid deceleration of the business cycle and a price contraction across several commodities. It therefore is associated with a negative aggregate demand shock that affects both real economic activity and prices. However, it only affects prices during June 2008, whilst the effect on aggregate demand is hypothesised to last until January 2009. The covid pandemic has the same effects on the endogenous variables, but the restriction only lasts one month. These restrictions are common across Aluminium, Copper and Nickel.

Finally, a positive expectational demand shock is imposed on Nickel's price series. Specifically, during March 2022, the month immediately after the invasion of Ukraine and during which price rose up to 270 per cent (Heilbron, 2024). This is characterised as an expectational demand shock, given Russia's role in nickel production and anticipation of sanctions led to a revision in market expectations of future supply-demand dynamics.

Table 2. Sign restrictions on impact responses

Dates	**Shock**	**Variable**	**Sign**	**Narrative**	**Metal**
June 2008	Aggregate demand	Real economic activity, Prices	Negative	Great Recession	Aluminium, Copper, Nickel
March 2020	Aggregate demand	Real economic activity, Prices	Negative	COVID pandemic	Aluminium, Copper, Nickel
March 2022	Expectational demand	Prices	Positive	Ukraine war	Nickel

Note: The narrative sign-restriction imposed on real economic activity for the Great Recession is assumed to last seven consecutive months.
Source: Author's conceptualisation.

Estimation of the reduced-form coefficient matrices A_i and the impact effects matrix B_0^{-1} allows for the estimation of structural impulse responses at different horizons $i = 0, 1, \ldots, h$, which are gathered in the matrix:

$$\Theta_i = [\theta_{y,\varepsilon,i}] \tag{5}$$

As in Kilian and Murphy (2014); Antolín-Díaz and Rubio-Ramírez (2018); Boer et al. (2024), the supply elasticity is derived from a metal-specific contemporaneous demand shock that displaces the demand curve and traces the supply. More formally, the supply elasticity at the i-th horizon ε_i^s is given by the ratio of the cumulative response of production to the cumulative response of prices:

$$\varepsilon_i^s = \frac{\sum_{j=0}^{i} \theta_{Q_{t,MD},j}}{\sum_{j=0}^{i} \theta_{P_{t,MD},j}} \tag{6}$$

Estimation is performed with Bayesian methods and independently for each metal. The lag order of each model is set to minimise the Akaike Information Criterion (AIC). Thus, $p = 12$ for aluminium and copper, and $p = 13$ for nickel. The R package *'bsvarSIGNs'*, developed by Wang and Woźniak (2025), is employed. This implementation, in turn, is fully based on the algorithms proposed by Arias et al. (2018). The models' priors assume that the growth of each, production and inventories, is independent and identically distributed. By contrast, real economic activity and prices follow a random walk. Furthermore, a hierarchical Minnesota prior as in (Giannone et al., 2015) is used when estimating the reduced-form coefficient matrices and shocks.

Sign-identified models do not allow for pointwise identification but set identification. Thus, a set of 1,000 models per metal is created. This allows for the computation of all objects of interest for each model. It is well established that the percentiles of this set might not reflect an actual model (Kilian and Murphy, 2012). Nevertheless, as is common in the literature, pointwise median and 68 per cent credible sets are reported to give a sense of the uncertainty around the estimates (Antolín-Díaz and Rubio-Ramírez, 2018; Boer et al., 2024).

3.2.2 Medium-term impact of trade restrictions

In the second part of the analysis, a surprise series z_t, explained in more detail in the next subsection, is employed as an external instrument. This allows recovering the structural impact vector associated with the metal's real price shocks. This vector can be interpreted, more generally, as precautionary demand shocks (a type of expectational demand shock). Let $\varepsilon_{ED,t}$ represent the shock associated with the metal's expectational demand at t, while $\boldsymbol{\varepsilon}_{-ED,t}$ is a vector gathering all the remaining structural shocks. The usual relevance and exogeneity conditions of an instrument imply:

$$\mathbb{E}(z_t \varepsilon_{ED,t}) = \alpha \neq 0 \tag{7}$$

$$\mathbb{E}(z_t \boldsymbol{\varepsilon}_{-ED,t}) = 0 \tag{8}$$

Analysing the covariance between the instrument z_t and the reduced-form innovations $\boldsymbol{u}_t$:

$$\mathbb{E}(z_t \boldsymbol{u}_t) = B_0^{-1} \mathbb{E}(z_t \boldsymbol{\varepsilon}_t) \tag{9}$$

Where the equality results from the linear mapping between $\boldsymbol{u}_t$ and $\boldsymbol{\varepsilon}_t$. Partitioning the columns of B_0^{-1}, the rows of $\boldsymbol{\varepsilon}_t$ and employing the relevance and exogeneity conditions above yields:

$$\mathbb{E}(z_t \boldsymbol{u}_t) = \begin{pmatrix} \boldsymbol{b}_{0,ED} \\ \boldsymbol{b}_{0,-ED} \end{pmatrix} B_{0,-ED} \begin{pmatrix} \mathbb{E}(z_t \varepsilon_{ED,t}) \\ \mathbb{E}(z_t \boldsymbol{\varepsilon}_{-ED,t}) \end{pmatrix} = \boldsymbol{b}_{0,ED} \cdot \alpha + \boldsymbol{b}_{0,-ED} \cdot \boldsymbol{0} \tag{10}$$

Further partitioning the rows of the vectors $\boldsymbol{u}_t$ and $\boldsymbol{b}_{0,ED}$:

$$\mathbb{E}(z_t \boldsymbol{u}_t) = \begin{pmatrix} \mathbb{E}(z_t u_{ED,t}) \\ \mathbb{E}(z_t \boldsymbol{u}_{-ED,t}) \end{pmatrix} = \begin{pmatrix} \boldsymbol{b}_{0,ED} \cdot \alpha \\ \boldsymbol{b}_{0,-ED} \cdot \alpha \end{pmatrix} \tag{11}$$

Notice that combining the last two equations one can find all the entries of $\boldsymbol{b}_{0,ED}$ subject to normalising on $b_{0,ED}$:

$$\frac{\boldsymbol{b}_{0,-ED} \cdot \alpha}{b_{0,ED} \cdot \alpha} = \frac{\mathbb{E}(z_t \boldsymbol{u}_{-ED,t})}{\mathbb{E}(z_t u_{ED,t})} \quad \Rightarrow \quad \widehat{\boldsymbol{b}}_{0,-ED} = \boldsymbol{b}_{0,-ED} = \frac{\mathbb{E}(z_t \boldsymbol{u}_{-ED,t})}{\mathbb{E}(z_t u_{ED,t})} \tag{12}$$

Once the impact vector associated with expectational demand shocks is identified, the computation of other quantities of interest, such as Impulse Response Functions (IRFs)[9] and Forecast Error Variance Decompositions (FEVDs), is straightforward, as explained in Montiel-Olea et al. (2021). The paper also illustrates how inference can be conducted using a delta-method procedure.

A key concern in instrumental variable applications is whether the relevance and exogeneity conditions are satisfied. The relevance condition can be assessed using a heteroskedasticity-robust first-stage F-statistic (Andrews et al., 2019), whereas the exogeneity condition cannot be directly tested. In this context, the surprise series derived from trade restriction announcements is plausibly uncorrelated with other structural shocks related to metals' supply, storage, or global economic activity.

It is well known that pre-testing on the first-stage F-statistic can introduce bias, particularly in the presence of weak instruments, which is a relatively common issue in the literature. To address this, Montiel-Olea et al. (2021) propose computing Anderson–Rubin (AR) confidence sets for the IRFs. These sets remain asymptotically valid even when the correlation between the instrument and the structural shocks tends to zero, that is, when $\mathbb{E}(z_t \varepsilon_{p,t}) = \alpha \approx 0$.

The model estimates the reduced-form parameters' matrices A_i and the reduced-form covariance matrix Σ_u for each metal independently. The lag order of each model is set to minimise the Hann–Quinn information criterion. Thus, $p = 1$ for aluminium and nickel, and $p = 2$ for copper. Then, instruments' strength is assessed, IRFs are computed, and inference is conducted both with the delta-method procedure and the AR confidence sets when possible.

The paper follows the methodology of Känzig (2021) to construct a proxy variable, the 'surprise index', to capture expectations' revisions associated with the announcements of the trade restrictions. This methodology is enhanced following the recommendations by Kilian (2024) to avoid potential issues associated with aggregation. Subsequently, the surprise index is utilised to disentangle precautionary demand

[9]The impulse response function describes how one variable in a time series system responds over time to a sudden shock in another variable, helping to understand dynamic interactions in the SVAR models.

shocks in the monthly VAR model. To construct the surprise index, the methodology uses the three-month metal-specific futures contract price. The daily surprises are the (log) price difference between the day of a trade restriction announcement and the preceding trading day. Formally, denoting the (log) price of the three months ahead contract on day d as $F^3_{t,d}$, the surprise is given by:

$$s^3_{t,d} = F^3_{t,d} - F^3_{t,d-1} \tag{13}$$

Following Pindyck (2001) commodities pricing model, $F^3_{t,d}$ can be decomposed into the expected price three months ahead and a risk premium:

$$F^3_{t,d} = \mathbb{E}_{t,d}(P_{t+3}) - \rho^3_{t,d} \tag{14}$$

Assuming the expectations are revised based on the trade restrictions and that these do not affect the intra-day risk premium $\rho^3_{t,d}$, yields:

$$s^3_{t,d} = \mathbb{E}_{t,d}(P_{t+3}) - \mathbb{E}_{t,d-1}(P_{t+3}) \tag{15}$$

Two details are worth noting at this point: (i) when no trade restrictions take place, $F^3_{t,d}$ and $F^3_{t,d-1}$ are identical, making the surprise equal to zero; and (ii) $s^3_{t,d}$ is at the day level, whereas the variables in the VAR model are at the monthly level, making an aggregation necessary. Whilst Känzig (2021) uses simple addition, the approach ignores the fact that daily surprises may carry over to the next month, as explained by Kilian (2024). Therefore, it is necessary to perform aggregation depending on how many days are left in the month and considering the surprises from the previous month. Formally, the monthly average surprise is given by:

$$s_t = \sum_{d \in t-1} s_{t,d} - \sum_{d \in t} s_{t,d} \frac{(T - d + 1)}{T} \tag{16}$$

The strength of the instrument is assessed in two ways: the computation of a heteroskedasticity-robust first-stage F statistic, which results from running a regression between the reduced-form innovations associated to the real price of the metal, and the surprise series. In addition, Montiel Olea et al. (2021) argue that a Wald test can be computed by employing entries from $\boldsymbol{b}_0$ and $\boldsymbol{\Sigma}_u$. A rejection of the null hypothesis implies that (i) the instrument is strong and (ii) the AR confidence set is a bounded interval of the impulse response coefficients. Results of both tests are presented in Table 3: even though none of the F statistics is above the rule-of-thumb of 10, these are still significant when compared to the Stock and Yogo (2002) critical values. However, while the Wald test is rejected for aluminium and copper, it cannot be rejected for nickel, suggesting that the instrument is not strong enough. This may be partly explained by the fewer number of days with effective restrictions for this metal, which make the surprise index less relevant for capturing precautionary demand shocks.

Table 3. Instrument Strength Assessment

Metal	**F-Stat**	**P-Val.**	**Wald-Stat**
Aluminium	9.32**	0	5.53
Copper	4.07*	0.05	4.55
Nickel	4.53**	0.03	3.53

Note: F-Stat significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Source: Author's calculations.

3.2.3 Short-term impact of trade restrictions on commodity returns and volatility

This section of the methodology employs a market model to analyse the cumulative abnormal returns from daily price series for each metal in response to the announcements of restrictive trade interventions. The purpose is to understand the short-term market price reaction to the announcement of trade interventions. The methodology explained in Campbell et al. (1998) is followed, whilst inference is conducted as explained by Patell (1976). Let the return of commodity c at day d be denoted by:

$$R_{cd} = \ln\left(\frac{P_{cd}}{P_{cd-1}}\right) \tag{17}$$

The objective is to identify a series of abnormal returns triggered by the announcement of the trade restrictions. Assuming that the commodity's return is related to the overall market, this can be more formally expressed by means of a regression model of the type:

$$R_{cd} = \alpha + \beta R_{md} + \varepsilon_{cd} \tag{18}$$

Where R_{md} is the market return, which in this case is proxied by the GSCI index. Under this framework, the abnormal returns are equivalent to the error term ε_{cd}. The usual procedure implies defining an estimation window that runs from T_0 through T_1, and an event window that runs from $T_1 + 1$ through T_2. Moreover, it is also helpful to define $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$, these are the number of days in the estimation and event windows, respectively. The next step is to estimate the linear regression with the days pertaining to L_1 to recover sample estimates of $\hat{\alpha}$ and $\hat{\beta}$. The coefficients are then used for predicting $\hat{\varepsilon}_{cd}$ during the event window. This allows to recover an abnormal return series that runs from T_1 to T_2. Taking $\tau = 0$ as the event date, $\hat{\varepsilon}_{c\tau}$ can be re-expressed relative to the event date – e.g., $\hat{\varepsilon}_{c,-10}$ would be the abnormal return 10 days before the announcement of the trade restrictions that affected commodity c. Finally, it is possible to compute the cumulative abnormal return between two days, τ_1 and τ_2, by simple aggregation of $\hat{\varepsilon}_{c\tau}$:

$$CAR_c(\tau_1, \tau_2) = \sum_{\tau=t_1}^{t_2} \hat{\varepsilon}_{c\tau} \tag{19}$$

Notice that from the regression model above expressed, the abnormal return estimate is identically and normally distributed – i.e., $\hat{\varepsilon}_{cd} = \varepsilon_{cd} \sim \mathcal{N}(0, \sigma_{\varepsilon}^2)$[10]. Since the GTA database has several trade restrictions per commodity, the above-described procedure is run for each commodity-trade restriction pair. The estimation window is set to 80 days, whilst the event window is set to 40 days – i.e., $L_1 = 80$ and $L_2 = 40$. Aiming to guarantee comparability, all the abnormal returns series are standardised by their sample standard deviation σ_{ε}^2. Finally, Patell (1976)'s standardised test statistic is employed for testing whether the trade restrictions have long-lasting effects on the commodities' returns. Given a set of sequences of standardised cumulative abnormal returns, one can test whether they average out to zero or not with the normally distributed test statistic:

$$Z = \frac{\sum_c CAR_c(\tau_1, \tau_2)}{\left[\sum_c \frac{L_1 - 2}{L_1 - 4}\right]^{1/2}} \tag{20}$$

4 Results

This section presents the results of a three-part analysis of price formation and the role of trade interventions in metal commodity markets that are central to the net-zero transition. The first part adopts a macroeconomic perspective to assess the historical

[10]This is a standard assumption in the market model and follows Campbell et al. (1998)

drivers of price formation, focusing on the relative importance of different structural shocks across aluminium, copper, and nickel. The second examines the medium-term effects of trade interventions on prices via expectational demand shocks, with particular attention to how policy announcements shape market expectations. The final part applies an event study approach to evaluate short-term price responses and volatility following trade policy announcements, quantifying their financial impact and relevance to transition risks.

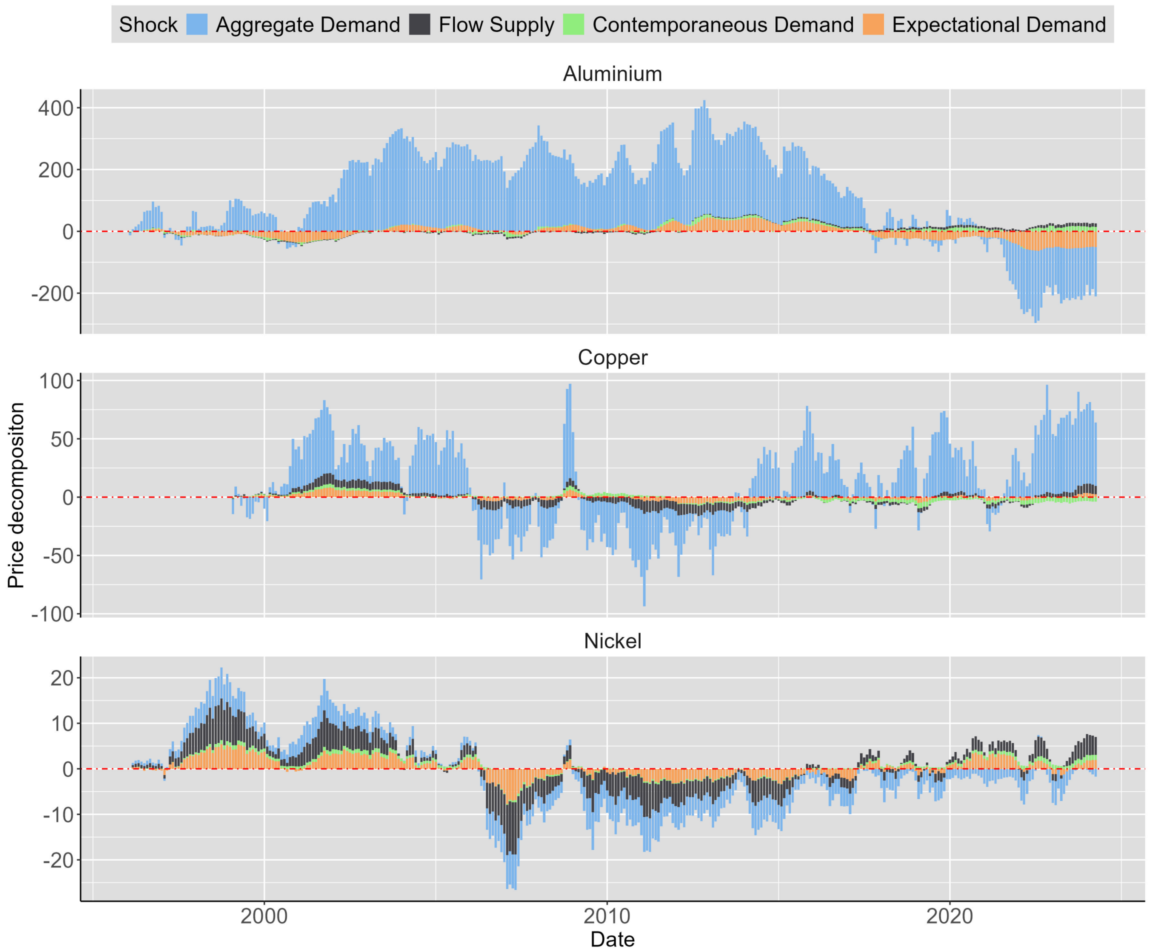
4.1 Macroeconomic perspective on commodity price formation

Under the assumption of stationarity, the VAR model can be expressed in a moving average form that allows a historical decomposition of the main variables into structural shocks[11]. This approach makes it possible to recover the impact of each structural shock on prices at every point in time, although decompositions for the earliest periods are less reliable due to the finite sample (Kilian and Lütkepohl, 2017).

For each metal, 1,000 admissible draws are generated, producing as many possible historical decompositions, offering a range of admissible models consistent with the imposed sign restrictions through set identification. These are averaged at the metal–date level for plotting (Figure 2). The decomposition isolates four hypothesised structural shocks: aggregate demand, flow supply, contemporaneous demand, and expectational demand, which are respectively mapped in our specification by four variables: real economic activity, production, prices, and inventories. Figure 2 shows each shock's contribution to deviations from the long-run mean.

[11] This method recovers the price series after subtracting deterministic components, meaning the axis scale is not directly comparable to observed market prices.

Figure 2. Historical decomposition of commodity price shocks



Note: Stacked bars represent each type of structural shock's contribution to aluminium, copper, and nickel prices for each month between 1995–2024.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and LSEG.

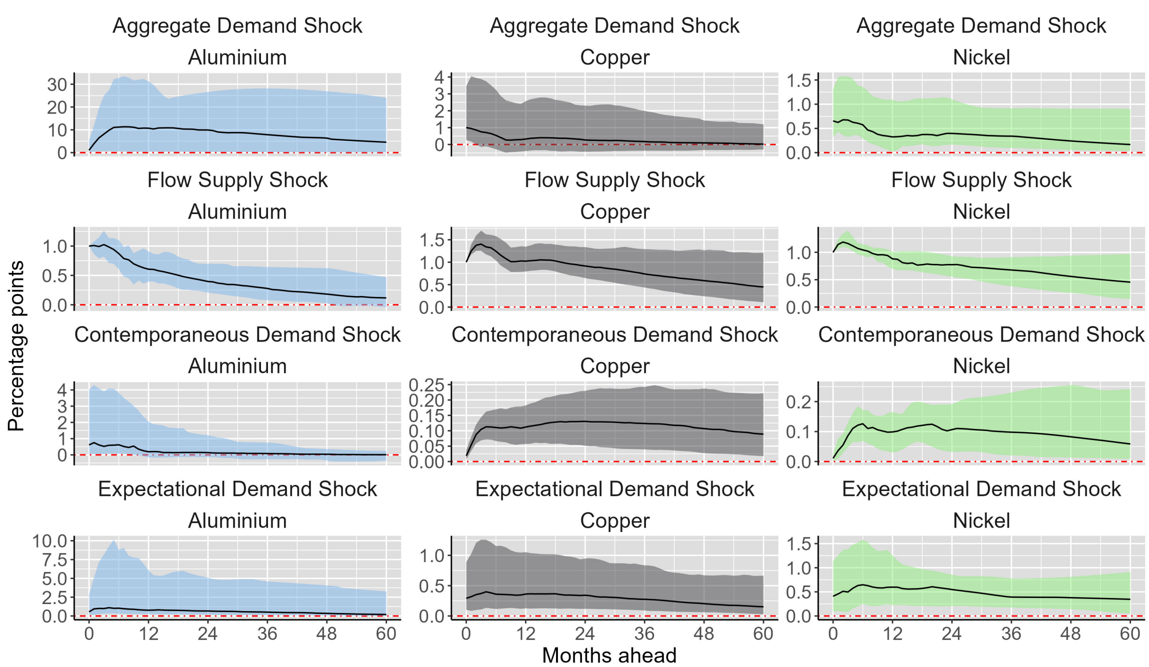
Aluminium and copper prices are dominated by aggregate demand shocks over time, where price shocks correlate with real economic activity. This reflects their widespread use across industrial sectors. Aluminium is integral to energy, transportation, construction, and consumer appliances, while copper is essential for electricity transmission and construction (European Aluminium, 2025; International Copper Association, 2023). These broad applications link their price movements closely to global macroeconomic conditions.

Nickel's price formation is shaped by a more diverse set of shocks. Post-2020, the greater prevalence of expectational demand shocks, may reflect policy developments such as Indonesia's export ban (2020) and sanctions on Russia (2022) (Global Trade

Alert, 2024). A moderate rise in contemporaneous demand after 2020 aligns with surging electric vehicle (EV) demand and the critical role of nickel in battery production (IEA, 2024). Finally, the greater role of flow supply shocks may be due to relative greater geographic concentration of supply for nickel (USGS, 2024).

The impulse response functions (IRFs) in Figure 3 show the long-term impact and persistence of the four shock types. Aggregate demand shocks produce sustained price increases for aluminium and nickel, persisting beyond five years, while copper's effect fades within three months. Flow supply shocks, arising from events such as strikes or mine shutdowns, show high persistence: aluminium prices take more than 4.5 years to normalise, while copper and nickel remain elevated for over five years, reflecting supply inelasticity. Contemporaneous demand shocks generate prolonged effects for copper and nickel but fade for aluminium within three quarters. Wider confidence intervals for copper and nickel indicate greater uncertainty in these estimates. Expectational demand shocks are especially persistent for nickel, with no decline even after five years, consistent with lasting revisions in market expectations.

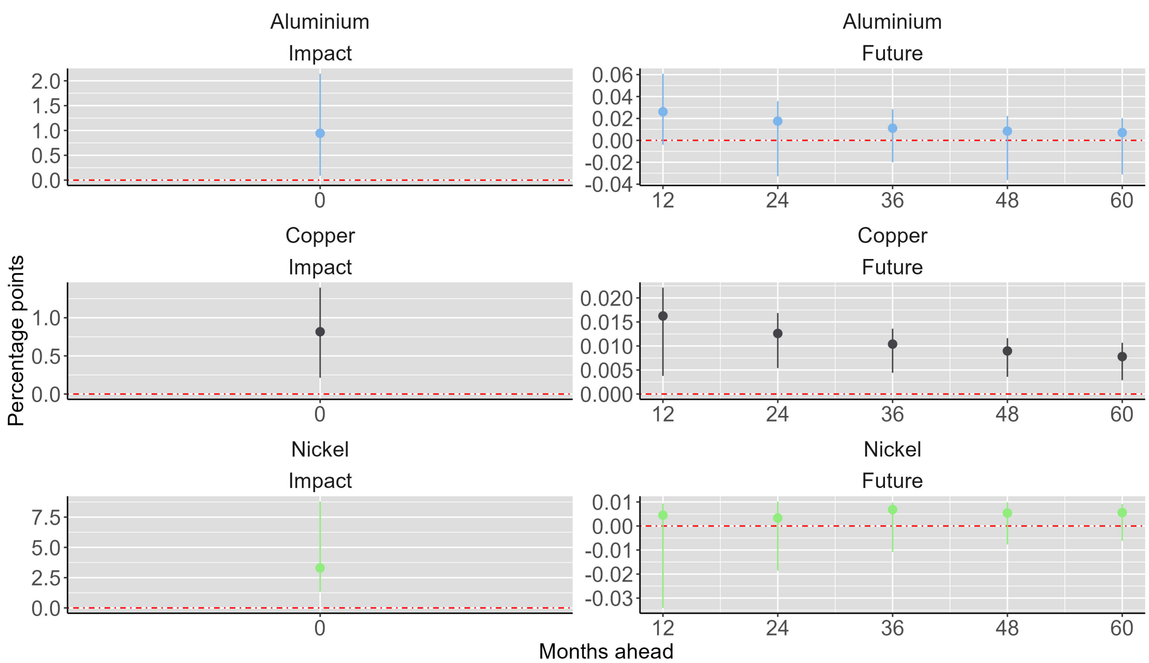
Figure 3. Price impulse response functions to structural shocks by metal



Note: Responses are normalised to a 1 per cent price increase. Blue brackets represent the 68 per cent confidence interval from the 1,000 simulations; the black line shows the median response.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and LSEG.

Supply elasticities, estimated from contemporaneous demand shocks and production IRFs, are shown in Figure 4. Median impact elasticities are 0.9 per cent for aluminium, 0.8 per cent for copper, and 3.3 per cent for nickel, with substantial uncertainty around the estimates. Longer-horizon elasticities remain close to zero for all metals, underscoring the inelastic nature of supply once spare capacity is absorbed. These results differ from Boer et al. (2024), who report higher long-run elasticities, particularly for copper.

Figure 4. Supply elasticities by metal



Note: Left panel: impact elasticities; right panel: five-year elasticities.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and LSEG.

Overall, aggregate demand is the dominant driver of aluminium and copper prices, while nickel is more responsive to expectational demand. Flow supply shocks play a comparatively larger role in nickel than in the other two metals, and supply inelasticity across all metals suggests that demand shocks—particularly from the energy transition—could generate prolonged price pressures.

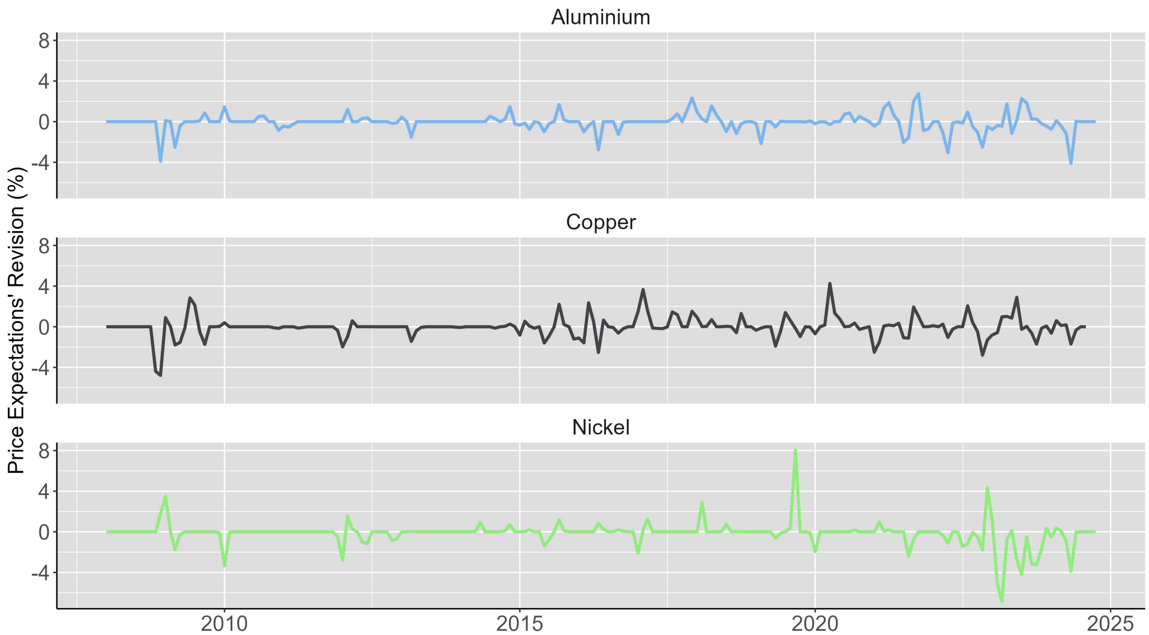
4.2 Medium-term impact of trade restrictions

As outlined earlier, the growing risk of geoeconomic fragmentation increases the likelihood of trade restrictions, potentially distorting global access to commodity supplies and influencing market prices. To assess the medium-term effects of restrictive trade announcements on aluminium, copper, and nickel prices, the analysis uses data from the Global Trade Alert (GTA) database. These announcements shape market expectations about future supply availability and are classified as expectational demand shocks, consistent with the literature (Känzig, 2021; Kilian, 2024).

In the model, such announcements are treated as exogenous events in commodity markets, representing unanticipated shifts in expectations. Based on this interpretation, the analysis calculates the average monthly revision in price expectations—expressed in per cent—during months when restrictive trade announcements occur (Figure 5). Aluminium and copper exhibit relatively modest adjustments, with upward revisions of up to $+4.3$ per cent and downward revisions of up to -4.8 per cent. In contrast, nickel displays substantially larger fluctuations, ranging from $+8.1$ per cent to -6.8 per cent.

These results are consistent with earlier findings showing that expectational demand is a more prominent driver of nickel price formation relative to aluminium and copper. Nickel prices therefore appear more sensitive to trade-related shocks. Furthermore, because the surprise index captures only unanticipated policy announcements recorded in the GTA database, deviations from zero occur more frequently for aluminium and copper than for nickel. This suggests a lower signal-to-noise ratio for the nickel series, which may reduce the robustness and interpretability of the instrumental variable structural vector autoregression (IV-SVAR) results for nickel.

Figure 5. Surprise series per metal: average monthly price revisions



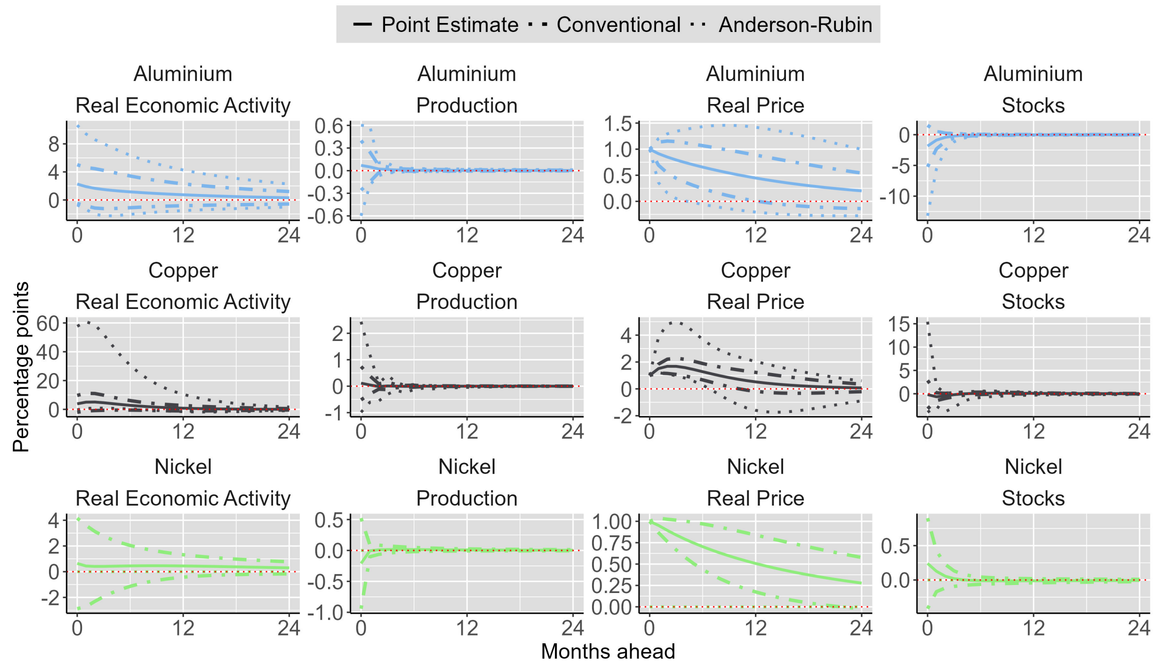
Note: Monthly average revisions in price expectations, expressed as a per cent change, in response to restrictive trade announcements classified in the Global Trade Alert Database.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and the GTA Database.

The impulse response functions (IRFs) for all variables and metals are presented in Figure 6, with the commodity price responses highlighted in Figure 7. Structural shocks are identified in terms of sign and scale, and all IRFs are normalised to represent a 1 per cent price shock. As the Wald statistic for nickel cannot be rejected, autoregressive (AR) confidence sets cannot be constructed for that metal. Nevertheless, the results are broadly consistent across commodities.

Price responses exhibit persistence, resembling patterns observed in oil market models. A 1 per cent precautionary (expectational) demand shock raises real aluminium and copper prices for up to 10 months, and nickel prices for up to 20 months. These effects attenuate more quickly when considering AR confidence bounds: aluminium's real price remains above baseline for at least four months, while copper's effect fades after six months.

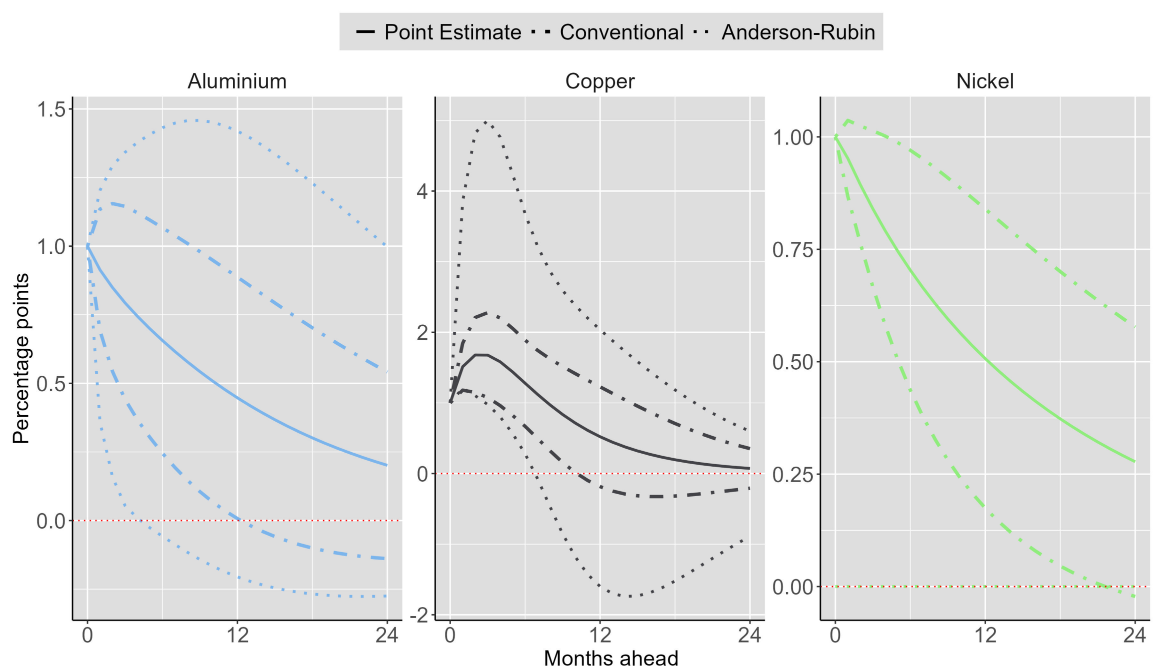
Copper prices increase by up to 4.8 per cent in the first two months following a shock, before gradually declining. Aluminium and nickel prices follow a smoother decay path immediately after the shock. While the magnitude and duration of these adjustments differ, the underlying response patterns are broadly similar.

Figure 6. IRFs to expectational demand shocks from trade announcements



Note: Solid lines indicate point estimates; dotted and dashed lines represent two types of confidence intervals.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro, LSEG, and the GTA Database.

Figure 7. Commodity price IRFs to trade announcements



Note: Solid lines indicate point estimates; dotted and dashed lines represent two types of confidence intervals.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro, LSEG, and the GTA Database.

Dissimilar to oil market models, the other variables in the system show no discernible response to expectational demand shocks. In oil markets, such shocks typically produce a negative production response, an increase in inventories, and a contraction in real economic activity (Kilian and Murphy, 2014; Kilian, 2009). These patterns reflect the foundational role of oil in the global supply of energy and macroeconomic performance. While the metals studied here are increasingly critical to the energy transition, their macroeconomic influence remains distinct from that of oil. As critical minerals become more central to energy generation; however, their responses to such shocks may broaden beyond prices alone.

4.3 Short-term impact of trade announcements on commodity markets

While the medium- and long-term effects of trade announcements can contribute to sustained commodity price increases, their short-term impacts primarily manifest through heightened volatility, which can exacerbate financial risks in derivative markets. This subsection examines the short-term cumulative abnormal returns (CAR) and potential volatility induced by restrictive trade interventions.

Unlike oil markets, where coordinated production decisions by OPEC represent more than 40 per cent of global output and directly shapes prices (OPEC, 2024), metal markets lack such coordinated structures. Trade interventions in metals are typically unilateral, vary widely in form, and are not announced through a centralised mechanism. This heterogeneity means not all restrictions necessarily lead to a revision in market expectations of future supply[12]. To minimise noise, the event study focuses on interventions that directly restrict global supply access—namely quotas, tariffs, and export bans[13]. The event window spans 20 days before and after each announcement to capture any anticipatory effects.

Figure 8 shows the standard deviation of CAR for aluminium, copper, cobalt, lithium, and nickel spot markets in response to trade announcements. For ore-related restrictions, CAR is statistically significant only for copper (after 20 days at the 5 per cent level) and nickel (after 5 and 10 days at the 1 and 10 per cent levels, respectively). For the broader set of restrictions—including ores and refined products—results are significant at the 1 per cent level for nickel, cobalt, and lithium. The cobalt results indicate an inverse relationship (negative CAR deviations), possibly reflecting data

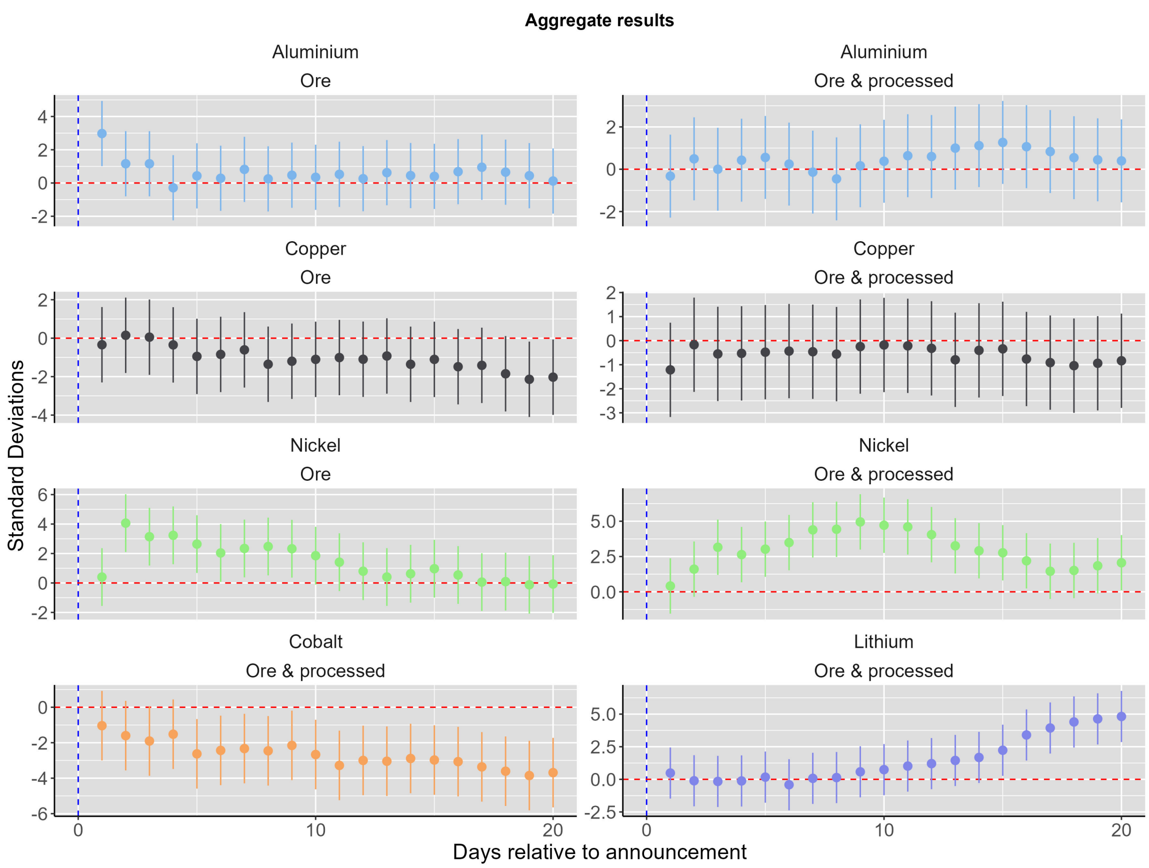
[12]The variation in trade event types adds complexity to the inference process. However, for this analysis, a level of homogeneity is assumed to assess the average short-term impact of trade interventions in spot markets.

[13]These include both import- and export-related interventions.

limitations, as only 17 valid trade intervention dates exist for cobalt. Lithium results are also constrained by limited post-2021 daily price data.

Overall, the results indicate stronger CAR responses for cobalt, lithium, and nickel than for aluminium or copper. This aligns with earlier findings that nickel prices are more heavily influenced by expectational demand shocks, suggesting that cobalt and lithium may share similar price formation dynamics. These findings are consistent with Khurshid et al. (2023), who report heightened nickel and lithium price responsiveness to expectational demand shocks following the invasion of Ukraine. The sensitivity of these minor metals may be due to their narrower application base, weaker ties to aggregate demand, and heightened exposure to revisions in expectations of future supply-demand balances. If sustained, higher prices and volatility could increase financial risks and threaten the viability of clean energy technologies dependent on these metals.

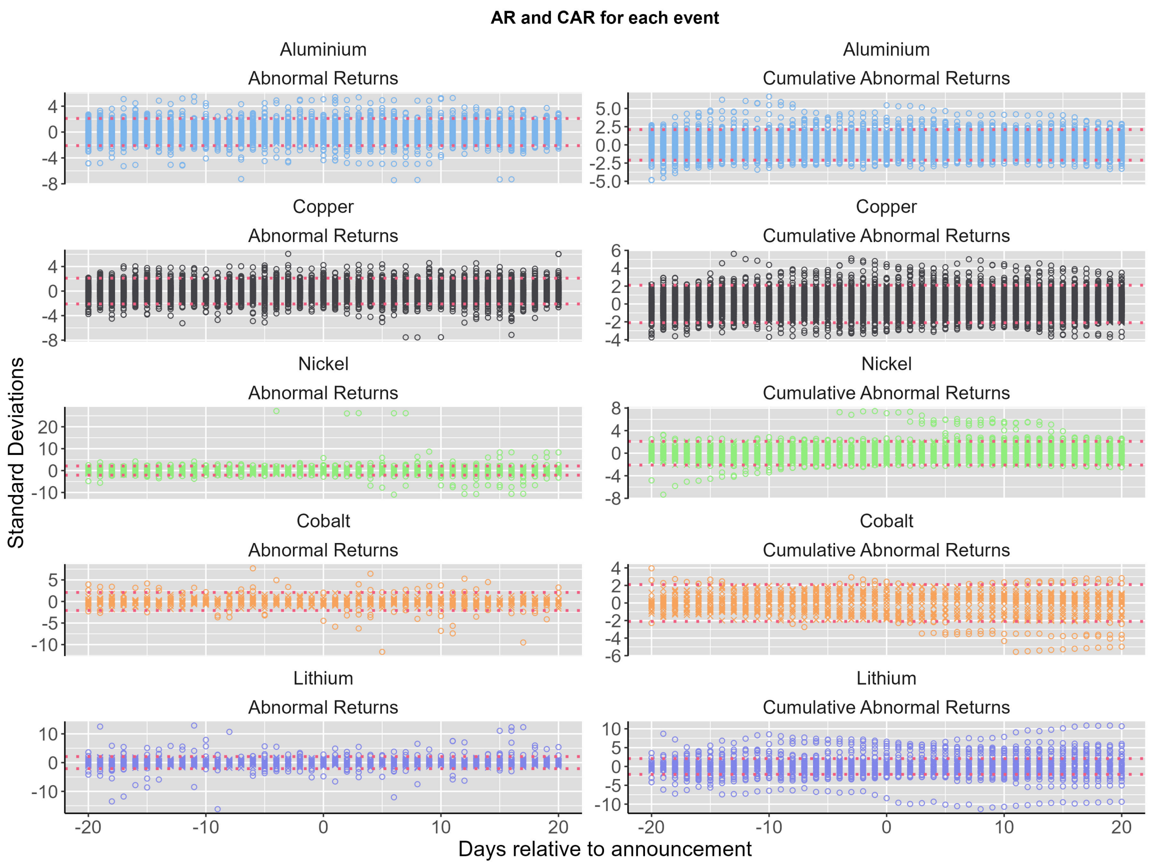
Figure 8. Cumulative abnormal returns (CAR) in response to trade announcements



Note: CAR in aluminium, copper, cobalt, lithium, and nickel spot markets in response to restrictive trade interventions (covering ores and refined products) over a 20-day event window before and after the announcement.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and the GTA Database.

Considerable variation exists in abnormal and cumulative abnormal returns across individual announcements. All metals show deviations exceeding two standard deviations over the 40-day event window (Figure 9). This variation likely reflects differences in the nature and market significance of individual announcements, with some events affecting key producers or critical supply chains. Such tail-end events exert disproportionately large effects on short-term prices and volatility.

Figure 9. Variation in AR and CAR across trade announcements for spot markets

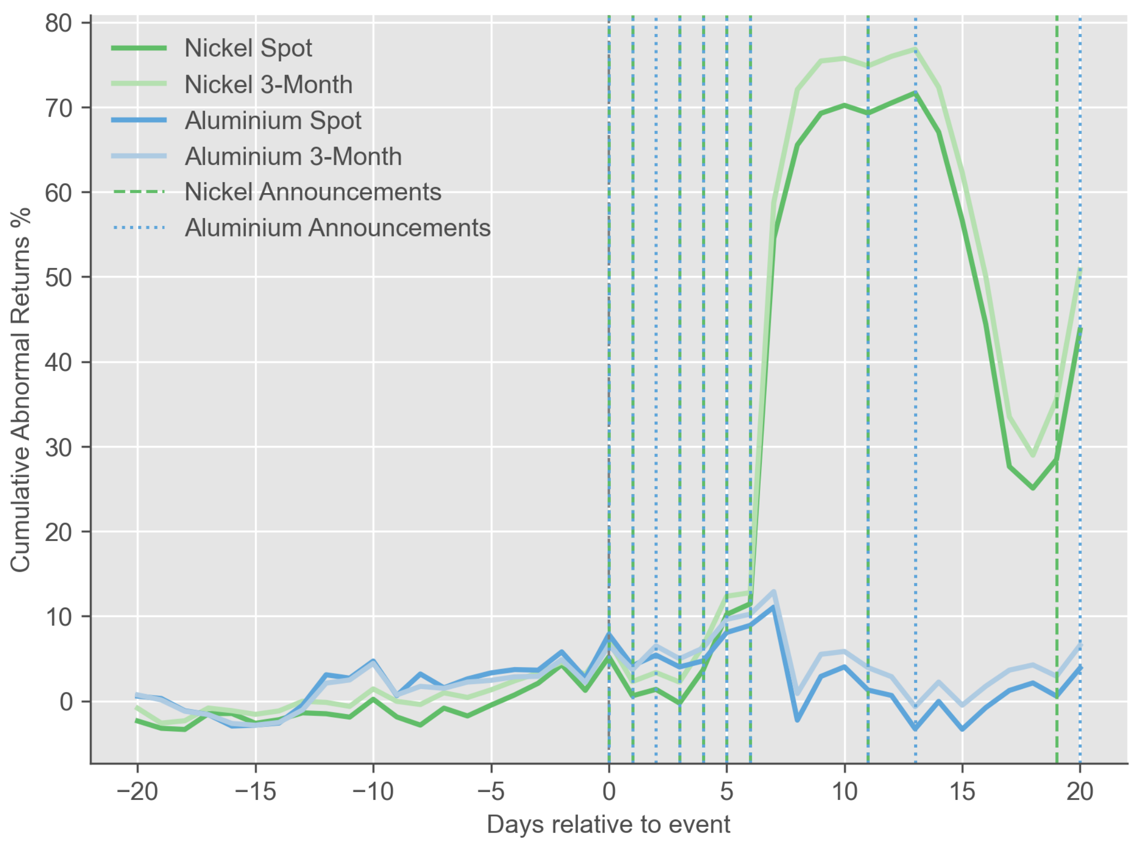


Note: Standard deviation in abnormal and cumulative abnormal returns for each trade announcement event.
Source: Authors' modelled calculations based on data from S&P Capital IQ Pro and the GTA Database.

The Russian invasion of Ukraine in February 2022 illustrates how geopolitical shocks can precipitate extreme commodity price responses. Russia accounted for over 5 per cent of global refined aluminium output and around 7 per cent of global nickel mine production prior to the invasion (USGS, 2024). Yet market reactions to the associated sanctions diverged sharply. Aluminium prices rose substantially, while nickel prices surged by 270 per cent in just three trading days in March 2022, prompting the London Metal Exchange (LME) to suspend nickel trading (Heilbron, 2024).

Figure 10 plots spot and three-month futures cumulative abnormal returns (CAR) for aluminium and nickel, measured against the GSCI benchmark, around the cluster of sanction announcements following the invasion. Nickel spot and futures markets exhibited exceptional CARs, exceeding 70 per cent within the ±20-day event window, while aluminium spot and futures reached maxima of only 11.1 per cent and 12.9 per cent, respectively. This stark divergence underscores differences in market sensitivity to sanctions, despite both metals being directly affected. Moreover, elevated futures prices for both metals post-sanctions are consistent with the expectational demand shock hypothesis: upward revisions to future scarcity expectations shifted term structures into contango, as described in standard commodity storage models (Ribeiro and Hodges, 2005).

Figure 10. Spot and Futures reaction to Russian sanctions



Note: Aluminium (blue) and nickel (green) returns in a 20-day window before and after the invasion of Ukraine. The blue and green dotted lines indicate trade intervention announcements for aluminium and nickel, respectively.
Source: Authors' calculations based on data from S&P Capital IQ Pro and the GTA Database.

Several factors explain the nickel–aluminium divergence. First, nickel prices are structurally more sensitive to expectational demand shocks, whereas aluminium is more closely tied to global industrial demand conditions. Second, the nickel market was already unusually tight, driven by surging electric-vehicle sector demand and post-pandemic recovery, which amplified the effect of any prospective supply disruption (Oliver Wyman (for LME Group), 2023; Daniel, 2022). Third, in the months preceding the invasion, concentrated short positions in nickel futures, relative to trading volumes, increased fragility. When trade restrictions were announced, these positions triggered forced short-covering, reducing liquidity and exacerbating price spikes (Oliver Wyman (for LME Group), 2023; Heilbron, 2024). Such positioning dynamics were largely absent in aluminium markets.

Overall, while trade announcements can generate substantial short-term price and volatility shifts, their magnitude depends critically on pre-existing market conditions, structural supply–demand dynamics, and the degree to which expectations dominate price formation.

5 Discussion

This paper offers new evidence on the role of structural shocks in shaping commodity price formation within selected TCM markets. The results reveal the complex interaction between demand- and supply-side forces, trade policy measures, and the energy transition, providing a framework for assessing potential disruptions to commodity markets. The discussion considers the short- and long-term effects of structural shocks on metal prices, with particular attention to their implications for the energy transition and related financial risks.

5.1 Demand-driven price dynamics and structural shocks from the energy transition

The findings indicate that demand-side shocks dominate price formation across the metals studied, consistent with prior research on metal and oil markets (Boer et al., 2024; Kilian, 2009). Aggregate demand shocks are the principal driver for aluminium and copper prices, while nickel is influenced by a wider range of shocks, with commodity-specific contemporaneous demand playing the smallest role. Market sentiment and expectations about future supply appear especially important for nickel, reflecting its geographically concentrated production and increasing relevance in low-carbon technologies.

Projected increases in demand for critical minerals due to the energy transition are therefore expected to exert significant upward pressure on prices (Boer et al., 2024). The trajectory and narrative of the transition, which determine the timing and intensity of materials demand, will be a major factor in shaping future price dynamics. For example, a ‘Delayed Transition’ scenario, as outlined by Miller et al. (2023), entails a more material-intensive and compressed demand pathway, potentially amplifying demand-related price shocks.

The demand implications of the transition differ from those in conventional energy markets such as oil, due to a structural shift from a flow-based system, where oil demand grows in line with economic activity, to a stock-based system focused on the one-off build-up of infrastructure, including renewable generation and energy storage capacity. This shift is likely to create an initial surge in demand for critical minerals. Although increased recycling may partially offset this demand, recycling rates differ substantially across metals and may require higher prices to become economically viable.

The effects of the transition on price formation depend on the type of structural demand shock it generates. If manifested as an aggregate demand shock, substantial and persistent impacts on aluminium, copper, and nickel prices are likely. In contrast, expectational shocks produce strong effects for nickel, but more moderate ones for aluminium and copper. For both expectational and contemporaneous demand shocks, copper and nickel prices are more likely to exhibit sustained increases than aluminium. Thus, a transition pathway that triggers acute demand surges in these metals, independent of the macroeconomic environment, would likely result in prolonged price pressures.

The persistence of higher prices and related inflationary effects depends critically on the prevailing demand shock type. Aggregate demand shocks, which historically dominate aluminium and copper price formation, would have broad inflationary consequences given the extensive use of these metals across multiple sectors. Miranda-Pinto et al. (2024) find that metal prices are already contributing to both core and headline inflation, a trend likely to strengthen as the economy becomes more mineral-intensive.

Conversely, if contemporaneous and expectational shocks dominate, inflationary effects may be more contained, concentrated in nickel and minor metals such as cobalt and lithium. These metals, which have narrower industrial uses, are more sensitive to transition-driven demand from low-carbon technologies. This aligns with the sharp increases in cobalt and lithium prices between 2021 and 2023, following rapid growth in EV production (IEA, 2024). Although expectational shocks may have less widespread inflationary effects, sustained increases in transition-critical metal prices could threaten the economic viability of clean energy technologies. At the macroeconomic level, such price shocks risk delaying low-carbon technology deployment, undermining net-zero targets. Evidence already links TCM price movements—particularly for minor metals—to the performance of clean energy sectors (Attílio, 2025).

In sum, demand shocks from the energy transition, whether aggregate, contemporaneous, or expectational, carry significant implications for price persistence and inflationary pressures. The composition of these shocks is likely to vary across commodities, and the relative weight of each type will be decisive in determining both commodity price trajectories and the broader impact on the energy transition.

5.2 Market expectations and trade announcements

The heightened responsiveness of nickel prices to trade announcements reflects the prominent role of expectational demand shocks in nickel price formation. Evidence from the surprise index and historical decomposition modelling confirms that market expectations are a key determinant of nickel price dynamics. Two factors likely underpin this phenomenon. First, nickel production is highly geographically concentrated, with a small number of countries dominating global supply (USGS, 2024), increasing sensitivity to perceived supply disruptions. Second, aluminium and copper have more diversified applications across multiple economic sectors, making their prices less reactive to revisions in market expectations compared to nickel, which is closely linked to the energy transition and low-carbon technologies. Consequently, expectational demand shocks exert a more pronounced influence on nickel prices, while their effect on aluminium and copper is comparatively muted.

For other transition-critical minor metals, such as lithium and cobalt, similar mechanisms may apply. These metals are both heavily influenced by demand from low-carbon technologies and subject to geographically concentrated production (USGS, 2024). If their price formation mechanisms resemble those of nickel, they may exhibit greater sensitivity to changes in market expectations of future supply-demand balances, particularly over the medium term. Rising geoeconomic fragmentation and associated trade restrictions would likely intensify these effects for metals that are more exposed to expectational demand shocks. Although data limitations currently prevent rigorous quantitative testing for minor metals, these hypotheses warrant further investigation.

The analysis indicates that while trade announcements can influence metal prices in the short-term, their long-term effects are limited. For aluminium, copper, and nickel, price impacts tend to dissipate over time, indicating that such interventions are less significant drivers of sustained price increases compared with other structural shocks. As a result, trade announcements are unlikely to materially affect the long-term affordability of low-carbon technologies. In the short term, CAR for most metals' spot prices respond only modestly to trade announcements, although considerable variation exists across individual events. This heterogeneity indicates that only certain interventions substantially shift market expectations of future supply-demand dynamics.

Nevertheless, tail-risk events demonstrate the potential for severe short-term volatility. For example, nickel prices rose sharply following trade-related announcements in the wake of Russia's invasion of Ukraine. This surge reflected a combination of strong EV-related demand, prior expectations of a supply surplus, and sudden revisions to market outlooks. Such volatility can elevate financial risks through abnormal returns and increased price fluctuations. Over the course of the energy transition, heightened demand for specific metals may further amplify these revisions in market expectations, leading to greater volatility and abnormal returns. While derivatives use in metal markets is currently limited to financial institutions and the mining sector, the expansion of hedging activities to other sectors could increase the potential for financial risk transmission.

The relatively muted short-term price effects of trade announcements may reflect the structural characteristics of metal markets. Unlike oil markets, where coordinated actions by producers such as OPEC can influence supply (Kilian and Murphy, 2014; Känzig, 2021), metal market interventions are typically unilateral and uncoordinated. The possibility of substituting between metals, coupled with increased recycling rates, further reduces the scope for sustained price manipulation. Moreover, extreme trade restrictions, such as export bans, have been rare and largely confined to a few supply-critical nations. However, the geographic concentration of production raises the risk that intensified geoeconomic fragmentation could trigger coordinated or extreme trade measures, particularly if geopolitical strategies related to the energy transition gain prominence. Such developments would heighten price volatility and reduce market predictability.

An escalation of geofragmentation, combined with strong transition-driven demand for metals, could significantly increase the macroeconomic relevance of metal price dynamics. While this paper considers only historical trade interventions, other studies have explored more extreme scenarios of fragmentation with broader economic repercussions (Aiyar et al., 2023). Potential effects include impacts on stock market performance and real economic activity, similar to patterns observed in oil markets, where price shocks, particularly those driven by geopolitical and expectational demand factors, affect equity markets and GDP growth (Känzig, 2021). Analogously, increased volatility in metal prices due to trade restrictions or abrupt changes in expectations could influence clean energy companies and industries reliant on TCMs. Early evidence indicates that clean technology equity volatility increases in response to extreme geopolitical risks (Pham and Hsu, 2025). These effects may intensify as metals such as nickel, lithium, and cobalt become more embedded in economic activity during the transition to net zero.

5.3 Future research

This paper examines the formation of commodity price shocks in metal markets within the broader context of the energy transition and geoeconomic fragmentation. The results highlight the influence of structural shocks on metal price dynamics, although substantial uncertainty remains regarding their precise effects across different commodities. Modelling and data limitations constrain the scope and certainty of the analysis, particularly in distinguishing between price formation mechanisms in different metal markets and assessing the impacts of diverse trade interventions. The evidence relies on historical data, which is used to infer and hypothesise about potential future price trajectories. The study focuses exclusively on primary supply and does not incorporate the potential mitigating role of increased recycling rates, which could offset some of the risks identified. Addressing these gaps requires further research to forecast metal price responses to structural shocks under alternative transition pathways and varying degrees of geoeconomic fragmentation; to expand quantitative assessments to a wider set of TCMs, providing a more comprehensive understanding of market vulnerabilities; and to refine the analysis of trade interventions, extending it to futures markets in order to capture changes in market expectations more effectively.

6 Conclusion

The analysis confirms that demand-side factors are the dominant drivers of price formation across aluminium, copper, and nickel markets. Results from the SVAR model indicate that aggregate demand shocks account for the majority of price movements in aluminium and copper, while expectational demand shocks play a more significant role in nickel markets. This suggests that market sentiment, future supply expectations, and trade policies are particularly influential in shaping nickel price dynamics. These findings align with existing research on oil markets, where global demand also plays a primary role in price formation. However, the effects of supply shocks appear more persistent in metal markets, indicating that supply-side constraints can lead to prolonged price pressures, particularly as demand for TCMs grows.

The study also highlights the increasing role of trade policy interventions in shaping market expectations. Using data from the GTA database, the analysis finds that restrictive trade announcements lead to significant revisions in price expectations, particularly in nickel markets. Nickel price expectations fluctuate between +8.1 and −6.8 per cent following trade announcements, while aluminium and copper exhibit smaller revisions, ranging between +3.0 and −5.0 per cent. This suggests that nickel markets are more exposed to risks from economic and political geoeconomic fragmentation. On average, the short-term price impact of trade announcements is limited, as indicated by the event study results, which show only minor deviations in CAR following trade interventions. However, specific instances demonstrate that trade announcements can have significant short-term impacts on both commodity price returns and volatility, which may be driven more by revisions in market expectations than by the announcements themselves.

These findings carry important implications for policymakers and market participants. The fivefold increase in export restrictions over the past decade exacerbates market uncertainty, increasing the risk of price volatility and supply disruptions. Moreover, sustained increases in commodity prices can raise the cost of clean energy technologies, potentially slowing the decarbonisation process. Further research is needed to improve understanding of how demand for TCMs from the energy transition and other sectors shapes commodity prices under different scenarios, and whether these price increases create a material constraint to the deployment of low-carbon technologies.

References

Aiyar, S., J. Chen, C. H. Ebeke, R. Garcia-Saltos, T. Gudmundsson, A. Ilyina, A. Kangur, T. Kunaratskul, S. L. Rodriguez, M. Ruta, T. Schulze, G. Soderberg, and J. P. Trevino (2023). Geoeconomic fragmentation and the future of multilateralism.

Alvarez, J., M. Andaloussi, C. Maggi, A. Sollaci, M. Stuermer, and P. B. Topalova (2023). Geoeconomic fragmentation and commodity markets. *IMF Working Paper*.

Americo, A., J. Johal, and C. Upper (2023). The energy transition and its macroeconomic effects. *BIS Papers*.

Andrews, I., J. H. Stock, and L. Sun (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual review of economics 11*, 727–753.

Antolín-Díaz, J. and J. F. Rubio-Ramírez (2018). Narrative sign restrictions for svars. *The American economic review 108*, 2802–2829.

Arias, J. E., J. F. Rubio-Ramírez, and D. F. Waggoner (2018). Inference based on structural vector autoregressions identified with sign and zero restrictions: Theory and applications. *Econometrica 86*(2), 685–720.

Attílio, L. A. (2025). Impact of critical mineral prices on energy transition. *Applied Energy 377*, 124688.

Bae, H. and Y. Kim (2021). Technologies of lithium recycling from waste lithium ion batteries: a review. *Materials advances 2*(10), 3234–3250.

Baumeister, C. and J. D. Hamilton (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review 109*(5), 1873–1910.

Baumeister, C. and J. D. Hamilton (2024). Advances in using vector autoregressions to estimate structural magnitudes. *Econometric Theory 40*(3), 472–510.

Baumeister, C., F. Huber, and M. Marcellino (2024). Risky oil: It's all in the tails. Technical report, National Bureau of Economic Research.

Bazilian, M., M. Bradshaw, J. Gabriel, A. Goldthau, and K. Westphal (2020). Four scenarios of the energy transition: Drivers, consequences, and implications for geopolitics. *Wiley Interdisciplinary Reviews: Climate Change 11*(2), e625.

Bloomberg L.P. (2025). Bloomberg terminal. Accessed February 2025.

Boer, L., A. Pescatori, and M. Stuermer (2024). Energy transition metals: Bottleneck for net-zero emissions? *Journal of the European Economic Association 22*, 200–229.

Bolhuis, M., J. Chen, and B. Kett (2023). *Fragmentation in Global Trade: Accounting for Commodities*. International Monetary Fund.

Caldara, D., M. Cavallo, and M. Iacoviello (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics 103*, 1–20.

Campbell, J. Y., A. W. Lo, A. C. MacKinlay, and R. F. Whitelaw (1998). The econometrics of financial markets. *Macroeconomic Dynamics 2*(4), 559–562.

Campos, R. G., J. Estefania-Flores, D. Furceri, and J. Timini (2023). Geopolitical fragmentation and trade. *Journal of Comparative Economics 51*, 1289–1315.

Carrara, S., P. Alves Dias, B. Plazzotta, and C. Pavel (2020). Raw materials demand for wind and solar pv technologies in the transition towards a decarbonised energy system.

Collins, G., C. A. Dahl, M. Fleming, M. Tanner, W. C. Martin, K. Nadkarni, S. Hastings-Simon, and M. Bazilian (2024). Projecting demand for mineral-based critical materials in the energy transition for electricity. *Mineral Economics 37*(2), 245–263.

Coulomb, R., S. Dietz, M. Godunova, and T. B. Nielsen (2015). *Critical Minerals Today and in 2030 An Analysis for OECD Countries*. OECD Publishing.

Dadush, U. and E. D. Prost (2023). Preferential trade agreements, geopolitics, and the fragmentation of world trade. *World trade review 22*, 278–294.

Daniel, W. (2022). Oil and nickel soar as russia-ukraine conflict roils commodities markets. https://fortune.com/2022/03/08/oil-nickel-commodities-markets-russia/. Accessed: 2025-08-08.

Deetman, S., H. S. de Boer, M. V. Engelenburg, E. van der Voet, and D. P. van Vuuren (2021). Projected material requirements for the global electricity infrastructure – generation, transmission and storage. *Resources, conservation and recycling 164*, 105200.

Demirer, R. and A. M. Kutan (2010). The behavior of crude oil spot and futures prices around opec and spr announcements: An event study perspective. *Energy Economics 32*(6), 1467–1476.

Downie, C. (2022). Geopolitical leverage in the energy transition: A framework for analysis and the case of australian electricity exports. *Energy Research & Social Science 93*, 102826.

Erbil, M. N. and M. S. K. Roache (2010). How commodity price curves and inventories react to a short-run scarcity shock. Technical report, International Monetary Fund.

Espagne, E., W. Oman, J.-F. Mercure, R. Svartzman, U. Volz, H. Pollitt, G. Semieniuk, and E. Campiglio (2023). Cross-border risks of a global economy in mid-transition. *184*.

European Aluminium (2025). Aluminium in use. https://european-aluminium.eu/about-aluminium/aluminium-in-use/. Accessed: 2025-02-08.

Evenett, S. J. and J. Fritz (2020). The global trade alert database handbook.

Faust, J. (1998). *The robustness of identified VAR conclusions about money*. Board of Governors of the Federal Reserve System.

Fund, I. M. (2023). Navigating global divergence: World economic outlook. *World Economic Outlook*.

Giannone, D., M. Lenza, and G. E. Primiceri (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics 97*(2), 436–451.

Global Trade Alert (2024). Global trade alert database. https://globaltradealert.org/. Accessed: 2024.

Góes, C. and E. Bekkers (2023). The impact of geopolitical conflicts on trade, growth, and innovation.

Heilbron, J. (2024). Central clearing and trade cancellation: The case of lme nickel contracts on march 8, 2022. *Office of Financial Research Working Paper* (24-09).

Huang, S., X. Wang, and Q. Ji (2025). How unexpected geopolitical risk affect the nonlinear spillover among energy and metal markets? *Energy Economics 142*, 108143.

Hund, K. L., D. L. P. Arrobas, T. P. F. Masllovet, T. J. Laing, and J. R. Drexhage (2023). Minerals for climate action: The mineral intensity of the clean energy transition (english).

IEA (2021). The role of critical minerals in clean energy transitions.

IEA (2024). Global critical minerals outlook 2024.

IEA (2024). Global ev outlook 2024. Technical report, International Energy Agency.

International Copper Association (2023). 2023 global view semis end use dataset. https://internationalcopper.org/trends-and-data/resource-library/?fwp_resource_type_filter=data-set. Accessed: 2025-02-08.

Islam, M. M. and K. Sohag (2024). Transmission and volatility mechanisms of mineral and oil prices in the context of clean energy transition: A global perspective. *Sustainable Futures 8*, 100384.

Jacks, D. S. and M. Stuermer (2020). What drives commodity price booms and busts? *Energy Economics 85*, 104035.

Karabulut, G., M. H. Bilgin, and A. C. Doker (2020). The relationship between commodity prices and world trade uncertainty. *Economic Analysis and Policy 66*, 276–281.

Khurshid, A., Y. Chen, A. Rauf, and K. Khan (2023). Critical metals in uncertainty: How russia-ukraine conflict drives their prices? *Resources Policy 85*, 104000.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American economic review 99*, 1053–1069.

Kilian, L. (2024). How to construct monthly var proxies based on daily surprises in futures markets. *Journal of economic dynamics control 168*, 104966.

Kilian, L. and H. Lütkepohl (2017). *Structural Vector Autoregressive Analysis* (1 ed.). Cambridge University Press.

Kilian, L. and D. P. Murphy (2012). Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market var models. *Journal of the European Economic Association 10*(5), 1166–1188.

Kilian, L. and D. P. Murphy (2014). The role of inventories and speculative trading in the global market of crude oil. *Journal of applied econometrics (Chichester, England) 29*, 454–478.

Kilian, L. and X. Zhou (2020). The econometrics of oil market var models. *Federal Reserve Bank of Dallas Working Paper Series*.

Kilian, L. and X. Zhou (2023, 1). *The Econometrics of Oil Market VAR Models*, Volume 45B, pp. 65–95. Emerald Publishing Limited.

Kowalski, P. and C. Legendre (2023). Raw materials critical for the green transition: Production, international trade and export restrictions.

Känzig, D. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *The American economic review 111*, 1092–1125.

London Stock Exchange Group (2024). World bureau of metal statistics from the london stock exchange group database. Accessed via LSEG Workspace.

Mertens, K. and M. O. Ravn (2019). The dynamic effects of personal and corporate income tax changes in the united states: Reply. *The American economic review 109*, 2679–2691.

Miller, H., S. Dikau, R. Svartzman, and S. Dees (2023). The stumbling block in 'the race of our lives': transition-critical materials, financial risks and the ngfs climate scenarios.

Miranda-Pinto, J., A. Pescatori, M. Stuermer, and X. Wang (2024). Beyond energy: Inflationary effects of metals price shocks in production networks.

Montiel-Olea, J. L., J. H. Stock, and M. W. Watson (2021). Inference in structural vector autoregressions identified with an external instrument. *Journal of econometrics 225*, 74–87.

Montiel Olea, J. L., J. H. Stock, and M. W. Watson (2021). Inference in structural vector autoregressions identified with an external instrument. *Journal of Econometrics 225*(1), 74–87.

NRC (2008). *Minerals, critical minerals, and the U.S. economy*. National Academies Press.

Oliver Wyman (for LME Group) (2023, January). Independent review of events in the nickel market in march 2022 — final report. https://www.lme.com/-/media/Files/Trading/New-initiatives/Nickel-independent-review/Independent-Review-of-Events-in-the-Nickel-Market-in-March-2022---Final-Report.pdf. Accessed: 2025-08-13.

OPEC (2024). 2024 world oil outlook 2050. https://publications.opec.org/woo. Accessed: 2025-02-08.

Overland, I. (2015). Future petroleum geopolitics: consequences of climate policy and unconventional oil and gas. *Handbook of clean energy systems*, 1–29.

Overland, I., M. Bazilian, T. I. Uulu, R. Vakulchuk, and K. Westphal (2019). The gegalo index: Geopolitical gains and losses after energy transition. *Energy Strategy Reviews 26*, 100406.

Patell, J. M. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical test. *Journal of accounting research*, 246–276.

Pham, L. and K.-C. Hsu (2025). Metals of the future in a world in crisis: Geopolitical disruptions and the cleantech metal industry. *Energy Economics 141*, 108004.

Pindyck, R. S. (2001). The dynamics of commodity spot and futures markets: A primer. *The Energy journal (Cambridge, Mass.) 22*, 1–29.

Ribeiro, D. R. and S. D. Hodges (2005). A contango-constrained model for storable commodity prices. *Journal of Futures Markets: Futures, Options, and Other Derivative Products 25*(11), 1025–1044.

Rubio-Ramírez, J. F., D. Waggoner, and T. Zha (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of economic studies 77*, 665–696.

Saadaoui, J., R. Smyth, and J. Vespignani (2025). Ensuring the security of the clean energy transition: Examining the impact of geopolitical risk on the price of critical minerals. *Energy Economics 142*, 108195.

Scholten, D., M. Bazilian, I. Overland, and K. Westphal (2020). The geopolitics of renewables: New board, new game. *Energy Policy 138*, 111059.

Sinn, H.-W. (2012). *The green paradox: a supply-side approach to global warming.* MIT press.

Sohag, K., Y. Sokolova, Š. Vilamová, and D. Blueschke (2023). Volatility transmission from critical minerals prices to green investments. *Resources Policy 82*, 103499.

S&P Global (2025). S&p capital iq platform. Accessed February 2025.

Stock, J. and M. Watson (2012). Disentangling the channels of the 2007–09 recession. *Brookings papers on economic activity 2012*, 81–156.

Stock, J. and M. Yogo (2002, 11). Testing for weak instruments in linear iv regression.

Uhlig, H. (2005). What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of monetary economics 52*, 381–419.

USGS (2024). Mineral commodity summaries 2024.

Vakulchuk, R., I. Overland, and D. Scholten (2020). Renewable energy and geopolitics: A review. *Renewable and sustainable energy reviews 122*, 109547.

Valero, A., A. Valero, G. Calvo, and A. Ortego (2018). Material bottlenecks in the future development of green technologies. *Renewable and Sustainable Energy Reviews 93*, 178–200.

Van de Graaf, T. (2018). Battling for a shrinking market: oil producers, the renewables revolution, and the risk of stranded assets. In *The geopolitics of renewables*, pp. 97–121. Springer.

Wang, X. and T. Woźniak (2025). Bayesian analyses of structural vector autoregressions with sign, zero, and narrative restrictions using the r package bsvarsigns. *arXiv preprint arXiv:2501.16711*.

Watari, T., B. C. McLellan, D. Giurco, E. Dominish, E. Yamasue, and K. Nansai (2019). Total material requirement for the global energy transition to 2050: A focus on transport and electricity. *Resources, conservation and recycling 148*, 91–103.

World Bank Group (2022). *Global economic prospects, January 2022.* World Bank Publications.