Energy Transition Metals: Bottleneck for Net-Zero Emissions?*

Lukas Boer†, Andrea Pescatori‡ and Martin Stuermer§

December 6, 2022

Abstract

The energy transition requires substantial amounts of metals, including copper, nickel, cobalt, and lithium. Are these metals a bottleneck? We identify metal-specific demand shocks, estimate supply elasticities, and study the price impact of the transition in a structural scenario analysis. Prices of these four metals would reach previous historical peaks but for an unprecedented, sustained period in a net-zero emissions scenario, potentially derailing the energy transition. Their production value would rise nearly four-fold to USD 11 trillion for the period 2021 to 2040. These four metals markets alone could become as important to the global economy as the oil market.

JEL classification: C32, C53, Q3, Q4, Q54.

Keywords: Conditional forecasts, structural vector autoregression, structural scenario analysis, energy transition, metals, fossil fuels, prices, climate change.

*The views in this paper are those of the authors and do not necessarily reflect the views of the International Monetary Fund. The online-appendix is available here. We are grateful to Christiane Baumeister, Christian Bogmans, Petya Koeva Brooks, Dolf Gielen, Ben Gilbert, Ryan Kellogg, Lutz Kilian, Christoffer Koch, Helmut Lütkepohl, Philipp Mattner, Lukas Menkhoff, Ervin Prifti, Ivan Petrella, Giorgio Primiceri, Ben Schumann, Gregor Schwerhoff and Nico Valckx for helpful suggestions, to Juan Antolin-Diaz, Juan Rubio-Ramirez and Ivan Petrella for sharing their code with us and to the International Energy Agency for sharing their data. We thank participants at the North American Summer Meeting of the Econometric Society 2022, the Rimini Centre for Economic Analysis Conference on Recent Developments in Economics, Econometrics and Finance 2022, the Royal Economic Society Annual Conference 2022, the Spring Meeting of Young Economists 2022, the Online Summer Workshop in Environment, Energy, and Transportation Economics (OSWEET), the US Association of Energy Economics North American Conference 2021 and seminars at the International Monetary Fund and Humboldt University Berlin for their valuable comments and feedback. We are grateful for excellent research assistance by Rachel Brasier, Wenchuan Dong and Piyusha Khot.

†International Monetary Fund, Research Department, Email: lboer@imf.org.

‡International Monetary Fund, Research Department, Email: apescatori@imf.org.

§International Monetary Fund, Research Department, Email: mstuermer@imf.org.

1 Introduction

To limit climate change, countries and firms are increasingly pledging to reduce carbon dioxide emissions. Reaching this goal could substantially boost the demand for metals like copper, nickel, cobalt, and lithium, which are the most important metals for the energy transition. For example, an electric car requires five times more of these metals than a conventional car. However, a more metals intense global economy raises concerns that supply might not catch up with soaring demand. This could induce increases in the cost of metals as inputs, thus, potentially delaying the energy transition.

We are the first to assess the implications of the energy transition on metal prices and their macroeconomic relevance. We model the energy transition as a sequence of metal-specific demand shocks in separate structural VAR models for each of the four metals, using zero, sign, and narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018). Exploiting a long historical data-set that partly starts in 1879, allows us to account for the lagged nature of the opening up of mines as well. We finally conduct a structural scenario analysis following Antolín-Díaz et al. (2021). The derived scenario price paths show that the four metals are potential bottlenecks for the energy transition and become macro relevant similar to crude oil.

We identify three structural shocks, namely an aggregate commodity demand shock (e.g., an unexpected expansion of the economy lifting the demand for all commodities), a metal-specific supply shock (e.g. a strike at a major mine), and a metal-specific demand shock (e.g., an unexpected increase in demand of specific metals due to the energy transition). We assume that metal-specific demand shocks have a positive impact on price and output but a negative on global economic activity, in line with the standard commodity market model (see e.g., Kilian, 2009, Baumeister and Peersman, 2013, Jacks and Stuermer, 2020, and others). We add narrative sign restrictions during historical periods of metal-specific demand shocks. In an extension we leave the impact effect on global economic activity unrestricted to avoid any *ex-ante* assumptions about the effects of the energy transition on the economy. To do so we introduce an "anchor" variable, in our case an additional commodity price, which we assume to be affected by aggregate commodity demand shocks but not by metal-specific demand shocks.

We conduct a structural scenario analysis following Antolín-Díaz et al. (2021). We take metal consumption scenarios for the energy transition from the IEA (2021a,b) as given, assuming that global consumption equals production over the long-term. The structural scenario analysis allows us to derive a sequence of exogenous metal-specific demand shocks that matches the global metal consumption scenarios. In other words, the algorithm finds a series of these shocks that incentivizes the metal output path needed for the energy transition. We then derive the implied price and revenue paths. The methodology allows us to deal with the limits of reduced-form conditional forecasts, namely that a missing causal mechanism confounds the interpretation. Our model has the advantage that it can distinguish among structural shocks (such as aggregate demand, commodity-specific demand, and supply shocks), which may have substantially different implications for the price. For example, higher metal consumption could also be driven by positive metal supply shocks, implying a lower price scenario.

We find that the four metals are potential bottlenecks for the energy transition. Inflation adjusted metals prices would reach peaks similar to historical ones but for an unprecedented, sustained period of roughly a decade in the IEA's Net-Zero Emissions Scenario. This would imply that real prices of nickel, cobalt and lithium would rise several hundred percent from 2020 levels, while the copper price would increase by one third. In the IEA's Stated Policy Scenario, which is based on current national policies, real prices for all four metals would broadly stay in the range of the 2020 average.

Our estimations show that the four metals could become as important to the macroeconomy as crude oil. In the net-zero emissions scenario, the demand boom could lead to a nearly fourfold increase in the value of metals production—totaling US$ 11 trillion accumulated over the next two decades for the four "energy transition" metals alone. This could rival the roughly estimated value of oil production in the net-zero emissions scenario from 2021-2040. This implies that the markets of these four metals may become more important for inflation, trade, and output globally. Metals producing countries could benefit from significant windfalls due to the energy transition.

Underlying these results, supply elasticities for all metals, except lithium, are quite inelastic over the short term, but more elastic over the long term. A metal-specific positive demand shock to price of 10 percent increases the same-year output of copper by 4.0 percent, nickel by 7.0 percent, cobalt by 3.3 percent, and lithium by 12.5 percent. After

20 years, the same price shock raises output of copper by 8.6 percent, nickel by 14.4 percent, cobalt by 8.6 percent, and lithium by 20.1 percent. This evidence is in the range of other studies in the cases of copper and nickel, but the long-run estimate for cobalt is substantially higher than in the literature (see the reviews in Dahl, 2020 and Fally and Sayre, 2018). We are the first to estimate supply elasticities for lithium. As our data-set captures a long series of commodity boom and bust periods, we account for the lagged nature of the opening up of mines, addressing a major drawback of estimating supply elasticities in the literature (see Dahl, 2020).

We show that our results are qualitatively robust to a broad set of alternative specifications. These include a four variable model with an "anchor" variable, a four variable model with anticipatory and contemporaneous metal-specific demand shocks, different measures of economic activity and trend specifications, as well as different sub-samples. Results of some specifications, especially with shorter sample periods, can lead to even higher price scenarios, as the implied supply elasticities are smaller.

Our analysis is subject to several limitations. First, the IEA consumption scenarios do not endogenously react to higher prices, potentially biasing our results upwards. This bias is limited by the inelastic demand of metals (Dahl, 2020). Second, we assume that supply elasticities stay constant. They could increase due to learning-by doing and enhanced recycling, or decline due to the environmental and social cost of mining. Third, we model the energy transition as an historically unprecedented upward shift in the distribution of metal-specific demand shocks (see critique in Lucas, 1976; Leeper and Zha, 2003).

Agents could change their decision rule, partly anticipating the metals demand increases and front-loading the price effect. However, we show that our results are robust to an extension of the copper market model with an anticipatory metal-specific demand shock that is linked to an increase in copper inventories.

Furthermore, plausibility statistics show that the scenarios imply historically large but not implausible shock series and the scenario paths of the global economic activity indices do not differ much from their unconditional forecasts. Finally, innovation, the technology mix, and policy-making lead to large uncertainty surrounding the consumption scenarios.

To our knowledge, we are one of the first to study metals and the energy transition from an economics perspective. The paper contributes to the academic literature by adding the IEA's metals consumption scenarios to structural VARs, identifying metal-specific demand shocks that resemble the energy transition using traditional and narrative sign restrictions, and by employing these shocks in a structural scenario analysis following Antolín-Díaz et al. (2021).

Our findings have important implications for integrated assessment models that introduce climate change and the energy transition into dynamic stochastic general equilibrium models (e.g., Nordhaus and Boyer, 2000, Hassler and Krusell, 2012, Golosov et al., 2014). These models do not include the critical role of metals as inputs and the potential rise in costs due to the energy transition. Including metals as an input into the production of renewable energies and batteries may capture these additional costs and help us better understand the impact of the energy transition on inflation.

Our results are also highly-relevant for policy makers, who work on the energy transition. We show that some metals are critical bottlenecks for the transition to net-zero emissions by 2050 based on state-of the art econometric methods. If unaddressed, the energy transition could become more costly and could be delayed.

The remainder of the paper is structured as follows. Section 2 provides a short description of the metals used in the analysis and introduces the data. Section 3 lays out the econometric model including the identification strategy and the setup of the structural scenario. Section 4 presents the results and Section 5 documents sensitivity analyses. Finally, Section 6 discusses some of the limitations of our analysis and concludes.

2 Metals Selection and Data

Our in-depth analysis focuses on four metals: copper, nickel, cobalt, and lithium. These four metals are considered as the most important metals that are highly impacted by the energy transition (see World Bank, 2020; IEA, 2021b). Copper and nickel are well-established metals that have been traded for more than a century on metal exchanges. They are broadly used across the economy and across low carbon technologies. Cobalt and lithium, instead, are minor but rising metals. They started being traded on metal exchanges in the 2010s and have gained in popularity because they are used in batteries for electric vehicles.[1]

[1] We do not consider graphite or vanadium, because their consumption is expected to increase significantly, albeit from a much lower base than the one for lithium and cobalt. For aluminum, while important, there are no comparable estimates available from the IEA for its usage in the energy transition. Rare earth elements (REE) and platinum group metals (PGM) are beyond the scope of our present analysis.

2.1 Historical Data Set

We use historical annual data for the real economic activity measure, i.e., a dry bulk cargo freight rate index, the global production and real prices of the respective four metals, as well as the real prices for cotton, barley, and coffee. We use the U.S. all urban consumers price index to adjust prices and the freight rate index for inflation. Data descriptions and sources are in the online-appendix.

Employing long sample periods, partly going back to 1879 for copper (the freight rates index is only available since 1879), 1900 for nickel, 1925 for cobalt, and 1955 for lithium, allows us to estimate the long-run relationships between the variables. This is important due to the long investment cycles in the industry. However, historical data can come with measurement problems. This is particularly a concern for the cobalt and lithium markets. These commodities were not traded on public exchanges for a long time. Their value chain and pricing are more complex than for copper and nickel. We have ensured that the data is as consistent as possible over time. We have also checked the history of these markets for signs of structural changes, which may be a moderate issue for the cobalt, lithium, and nickel markets. We attribute some of the relatively broad sets of admissible draws to some remaining measurement errors.

For our robustness checks we use annual copper inventory data starting in 1882. Moreover, we employ historical data on cotton prices since 1879. Cotton is a major non-metal

These metals are quite heterogeneous. REE refer to 17 metals and PGM to 6 metals. Some REE are important for wind turbines and electric vehicles, while some PGM are relevant for hydrogen. The energy transition is expected to have a modest contribution to their demand growth, especially for REE.

input for industrial production. Its market is liquid and well documented. At the same time, its production and consumption should be uncorrelated to the ones of the selected metals, except for movements due to aggregate demand shocks, hitting all commodities at the same time. This is an important assumption for our identification scheme in the four-variables model. See the online-appendix for plots of the time series.

2.2 Metals Consumption Scenarios

The IEA (2021b) provides metals consumption forecasts for the Stated Policy Scenario that is based on the status quo of implemented policies in early 2021 and IEA (2021a) for the Net-Zero Emissions (NZE) Scenario. Figure 1 shows historical production levels for copper, nickel, cobalt and lithium along with future consumption paths in the two scenarios.

The NZE scenario is based on the premise that global temperature increases can be limited to 1.5°C in 2050. It assumes that there are net-zero CO2 emissions in 2050, including the energy sector. It implies that renewable energies become the leading source of electricity worldwide before 2030. In the transportation sector, the scenario assumes that electricity will cover 60 percent of energy consumption in addition to the broad use of hydrogen for trucks and shipping. Battery demand is expected to increase from 0.16 TWh in 2020 to 14 TWh in 2050, with 86 percent of the stock of cars being powered by electricity. We concentrate on this scenario which is the most ambitious with the highest chance of limiting global warming to 1.5°C (IPPC 2021).

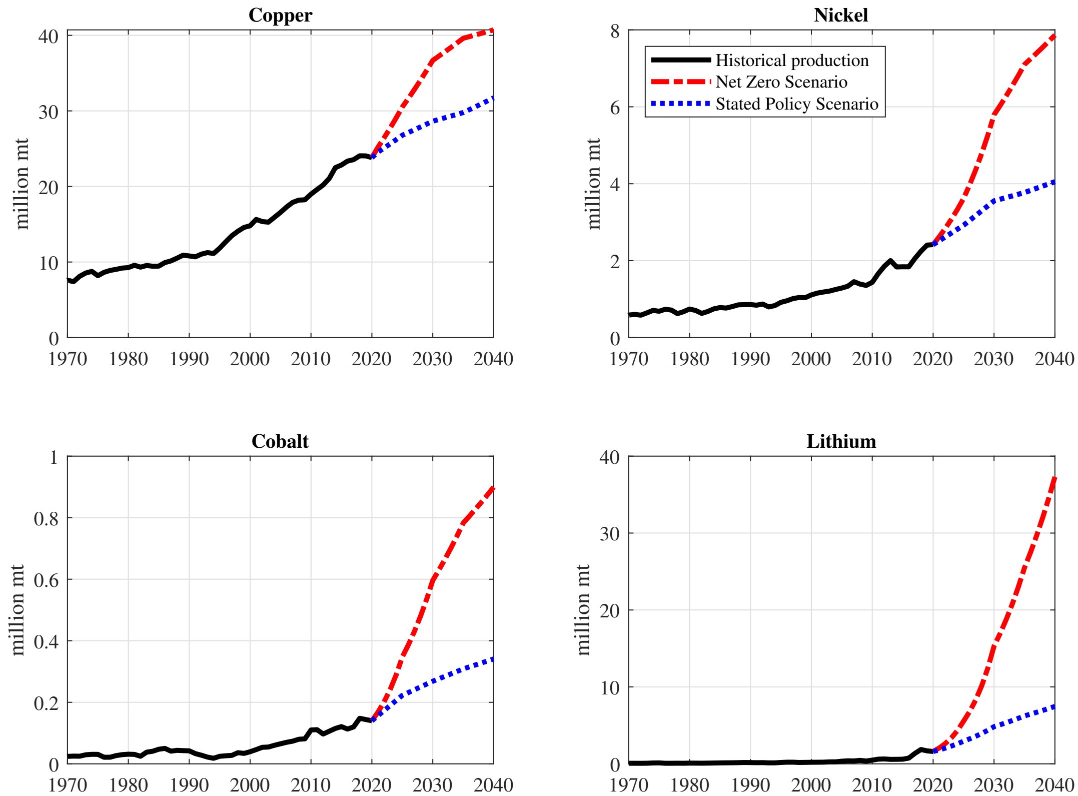

Figure 1: Metals consumption in the IEA's Net-Zero Emissions Scenario and the Stated Policy Scenario.

Notes: Lithium refers to lithium ore.

The total consumption of lithium and cobalt would rise more than twentyfold and sixfold, respectively, driven by clean energy demand in the NZE scenario. Copper and nickel would see twofold and fourfold increases of total consumption, respectively. The NZE scenario of the IEA also implies that the consumption of the respective metal grows at a high rate between now and 2030, as the switch from fossil fuels to renewable energies requires large initial investments, but slows slightly in the later part of the scenario horizon.

Metals consumption in the stated policy scenario follows more or less an extended historical trend.

3 Econometric Model

We set up separate VAR models for each metal. Each reduced-form model includes three endogenous variables $\mathbf{y}_t = (\mathbf{REA}_t, \mathbf{\Delta Q}_t, \mathbf{P}_t)'$, namely the log of a global real economic activity index (a global dry bulk cargo freight rate index) $\mathbf{REA}_t$, the percentage change of global production of the respective metal $\mathbf{\Delta Q}_t$, and the log of the real price of the respective metal $\mathbf{P}_t$. We estimate

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{\Pi}\,\mathbf{D}_t + \mathbf{u}_t\ , \tag{1}$$

with a lag length of $p = 4$, where $\mathbf{A}_i$ are the reduced-form VAR coefficients and $\mathbf{u}_t$ the reduced-form forecast errors. These errors have no economic interpretation. The matrix of deterministic terms $\mathbf{D}_t$ consists of a constant and dummies for the years during each of the two world wars and the three consecutive years. For copper and nickel, we add a linear trend to the regression due to the longer sample period that exhibits a declining trend in production growth. We discuss alternative trend specifications in detail in the sensitivity section. The analysis is performed at an annual frequency. The reduced-form VAR in (1) can be expressed in a structural form given by

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{\Gamma}\,\mathbf{D}_t + \boldsymbol{\varepsilon}_t. \tag{2}$$

In equation (2), $\boldsymbol{\varepsilon}_t$ are independent structural shocks with an economic interpretation. These are related to the reduced-form errors via the linear transformation $\mathbf{u}_t = \mathbf{B}_0^{-1}\boldsymbol{\varepsilon}_t$. Thus, $\mathbf{B}_0^{-1}$ contains the impact effects of the structural shocks on the three endogenous variables in $\mathbf{y}_t$. By assuming a unit variance for the uncorrelated structural shocks, i.e., $\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathbf{I}_n$ (an identity matrix), the reduced-form covariance matrix $\mathbf{\Sigma}_u$ is related to the structural impact multiplier matrix as $\mathbf{\Sigma}_u = \mathbb{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{B}_0^{-1}\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t')\mathbf{B}_0^{-1\prime} = \mathbf{B}_0^{-1}\mathbf{B}_0^{-1\prime}$.

3.1 Identification

Without further information it is not possible to identify $\mathbf{B}_0^{-1}$ and thereby the structural form in (2). The literature has come up with different restrictions placed directly on $\mathbf{B}_0^{-1}$ to solve this identification problem. We apply conventional sign restrictions (e.g., Faust, 1998, Canova and Nicolo, 2002, and Uhlig, 2005) on the elements in $\mathbf{B}_0^{-1}$, i.e., we assume that the structural shocks have either a positive or negative effect on the endogenous variables on impact. We base these impact restrictions on economic intuition as specified in Table 1. We also impose narrative sign restrictions, which we explain further below.

	Global economic activity	Global metal production	Real metal price
Aggregate demand shock	+	+	+
Metal supply shock	+	+	-
Metal-specific demand shock	-	+	+

Table 1: Sign restrictions on impact effects

We interpret the first shock as an aggregate demand shock that is related to the global business cycle and thereby affects the demand for metals. A positive shock increases global economic activity, the global production of the respective metal and its price.[2]

We label the second shock as a metal supply shock, capturing, for example, strikes, other production outages, or the earlier than expected opening up of a major mine. A positive shock that increases global metal production is assumed to drive up global economic activity, but to decrease the real metal price on impact.

We interpret the third shock as a metal-specific demand shock that characterizes most closely the energy transition in our structural scenario analysis. This shock represents a shift in the demand curve due to factors that affect the demand for only specific metals. Note that this shock may also capture precautionary demand shocks, namely shifts in the demand for above-ground inventory due to forward-looking behavior.[3] This is important, because the energy transition may also affect metal markets through this anticipation

[2] In this paragraph and in the following, we describe the assumptions about the sign restrictions normalizing such that the underlying shock increases the metal price. We assume that the shocks are symmetric, and hence, the reverse effects hold.

[3] For our historical sample period there is no data on global metal inventories available for lithium, cobalt and nickel. However, we present results for copper for which data are available in Section 5.2.

channel. We assume that a positive shock increases the production and price of the respective metal. It decreases global economic output on impact as a result of the metal price increase (see also Kilian, 2009; Baumeister and Peersman, 2013). This assumes that the energy transition is a negative cost shock that makes parts of the capital stock obsolete and sees workers reallocate to renewable energy and electric automobile sectors. We relax this assumption in our sensitivity analysis, as described in chapter 3.2.

It is important for the scenario analysis that the metal-specific demand shock resembles the energy transition as closely as possible. Narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) help us to sharpen the identification of the different structural shocks, and thus, the distinction between them.[4] These restrictions are imposed on the importance of specific shocks during specific historical episodes (see Table 2). We source the events of the narrative sign restrictions from historical market accounts from U.S. Geological Survey (2013).

Examples include the Great Depression and the Great Recession, for which we specify aggregate commodity demand shocks as the most important drivers of economic activity as well as of copper and nickel prices. These crisis episodes hit commodity markets broadly and should not be mistaken as shocks specific to the energy transition metals.[5]

[4]If we do not include any narrative sign restrictions, inference is less sharp. The impact of the energy transition on prices is muted for cobalt (price peaks at USD 54,000), lithium (USD 11,000), and nickel (USD 22,000), because we assume that the metal specific demand shock is the most important contributor to the strong prices increases in 2017 (both cobalt and lithium) and 1988, respectively. As production increases were strong but still relatively modest compared to price increases during these years, the estimated supply elasticities are small, leading to higher prices in the scenarios with the narrative sign restrictions compared to the case without narrative sign restrictions. The results for copper are robust (USD 7,000 price peak without the narrative sign restrictions). In the online appendix we have plotted IRFs for each model without narrative restrictions.

[5]Copper was broadly used during the Great Depression. Hence, we assume that the aggregated com-

Metal	Year	Shock	Variable	Sign	Contribution	Narrative
Cobalt	1930	AD	REA	-	largest	Great Depression
	1994	MS	Price	-		Zaire declares autonomy
	2009	AD	REA	-	largest	Great Recession
	2009	AD	Price	-	largest	Great Recession
	2017	MD	Price	+	largest	EV batteries demand
Copper	1930	AD	REA	-	largest	Great Depression
	1930	AD	Price	-	largest	Great Depression
	1966	MD	Price	+	largest	Vietnam War
	1967	MS	Production	-		Strike
	2009	AD	REA	-	largest	Great Recession
	2009	AD	Price	-	largest	Great Recession
Lithium	2009	AD	REA	-	largest	Great Recession
	2017	MD	Price	+	largest	EV batteries demand
Nickel	1930	AD	REA	-	largest	Great Depression
	1969	MS	Price	-	largest	Strike
	1988	MD	Price	+	largest	Stainless steel demand
	2009	AD	REA	-	largest	Great Recession
	2009	AD	Price	-	largest	Great Recession

Table 2: Narrative sign restrictions

Notes: AD = Aggregate commodity demand shock, MS = Metal supply shock, MD = Metal-specific demand shock, REA = Real Economic Activity Index, largest = the contribution of the shock to the fluctuation of the respective variable in the specified year is larger than the contribution of any other type of shock.

modity demand shock is not only the largest and negative contributor to fluctuations in global economic activity but also to copper prices. In contrast, cobalt and nickel were only used in small quantities in narrow sectors at the time. Cobalt was historically used for pigments in paints (Krebs, 2006), while nickel's use broadened out in the 1930, but was still mainly used in coinage and for producing decorative items (Nickel Institute, 2022). We therefore stay agnostic about the impact of the aggregate commodity demand shock on the two prices. During the Great Recession, we assume that the aggregate commodity demand shock has the largest and a negative impact on both global economic activity and the respective commodity prices in the models for cobalt, copper, and nickel. Lithium was still used mostly used for producing ceramics and other specialized tasks during that time. Only 20% of consumption went into batteries according to the U.S. Geological Survey (2008). Hence, we only assume that the aggregate commodity demand shock has a negative impact on global economic activity but are agnostic about its impact on lithium prices.

Historical episodes that come potentially closer to resembling the metal-specific demand shock of the energy transition are the unexpected increase in stainless steel demand in 1988 that pushed up nickel prices (U.S. Geological Survey 2013, p.106-7)[6], and the unexpected rise in electric vehicle batteries demand in 2017, driving up lithium and cobalt prices. In 2017 lithium prices more than doubled and cobalt prices increased by 70%. These price increases might have represented first expectations of a nascent energy transition. It is noteworthy that 2017 lithium production also adjusted quite strongly to demand and increased by over 80% in the same year. For copper, we assume that a metals-specific demand shock due to high demand for copper in the weapons industry at the height of the Vietnam War was the largest and positive contributor to the price increase in 1966 (see Sousa 1981, p. 9).

We amend these narrative sign restrictions on the contributions of the aggregated demand shock and the metal-specific demand shock by sign restrictions on the metal supply shocks. The narrative evidence suggests that the negative supply shock to nickel markets was the largest contributor to price movements due to strikes in Canada's two largest nickel mining companies. This led to an outage corresponding to roughly 10% of global production in 1969. In contrast, the narrative evidence is less clear about the relative contribution of the cobalt supply shock in 1994 related to Zaire declaring autonomy and the 1967 copper supply shock due to a strike in the U.S. That's why we only impose

[6] Apart from the main factor of higher stainless steel demand, U.S. Geological Survey (2013) list lower nickel supply as a further reason for increased prices in 1988 which they link to lower nickel prices in the early and mid 1980s. Thus this additional factor can be interpreted rather as a response to market conditions than a negative supply shock in that year.

a negative sign but do not specify the contribution of these two shocks.

3.2 Extended 4-Variables Model using an "Anchor" Variable

To avoid any *ex-ante* assumptions about the immediate effects of the energy transition on the economy, we propose a novel identification strategy in a sensitivity check. We augment the standard three-variables commodity market model with the price of cotton as an "anchor" variable. Compared to the aggregate demand shock, the metal-specific demand shock is "anchored" on this variable, the cotton price, via the zero (or exclusion) restriction displayed in the last row of Table 3. We assume that the metal-specific demand shock and similarly the metal supply shock have no effect on the cotton price on impact while a positive aggregate demand shock raises the price of all commodities, i.e., metals and cotton.

This identification relies on the assumption that the anchor variable is not a substitute for the analyzed metal.[7] For example, an unexpected increase in aggregate commodity demand due to a booming global economy would raise prices for both lithium and cotton. In contrast, an unexpected increase in lithium demand for batteries (a positive lithium-specific demand shock), drives up the lithium price but not the price for cotton on impact. We complement the exclusion restrictions imposed on the anchor variable by traditional and narrative sign restrictions.

[7] Using a commodity price index as an anchor variable would not constitute a sensible choice if it includes commodities that are substitutes for energy transition metals (e.g. biofuels, steel, or aluminum).

	Global economic activity	Global metal production	Real metal price	Real cotton price
Aggregate commodity demand shock	+	+	+	+
Metal supply shock	+	+	-	0
Metal-specific demand shock		+	+	0

Table 3: Sign and zero restrictions on impact effects

This method can be applied more generally to disentangle aggregate (demand, supply, or financial) from sectoral (demand, supply, or financial) shocks.[8] A drawback to using impact exclusion restrictions in our application results from the annual frequency of our data. Even if the cotton price is not affected via a direct effect, a second-round effect via the transmission channel of the metal-specific demand shock on global economic activity might eventually affect the cotton price. This second-round equilibrium effect could already be present within the first year.[9]

[8]It might be helpful to describe the "anchor" variable in contrast to a proxy variable, i.e., an instrumental variable in VAR studies, usually employed to identify one of the structural shocks (Stock and Watson, 2012; Mertens and Ravn, 2013). The proxy variable needs to be sufficiently correlated with the shock of interest - the relevance condition - and uncorrelated with all other shocks - the exogeneity condition. While the proxy identifies a specific shock, the "anchor" variable assists in differentiating between different shocks. In the case of the "anchor" variable the focus is on the exogeneity condition that must hold for the metal-specific demand shock on impact, while the relevance condition must hold for the aggregate demand shock.

[9]The assumption that metals and cotton are no substitutes would be more credible at the monthly or quarterly frequency. Unfortunately, there are no such high frequency data available for cobalt, nickel, and lithium for a sufficiently long sample period.

3.3 Computation of Supply Elasticities

As we aim at pinning down the effect of the energy transition – represented by a metal-specific demand shock – on metals supply and ultimately prices, we define the supply elasticities as the metal production response relative to the price response given a metal-specific demand shock.[10]

We obtain supply elasticities using the estimated $\mathbf{B}_0^{-1}$ matrix of structural impact effects and the reduced-form parameters $\mathbf{A}_i$. The responses of the $n = 3$ variables in $\mathbf{y}_t$ to the structural shocks $\boldsymbol{\varepsilon}_t$ can be traced over time via $\boldsymbol{\Theta}_h = \boldsymbol{\phi}_h \mathbf{B}_0^{-1}$ for $h = 1, 2, \ldots$ where $\boldsymbol{\Theta}_h$ is an $(n$ x $n)$ matrix of structural impulse responses for the horizon h and $\boldsymbol{\phi}_h = \sum_{j=1}^{h} \boldsymbol{\phi}_{h-j} \mathbf{A}_j$ and $\boldsymbol{\phi}_0 = \mathbf{I}_n$ (Lütkepohl, 2005).

The impact supply elasticity $\boldsymbol{\eta}_S$ is calculated as the ratio of the metal production response to a metal-specific demand shock (MD) relative to the price response to the same shock written as $\boldsymbol{\eta}_{S,0} = (\boldsymbol{\Theta}_0)_{MD,Prod} / (\boldsymbol{\Theta}_0)_{MD,Price}$.

Demand shocks shift the metal demand curve along the metal supply curve, thereby tracing out its shape, which gives the supply elasticity. Elasticities over longer horizons are based on the cumulative output response and the cumulative price change response

[10] This definition of supply elasticities follows Kilian and Murphy (2014) and is broadly used in the literature, see, e.g., Ludvigson et al. (2017), Antolín-Díaz and Rubio-Ramírez (2018), Basher et al. (2018), or Herrera and Rangaraju (2020). It entails that a metal-specific demand shock does not only trigger a response in price but also a response in other variables. A supply elasticity that takes into account the ceteris paribus requirement is obtained directly from the impact elasticity in the structural $\mathbf{B}_0$ matrix (see Baumeister and Hamilton, 2021). The relevant element of this matrix indicates the simultaneous response of metal output to a change in the metal price holding all other variables constant. We also report results based on this definition. We focus on the former results because in the context of this paper we are interested in the effect of a metal-specific demand shock on metals supply in a dynamic way.

and are calculated as

$$\boldsymbol{\eta}_{S,h} = \sum_{i=1}^{h} (\boldsymbol{\Theta}_i)_{MD,Prod} / \sum_{i=1}^{h} (\boldsymbol{\Theta}_i)_{MD,Price}. \tag{3}$$

3.4 Structural Scenario Analysis

We conduct structural scenario analysis for the price of each metal following the framework of Antolín-Díaz et al. (2021). Our object of interest is a conditional forecast $\mathbf{y}_{T+1,T+h} = (\mathbf{y}_{T+1} \ldots \mathbf{y}_{T+h})$ over the next $h = 20$ years for the endogenous variables, where T denotes the year 2020. The conditional forecast restricts some of the variables in $\mathbf{y}_{T+1,T+h}$ and a subset of the future shocks $\boldsymbol{\varepsilon}_{T+1,T+h}$, thereby linking the path of future variables directly to certain shocks. We briefly lay out the underlying intuition tailored to the metal consumption scenarios from the IEA (2021b).

We take the consumption scenarios for each metal as given, thus pre-specifying the future metal consumption in the conditional forecast $\mathbf{y}_{T+1,T+h}$. We set global consumption equal to global metal production in the IEA scenarios, assuming that there are no short-term changes in inventories. The future paths of global economic activity and the metal price are left unspecified. Concerning the paths of future shocks, we constrain the aggregate demand shock and the metal supply shock to their unconditional distributions. The algorithm then finds a series of metal-specific demand shocks that incentivizes the metal production path needed for the energy transition. We derive the implied price and revenue paths from these shocks.

Compared to traditional conditional forecasts, this methodology has the advantage that it can attribute the future path of endogenous variables to the path of a specific structural shock. As we deem the energy transition as a scenario resulting from a series of metal-specific demand shocks, it is important to specify this directly and not attribute the energy transition to exogenous increases in metal supply or some combination of other shocks.

For example, in our case the classical reduced-form conditional forecasting question is "What is the likely path of the metal price, given that metal production has to increase by a certain amount due to the energy transition?" The answer is confounded by a lack of causal structure. Metals prices could be high, boosting supply to reach the scenario output. However, it could also be the opposite: supply shocks could drive supplies upward, thus driving prices down.

Due to the structural scenario framework, we can handle this reverse causality in the scenario. We can ask the more precise question "What is the likely price path if metal-specific demand shocks due to the energy transition increase metal production as needed?" Hence, the structural scenario is a conditional forecast of the variables in our model that generates the scenario metal output path with the restriction that only the commodity-market specific demand shock series can deviate from its unconditional distribution. The metal production and consumption path of the respective metal is exogenously given. Please see Section 1 in the online-appendix for more details on the structural scenario analysis as formalized by Antolín-Díaz et al. (2021).

3.5 Structural Scenario Plausibility

Antolín-Díaz et al. (2021) provide a statistic to judge how plausible a structural scenario is. The concept is closely related to the statistic for modest interventions by Leeper and Zha (2003). It compares the characteristics of the different shocks over the scenario horizon to their historical counterparts. Based on entropic forecast tilting (see Robertson et al. 2005 and Giacomini and Ragusa 2014) the Kullback-Leibler (KL) statistic

$$D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF}) = \frac{1}{2}\big(tr(\mathbf{\Sigma}_\varepsilon + \mu_\varepsilon'\mu_\varepsilon - nh - ln(det\mathbf{\Sigma}_\varepsilon)\big) \tag{4}$$

represents a divergence of the distribution of shocks compatible with the structural scenario $\mathcal{N}_{SS}$ from the distribution of the unconditional forecast $\mathcal{N}_{UF}$. The statistic depends on μ_ε, the mean, and $\mathbf{\Sigma}_\varepsilon$, the covariance of the restricted future shocks.

Antolín-Díaz et al. (2021) calibrate the statistic to a scale between 0.5 and 1 such that it displays the divergence between two binomial distributions, one with probability q and one with probability 1/2.[11] In other words, the calibrated KL statistic gives an indication of how far away the scenario is from the unconditional path represented by the comparison of the flip of a fair and a biased coin.

[11] The statistic is calibrated to the parameter q that solves the equation $D_{KL}(\mathcal{B}(nh, 0.5)||\mathcal{B}(nh, q)) = D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$ where $\mathcal{B}(m, p)$ denotes the Binomial distribution for m independent experiments with success probability p. The solution to the equation is $q = \frac{1}{2}\big(1+\sqrt{1-e^{-\frac{2z}{nh}}}\big)$, where $z = D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$.

3.6 Estimation and Inference

Estimation and inference are based on standard Bayesian techniques laid out in Waggoner and Zha (1999), Rubio-Ramirez et al. (2010), and Antolín-Díaz et al. (2021). The aim is to draw from a joint posterior distribution of both the structural parameters and the conditional forecast

$$p(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+ | \mathbf{y}^T, \mathbf{IR}(\mathbf{B_0}, \mathbf{B}_+), \mathbf{R}(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+)) \ , \tag{5}$$

where $\mathbf{y}^T$ is the historical sample, $\mathbf{B'}_+ = [\mathbf{B'}_1 \ldots \mathbf{B'}_p \boldsymbol{\Gamma}]$ collects the structural VAR lag coefficients including the exogenous parts, $\mathbf{IR}(\mathbf{B_0}, \mathbf{B}_+)$ are the identification restrictions and $\mathbf{R}(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+)$ the structural scenario restrictions. Note that the structural scenario restrictions depend on the structural VAR parameters via equation (2) in the online-appendix.

To draw from this distribution, we use the algorithm from Antolín-Díaz et al. (2021) that builds on Waggoner and Zha (1999). The algorithm uses a Gibbs sampler procedure that iterates between draws from the conditional distributions of the structural parameters and the conditional forecast.[12]

Hence, we pick a random draw of structural parameters out of 25,000 potential draws that relies both on the actual data and on a structural forecast. We use the structural

[12]Each draw of structural parameters must consider the restrictions implied by the structural scenario, i.e., the forecasted path of the variables and the restrictions on the non-driving shocks (in our case the aggregate commodity demand shock and the metal supply shock).

parameters from this randomly picked draw to then draw the scenario paths of the price series and the economic activity index for the structural scenario that fits the specified metal production path. The next 25,000 draws for structural parameters rely on the original data and the data from the just drawn structural scenario.

We use a Minnesota-type prior with standard shrinkage parameters (see Giannone et al., 2015) in combination with a sum-of-coefficients prior (Doan et al., 1984) and a dummy-initial-observation prior (Sims, 1993) to estimate equation (1) and the conditional forecasts.[13] Our prior specification assumes that metal production growth is independent and identically distributed, while the log of the real activity index and the logs of the price levels follow a random walk.

Identification via sign restrictions (with additional zero restrictions in our extension) does not yield point estimates but instead sets of possible parameter intervals for the different elements in $\mathbf{B}_0^{-1}$. For each model we obtain a set of 1,000 admissible draws, where each draw consists of a conditional forecast, future shocks, and an associated $\mathbf{B}_0^{-1}$ matrix that satisfies the identifying restrictions. These draws are also used for inference, i.e., they yield an indication of the uncertainty around the pointwise median estimates. Following Antolín-Díaz and Rubio-Ramírez (2018) and Antolín-Díaz et al. (2021), we report pointwise median and percentiles of impulse responses for our set-identified structural VAR

[13]The variance for the priors on the reduced-form VAR coefficients is given by $var\Big((A_i)_{j,j}\Big) = \frac{\lambda^2 \psi_j}{i^\alpha}$, where i denotes the lag and j the variable. The tightness parameter λ is set to 0.2, the decay parameter is $\alpha = 2$, and the scale parameters ψ_j are set to the OLS residual variance of an auto-regressive model for each variable j. The variance for priors on the exogenous variables are set to 1,000. This should shrink the reduced-form VAR towards a more parsimonious naïve benchmark and helps to maximize the out-of-sample forecast, in which we are particularly interested.

models, as it is common in the literature.

The literature has made substantial recent progress on inference in Bayesian models, which is important to take into account when interpreting our results. First, Baumeister and Hamilton (2015, 2020) and Watson (2019) remark that readers are used to associating error bands with sampling uncertainty, but in large-sample sign-restricted SVARs these error bands only result from the prior for the rotation matrix Q, not sampling uncertainty. Inoue and Kilian (2020) point out that the share of uncertainty resulting from the prior on Q tends to be rather small in most applications, in particular, when assuming several sign restrictions.

For our baseline model with three variables the Haar prior placed on the rotation matrix Q is uninformative about the structural impulse responses (a special case as Baumeister and Hamilton 2015 show). However, the concern of an informative prior materializes when we extend the model to the four-variables case in the sensitivity section. We note that these sensitivity results are not based on a large sample and we use a large number of different sign restrictions. We still recognize that in this case our inference summarizes both prior uncertainty and sampling uncertainty to some extent. We therefore report the full set of impulse responses to provide the reader with a better sense of the uncertainty around the estimates.

Second, we note that the posterior median response function does not represent one of the structural models. Thus, we also report the Bayes estimator under a quadratic loss function following Inoue and Kilian (2021). The loss function ranks the admissible models according to each model's joint quadratic distance between its impulse responses and the impulse responses of all the other admissible models. The Bayes estimator is the model with the smallest joint quadratic distance, meaning that it is closest to the set of all admissible models. The results are rather insensitive to the choice of the loss function.

4 Empirical Results

4.1 Price Elasticity of Metals Supply

Supply elasticities summarize how quickly firms increase output in reaction to a price increase. The model allows us to estimate these elasticities at different horizons for each of the metals.

The elasticities result from the impulse responses of metal production and prices to a metal-specific demand shock, as shown in Figure 2.[14] The impulse response functions show an increase in the prices of the four metals as a response to the metal-specific demand (MD) shock that persists for several years. The impact of that shock on production is also quite persistent but rather muted for all metals, except lithium. The impulse responses from the Bayes estimator under quadratic loss are rather similar to the pointwise median impulse responses and mostly lie within the 68% pointwise credible sets.

Figure 3 shows the estimates of our supply elasticities for copper, nickel, cobalt, and lithium. Supply is quite inelastic over the short term, as it can only be expanded through

[14]The reader is referred to the online-appendix for the complete sets of impulse responses.

more recycling and higher utilization of existing mining capacity. A demand-induced positive price shock of respectively 10 percent increases the same-year output of copper by 4.0 percent, nickel by 7.0 percent, cobalt by 3.3 percent, and lithium by 12.5 percent.[15]

These elasticities are broadly in line with impact elasticities obtained directly from the $\mathbf{B}_0$ matrix (with 68% pointwise credible sets) (see Baumeister and Hamilton, 2021). For copper the one year supply elasticity is 0.26 [0.22, 0.31], for nickel 0.63 [0.50, 0.77], for cobalt 0.32 [0.25, 0.40], and for lithium 1.13 [0.79, 1.52].

[15]The supply elasticities based on the Bayes estimator are also in line with the baseline results.

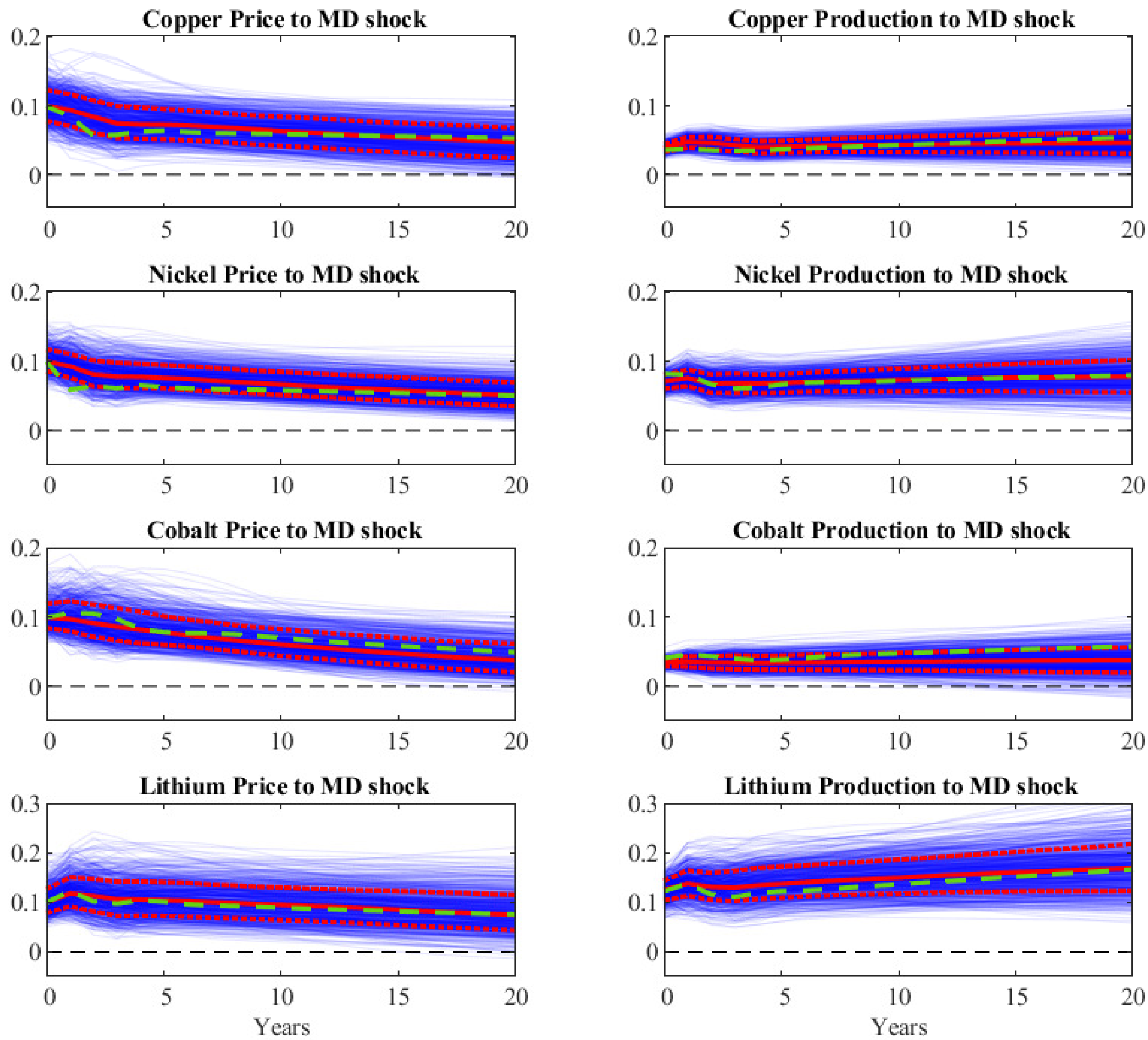

Figure 2: Impulse responses of metal production and price to a metal-specific demand (MD) shock.

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the 68% joint credible set under quadratic loss (blue lines). The full set of impulse responses is in the online-appendix. All impulses are scaled by the same factor such that the shock is normalized with the median response of the metal price being 10% on impact. The responses are derived from four different VAR models, one for each metal. The y-axes for lithium differ from the others.

In the long-term, however, supply is more elastic. Firms build new mines, innovate in extraction technologies and conduct exploration. After 20 years, the same price shock raises output of copper by 8.6 percent, nickel by 14.4 percent, cobalt by 8.6 percent and lithium by 20.1 percent.

The supply elasticities for lithium are much larger than for the other three metals. This is in line with the different ways of producing the four metals. Copper, nickel, and cobalt are extracted in mines, which often require capital intensive investment and involve long lead times of 16 years on average from exploration to construction (IEA, 2021b). In contrast, lithium is often extracted from mineral springs and brine, where salty water is pumped from the deep earth. Lead times to open new production facilities are much shorter with up to 7 years. Other factors such as innovation in extraction technology, market concentration and regulations also influence supply elasticities.

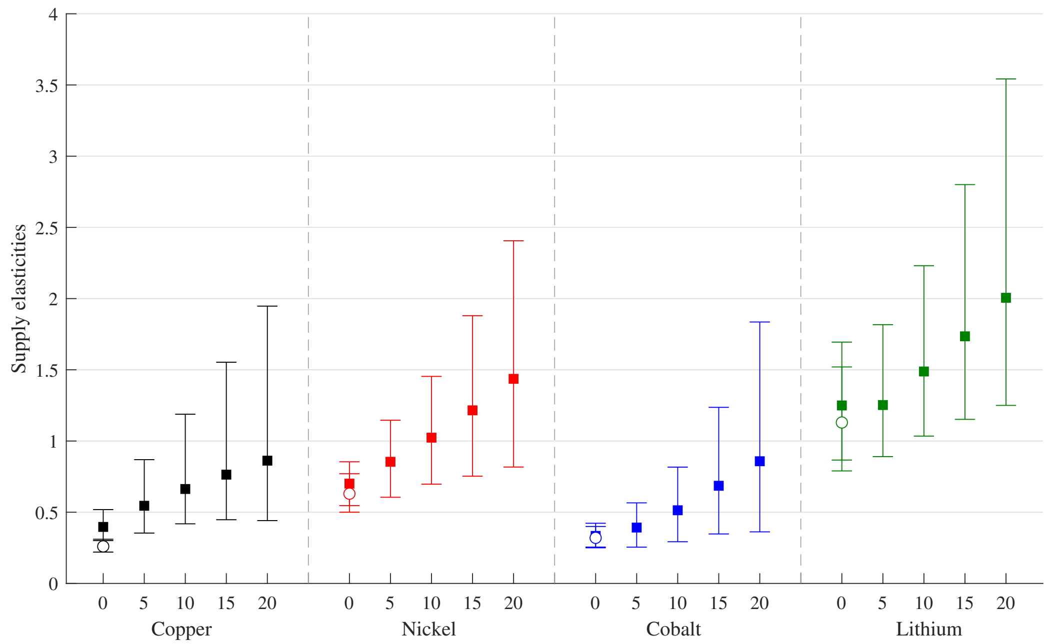

Figure 3: Supply elasticities at annual horizons based on the metal-specific demand (MD) shock.

Notes: We calculate the elasticities via equation (3) for each of the 1,000 draws to construct the median and the 68 % pointwise credible sets. Circles show supply elasticities directly obtained from $\mathbf{B}_0$ matrix with 68% pointwise credible sets.

4.2 Price Forecasts

Results in Figure 4 show that the four metals are potential bottlenecks for the energy transition.[16] Prices of cobalt, lithium, and nickel would rise several hundred percent from annual average levels in 2020 in the net-zero emissions scenario. The copper price would be up by about one third, as it would face more moderate consumption increases. Inflation adjusted prices of the four metals would reach peaks roughly similar to previous historical

[16]We present the following results based on the point-wise median and credible sets for expository purposes, as the impulse responses and the estimated supply elasticities based on the Bayes estimator under quadratic loss are rather similar to the point-wise median impulse responses and mostly lie within the 68% point-wise credible sets.

price peaks. However, prices would stay at these high levels for more than a decade, far longer than during previous peak periods. Real prices for all four metals would broadly stay in the 2020 annual average range in the stated policy scenario.

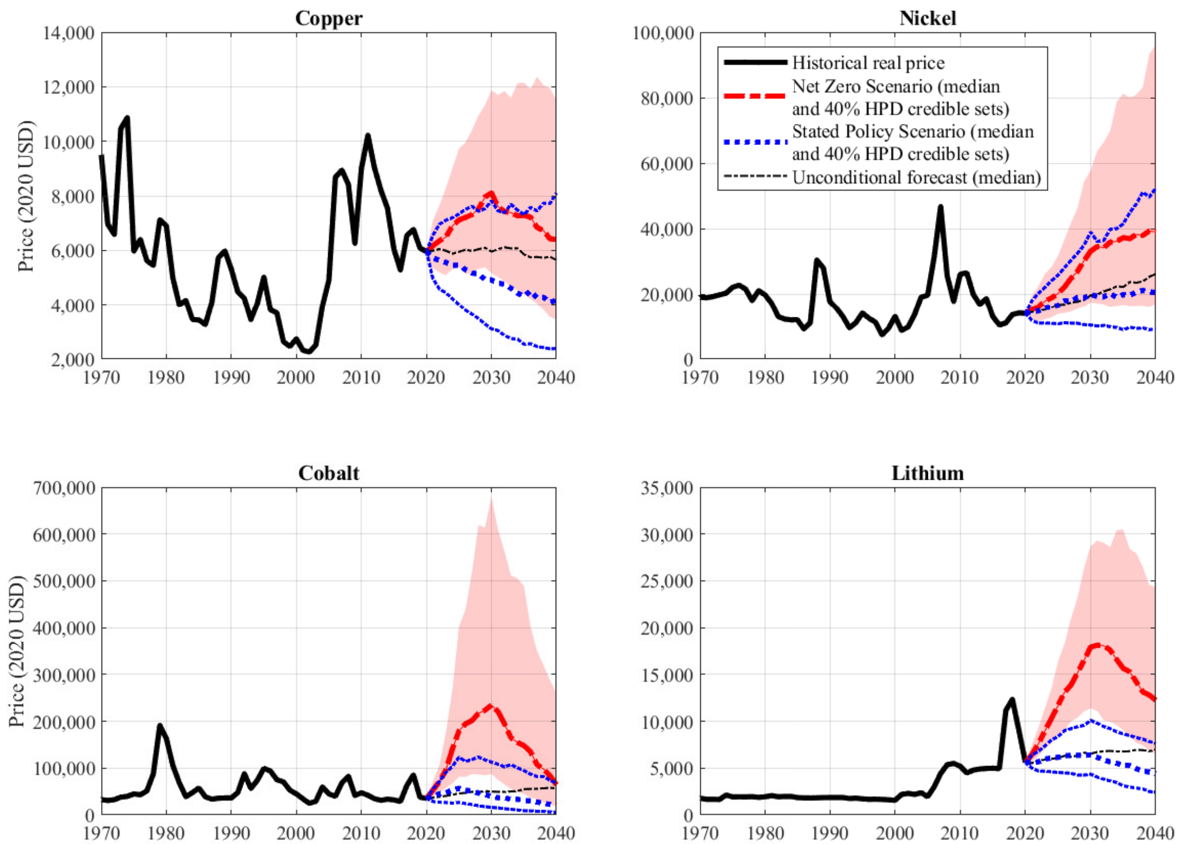

Figure 4: Price scenarios for the stated policy scenario and the net-zero emissions scenario based on the median and 40% pointwise credible sets.

Prices peak mostly around 2030 for two reasons: First, the steep rises in demand are front-loaded in the net-zero emissions scenario. In contrast to fossil fuels-based energy production, which needs a flow of fossil fuels, renewable energy production only uses metals upfront for the construction of wind-turbines or batteries, for example. Second, the initial price boom induces a supply reaction, which reduces market tightness after 2030.

The price scenarios are subject to high uncertainty, reflected in the large, implied bounds. Large confidence bands (we therefore represent 40% highest posterior density credible sets here in line with Antolín-Díaz et al., 2021) may originate from the uncertainty about the reduced-form VAR coefficients, measurement errors in the historical data, uncertainty about other future shocks influencing the price along the forecast horizon, and the uncertainty around the structural impact effects of the different shocks. We also present more conventional 68% credible sets in the online appendix which include extensive increases in prices and if at all minor declines from 2020 levels. In general, confidence bands around structural scenario forecasts are rather large (compare the applications on monetary policy and bank profitability stress-testing in Antolín-Díaz et al., 2021).

Another source of uncertainty is the uncertainty that surrounds the consumption scenarios. First, demand for each metal will depend on technological change that is hard to predict. Second, the speed and direction of the energy transition depend on policy decisions that can have a major impact on metals consumption. Finally, the mix of different sources of energies and the role of hydrogen and carbon capture and storage are quite uncertain.

4.3 Plausibility of the Scenarios

We model the energy transition as an upward shift in the distribution of metal-specific demand shocks. It is possible that agents change their decision rule, partly anticipating the metals demand increases and front-loading the price effect (see critique in Lucas, 1976; Leeper and Zha, 2003).

As a first indication of the scenario plausibility, Figure 5 graphs the mean of the metal-specific demand shock series over the scenario horizon. The mean for cobalt and lithium is slightly above one standard deviation in the first year. The means for all four metal shock series display a decreasing trend over the scenario horizon. For the cases of copper and nickel the mean does not rise above 0.6 standard deviations. From 2030 onward the mean of the shocks turn mostly negative. This demonstrates that the Net-Zero Emissions Scenario from the IEA (2021a) implies historically large, but not excessive, shocks on a repeated basis for the first half of our scenario horizon. We present the distribution of the shock series on impact in the online-appendix.

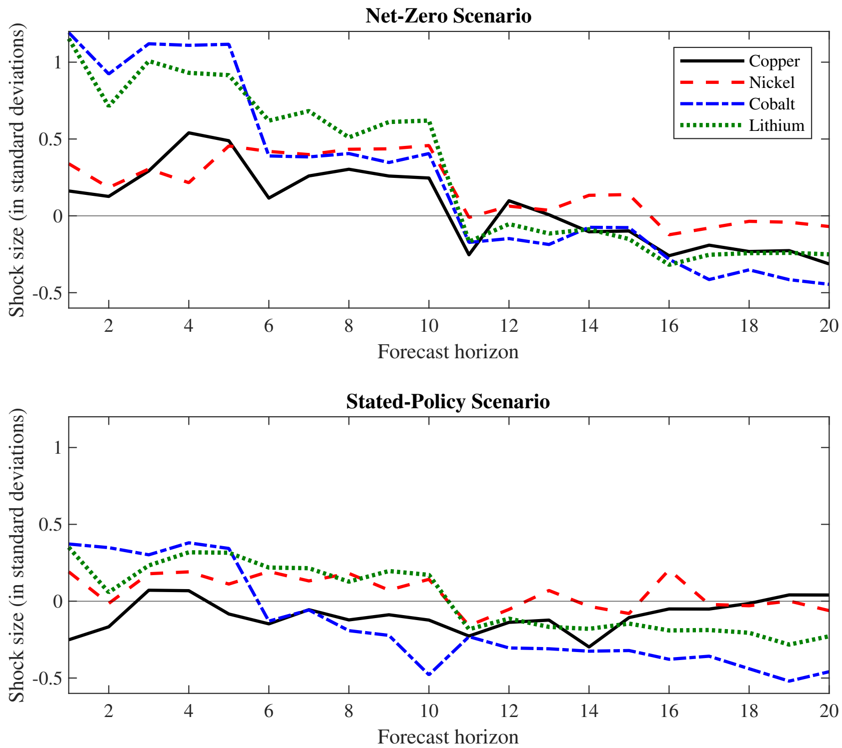

Figure 5: Point-wise mean of the metal-specific demand shock series over the scenario horizon in the net-zero emissions and stated policy scenarios.

The KL statistic measures the extent to which the distribution of shocks during the scenario period deviates from its unconditional counterpart. Hence, it does not only take into account the median shock series but also its variance. We use this measure to judge how unusual the scenarios are and whether one should expect a structural break in the model equations. Table 4 reports the plausibility statistics for the four metals in the net-zero emissions scenario. The scenario shock series lead to relatively high KL plausibility statistics, however, not signalling completely implausible policy scenarios with respect to historical precedent.[17]

	Calibrated KL Statistic
Copper	0.90
Nickel	0.88
Cobalt	0.90
Lithium	0.76

Table 4: Plausibility statistics for the NZE scenario

Regarding the possible anticipation by agents, one would most probably observe an even stronger and front-loaded price effect than in our scenarios. Moreover, we believe that the unpredictability of technological change, the uncertain iterative process of policy making, and the heterogeneous speed in the energy transition across countries, makes the full anticipation of the metals demand induced by the energy transition unlikely.

As a further plausibility exercise, we complement the KL plausibility static with an evaluation of the implied macroeconomic costs associated with the surge in metal prices due to the energy transition. Here, we focus on copper because it is the metal with the largest value of global production both historically and in the scenarios across the four metals. To asses the potential macroeconomic costs, we also rely on the global industrial production index from Baumeister and Hamilton (2019), a more conventional measure of economic activity compared to the freight rate index and that does not include the service sector as global GDP does. The index covers industrial production of the Organization of Economic Cooperation and Development (OECD) and six major non-member economies.

[17]Antolín-Díaz et al. (2021) note that for a system with only only one active policy shock, a one-time 2 s.d. shock leads to $q = 0.6$, a sequence of 1 s.d. shocks over 12 periods or a single 3.5 s.d. shock to $q = 0.67$ and a single 10 s.d. shock to $q = 0.9$.

It is available starting in 1958. Note, however, that the model is not set up to explain economic activity which is driven by a range of factors outside the model. That's why there is likely an omitted variable bias that creates an upwards bias of the estimates.

The results show that the negative impact of a copper-specific demand shock on global industrial production is non-negligible but modest. It therefore supports the plausibility of the scenario. A 20 percent increase in the price due to such a shock reduces global industrial production growth by about 0.03 percentage points (Figure 25 in the online appendix).

Figures 9 to 11 in Section 3.6 of the online appendix illustrate the implied scenario for the freight rate index, global real GDP and industrial production in the net-zero emissions scenario. In line with the first two measures the pointwise median scenario for global industrial production growth would stay relatively close to the unconditional median forecast, being first lower and then exceeding it. The 40% credible sets for the conditional forecasts of the three measures of global economic activity always include the respective unconditional forecasts.

4.4 Revenue Forecasts

We estimate that the energy transition could provide significant windfalls to metals producing firms' and countries in the net-zero emissions scenario. The potential metal demand boom could lead to a fourfold increase in the value of metals production, totaling US$ 11.1 trillion accumulated between 2021 and 2040 for the four energy transition metals alone, providing potentially significant windfalls to commodity producers (see Table 5). Most of it would come from copper and nickel, but the revenues from lithium and cobalt could also be substantial.

	Historical (1999-2018)	**Stated Policy Scenario** (2021-2040)	**Net-Zero Scenario** (2021-2040)
Selected Metals	3,043	4,373	11,131
Copper	2,382	2,747	4,892
Nickel	563	1,298	3,383
Cobalt	80	198	1,651
Lithium	18	130	1,205
Fossil Fuels	70,090		19,101
Crude Oil	41,819	-	12,906
Natural Gas	17,587	-	3,297
Coal	10,684	-	2,898

Table 5: Estimated accumulated value of global metal production from 2021-2040

Notes: Estimates are in billion 2020 USD and refer to the median. As a yardstick, we calculate back-on-the envelope the value of fossil fuels production. In the IEA Net-Zero Emissions scenario, consumption of oil drops 54%, natural gas 45%, and coal 80%. We assume that prices of crude oil average 30 USD/b, about half of the average real price from 1970 to 2020 and coal prices average 40 USD/mt, about half of the average real price from 1979 to 2020. Due to a likely further rise of LNG trade and the structural break of the shale gas revolution, we assume natural gas prices to average 1.50 USD/mBtu, half of 2020.

The estimated value of production of these four energy transition metals alone would rival the estimated value of crude oil production in the IEA's Net-Zero Emissions scenario (see Table 5). It would still be substantially below the total value of all fossil fuel production. It is also important to keep in mind that there are other metals that will be affected by the energy transition.

More specifically, Figure 6 shows that the revenue would strongly increase during the 2020s but then in the 2030s flatten out for copper and to a lesser extent for lithium, reverse for cobalt, or increase further for nickel. Annual copper revenues would roughly double from around 150 USD billion in 2020 to nearly 300 billion USD in 2030. The nickel market would reach a similar level in the late 2030s while being much smaller in 2020 with annual revenues of 34 billion USD.

Cobalt and lithium markets are, as of 2020, comparatively small with annual values of 4.9 billion USD and 2.3 billion USD, respectively. However, the relative increase would be much larger for these two minor, but rising, energy transition metals. For cobalt, annual revenues reach a peak of 135 billion USD in 2030 in the net-zero emissions scenario. Cobalt production revenues could decline afterwards due to the decreasing scenario price from 2030 onwards as supply re-adjusts. Annual lithium revenues would steadily increase by a factor of 50, reaching 110 billion USD in 2040. In the stated policy scenario, estimated revenues would increase moderately to historical highs for nickel, cobalt and lithium and remain constant for copper.

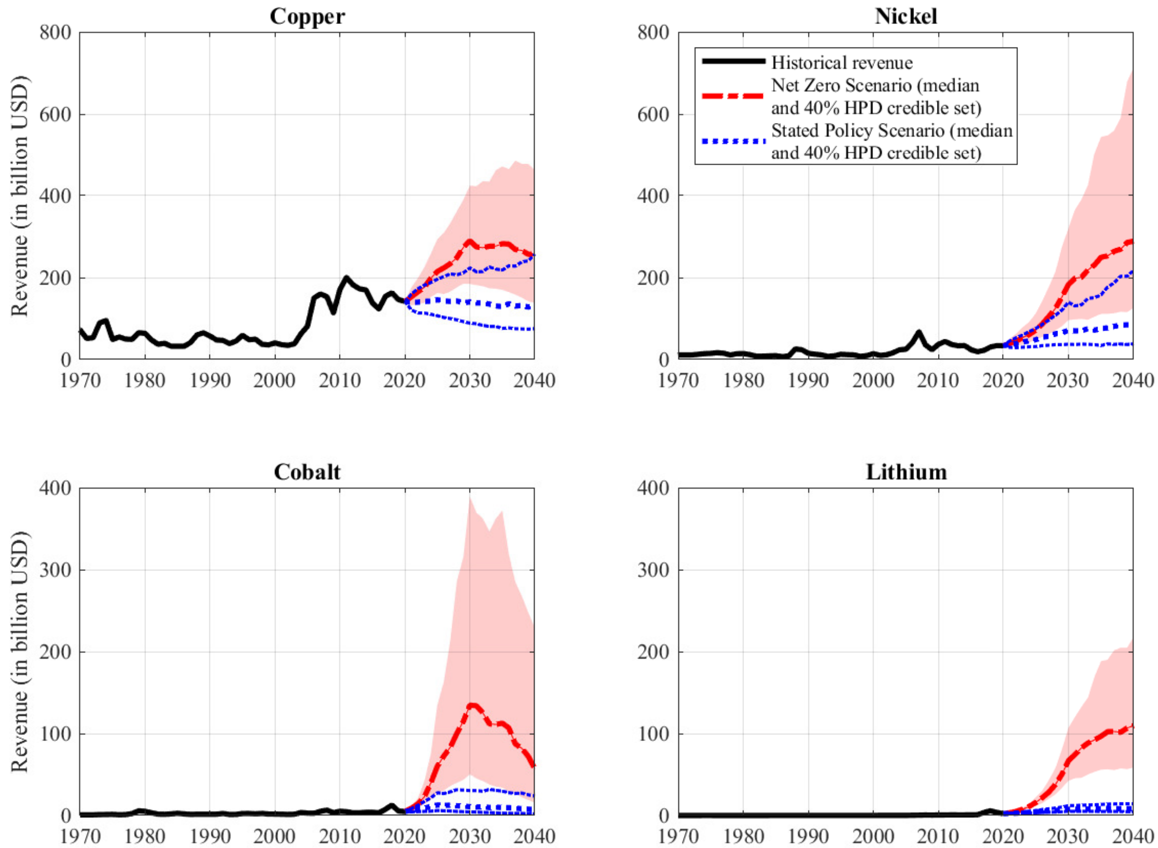

Figure 6: Annual revenues (in real US$) in the stated policy and the net-zero emissions scenario with 40% pointwise credible sets.

5 Sensitivity Analysis

We perform several robustness checks of the results with respect to the estimated elasticities, the maximum scenario prices, and the estimated total revenues. We lay out the results for copper and lithium in Tables 6 and 7 and compare them to our baseline. The online-appendix contains the analogous tables with sensitivity analyses for nickel and cobalt.

5.1 Adding an "Anchor" Variable

Results from the three-variables model are highly robust to including the "anchor" variable in the VAR. The impulse responses from the two models are similar (see the online-appendix). A minor difference emerges in the now unrestricted effect of the metal-specific demand shock on global economic activity. The impulse responses still display negative point estimates for all metals that are now, however, indistinguishable from zero. Overall, there exist only minor differences in terms of elasticities, maximum prices and total revenue across the two models, as Tables 6 and 7 show.

Results are robust when we replace the real cotton price with real prices for barley and coffee (both sourced from Jacks and Stuermer, 2020), as well as the historical US equity total return series from Jordà et al. (2019) (see the working paper version Boer et al. 2021).

	Elasticities		Scenario Analysis	
	Impact	20 Years	Max Price USD per mt	Total Revenue Tril. USD
Baseline	0.40	0.86	8,107	4.89
Altern. Sample & Trend				
1880-2020, no trend	0.44	0.88	6,072	3.4
1955-2020, with trend	0.24	0.31	13,885	7.6
1955-2020, no trend	0.24	0.32	11,469	6.1
Altern. Econ. Act. Var.				
Global Real GDP	0.21	0.20	22,030	12.0
Industr. Prod. (1958-2020)	0.13	0.24	20,033	9.3
No Uncertainty	0.35	0.83	7,951	4.9
Anchor Variable	0.39	0.81	10,030	6.5
Inventories Model				
Contemp. MD Shock	0.23	0.57	7,819	4.9
Expec. MD Shock	0.48	0.56		

Table 6: Sensitivity: Copper model

Notes: US Dollar (USD) refers to real 2020 prices, adjusted for inflation based on the US-CPI. The inventories model shows the supply elasticites for the contemporaneous copper-specific demand shock and the elasticities for the expectational shock as both shocks are used simultaneously to drive metal production.

	Elasticities		Scenario Analysis	
	Impact	20 Years	Max Price USD per mt	Total Revenue Tril. USD
Baseline	1.25	2.01	18,120	1.2
Altern. Sample & Trend				
1955-2020, trend	1.27	2.12	20,590	1.4
Altern. Econ. Act. Var.				
Global Real GDP	1.26	2.20	15,756	1.1
Industr. Prod. (1958-2020)	1.28	2.17	16,666	1.1
No Uncertainty	1.11	1.92	19,340	1.3
4-Variables Model	1.34	2.12	19,500	1.3

Table 7: Sensitivity: Lithium model

Notes: US Dollar (USD) refers to real 2020 prices, adjusted for inflation based on the US-CPI.

5.2 Inventories and Expectational Metal-Specific Demand Shocks

One of the shortcomings of the three variable model is that the identified metal-specific demand shock groups together contemporaneous and expectational demand components and cannot differentiate between them. Concerning the energy transition, it is plausible to assume that agents anticipate the future increase of metal demand, at least in part. Kilian and Murphy (2014) and Känzig (2021) show that expectations about future commodity demand and supply play a crucial role for explaining variations in commodity prices.

We extend the three variables copper model by global inventories which allows us to differentiate between contemporaneous and expectational demand components. We source our data from Rausser and Stuermer (2020), who have pieced together data going back to 1882.[18]

We identify two types of metal-specific demand shocks, a contemporaneous one and an

[18] Out of the four metals long series of global inventory data are only available for copper.

expectational one, using sign restrictions as shown in Table 8. Both shocks are assumed to increase metal production and prices, while decreasing economic activity as a result of a positive shock in the first year. We presume that the two shocks differ in their impact on inventories, however. A positive contemporaneous metal-specific demand shock decreases inventories during the first year. Agents draw down inventories in response to a shift in the demand curve as more of the metal is used as an input into production. The expectational shock is assumed to lead to a built-up in inventories, because agents anticipate higher future metals demand. This shifts the demand for above-ground inventory due to forward-looking behavior.[19]

We allow both types of metal-specific demand shocks to jointly drive the scenario output path, assuming that some of the metals demand due to the energy transition is anticipated. The aggregate commodity and metal-specific supply shocks are restricted to their unconditional means.

Impulse responses show that the expectational copper-specific demand shock has a rather short-lived effect on copper output compared to the very persistent output response of the contemporaneous copper-specific demand shock (see Figure 24 in the online appendix). The overall scenario price path is highly robust to this extended modelling choice implying that our baseline metal-specific demand shock includes both elements of anticipatory and contemporaneous metal-specific demand shocks (see the last two lines in Table 6).

[19]Narrative sign restrictions are the same restrictions as listed in Table 2. The 1966 copper-specific demand restriction for the Vietnam War is placed on the contemporaneous copper-specific demand shock as the war led to an immediate demand for copper accompanied by a rundown in inventories.

	Global economic activity	Global metal production	Real metal price	Global metal inventories
Aggregate commodity demand shock	+	+	+	
Metal supply shock	+	+	-	
Contemporaneous metal-specific demand shock	-	+	+	-
Expectational metal-specific demand shock	-	+	+	+

Table 8: Sign restrictions on impact effects for the copper model including global inventories.

5.3 Alternative Economic Activity Index

We use annual data on global real GDP instead of the freight rate index as a proxy for global economic activity. We plot the two series in the online-appendix. The disadvantages of using GDP over freight rates are that it also includes the service sector and that reliable historical data is only available for a small subset of countries. Both factors may bias our results. On the plus side, it seems to better represent movements in economic activity during the Great Depression period than the freight rate index.

The results based on a model with global real GDP show lower estimated elasticities. In particular, the estimated long run elasticity is not higher than the front year in the case of copper. As a result, maximum prices and revenues for copper, nickel, and cobalt are substantially higher for the median compared to the baseline. The results are about the same for lithium. The online-appendix shows the impulse responses from the different models using global real GDP.

Results using the global industrial production index from Baumeister and Hamilton (2019) are roughly similar to those results for the global real GDP model. The drawback is that the industrial production series only starts in 1958 and thus shortens the sample significantly.

We chose the results based on the freight rate index for our baseline due to its more favorable characteristics, but also because results are more conservative in terms of price and revenues scenarios. However, we note that the risk is to the upside based on the results for these alternative measures of economic activity.

5.4 Alternative Trend Specification

We chose to include linear trends in the copper and nickel regressions due to their relatively long sample periods and negative trends in metal output growth. In contrast, we did not include linear trends into the specifications for cobalt and lithium with its shorter sample periods.

The estimated supply elasticities are quite robust to the inclusion or non-inclusions of these linear trends across all four metals. The estimated maximum prices and revenues are also quite robust in the case of copper and lithium but show some sensitivity for nickel and cobalt.

There are negative trends in output growth for copper, nickel and cobalt. While yearly production growth averaged 4.2% for copper since 1880, 7.1% for nickel since 1900 and

6.5% for cobalt since 1925, yearly average growth rates decreased to 2.5%, 3.5% and 4.9% since 1990, respectively. This explains why the estimated maximum price and revenues are lower when not including linear trends. The models yield unconditional forecasts with higher production growth rates in this case. In contrast, including a linear trend leads to lower production growth in the unconditional forecast, and therefore, to higher estimated maximum prices and revenues. Due to the shorter sample for cobalt and the smaller relative change in average growth rates over the years, we report the baseline cobalt model without a trend.

5.5 Alternative Sample Period

Using a long sample period allows us to cover multiple periods of booms and busts in the metals markets and to obtain a more solid foundation for the scenario exercise. However, we still check for the robustness of results based on a shorter period, starting in 1955, the same year that the available data for lithium starts. This allows us to deal with some of the volatility in the variables in the interwar period.

Sensitivity results show that based on the shorter sample period, elasticities are substantially lower, while prices and revenues are higher compared to the longer sample periods. One reason for this is that growth rates of output tend to be smaller in the later parts of the sample. In the case of nickel, an upward trend in prices, driven by the 2010s, may play an additional role. For cobalt the short sample seems to make results sensitive to the inclusion of a trend. As the sample starts in 1955, it includes only 65 observations, covering only a few periods of boom and bust in prices. Further, fewer degrees of freedom make these estimates less reliable. Longer sample results are preferable for our twenty-year scenario horizon. However, we note that the price risk is to the upside based on this set of sensitivity results.

6 Conclusion

We examine to what extent metals that are critical to the energy transition may become a bottleneck. We estimate that the elasticity of supply of key energy transition metals is low in the short term but higher in the long term, especially for lithium. We identify metal-specific demand shocks that resemble the energy transition using narrative sign restrictions. We the show how to use them in a structural scenario analysis. We find that prices of copper, lithium, cobalt, and nickel could rise up to several hundred percent compared to their average 2020 levels in a net-zero emissions scenario, representing a major bottleneck. The four metals prices would roughly increase to historical peaks in real terms, remaining there for an extended period, longer than previously seen. Over the next 20 years, these four metals markets alone could become as important to the global economy as the oil market in a net-zero emissions scenario.

We examine our question using state-of-the art structural scenario analysis following Antolín-Díaz et al. (2021). This provides a significant improvement over reduced form conditional models, as we can identify the underlying shock driving the energy transition. By this we avoid confounding demand and supply shocks, which would lead to misleading price scenarios.

Our model assumes that supply elasticities stay constant in the future, incorporating the average technological change in extraction technology over the long sample period. This is in line with the idea that technological change offsets the depletion of high quality mineral deposits (see Stuermer and Schwerhoff, 2015). However, these elasticities could be higher due to technological change or non-linear economies of scale, as firms figure out faster ways to expand supplies through mining but also through enhanced recycling. At the same time, the environmental and social costs of mining could also decrease these elasticities in the future. Our robustness checks suggest that elasticities are lower for most metals in the more recent part of the sample. Overall, we believe that a constant elasticity is a balanced assumption for the scenarios.

We take the metals consumption scenarios from the IEA (2021a,b) as exogenously given, which may bias upward our results. We believe that this is still a reasonable approach. First, demand elasticities for the examined metals are relatively low (see Dahl, 2020). Second, innovation cycles of energy technologies are quite long. For example, the development and commercialization of lithium-ion batteries took 30 years (see IEA, 2021a). Finally, the IEA Net-Zero Emissions scenario already incorporates that innovations in clean energy technologies are much more rapid than historical benchmarks.

We model the energy transition as a series of global metal-specific demand shocks over a twenty year horizon. While metal-specific demand shocks capture the forward looking nature of commodity prices, it is possible that the shift in the distribution of metal-specific demand shocks, while somewhat plausible based on the KL statistics, could induce agents to change their decision rules, partly anticipating the increase in metals demand (see also Lucas, 1976; Leeper and Zha, 2003). This type of anticipation, however, would most probably lead to an even stronger and front-loaded price effect than in our scenarios. Moreover, we believe that the unpredictability of technological change, the uncertain iterative process of policy making, and the heterogeneous speed in the energy transition across countries, makes the full anticipation of the metals demand induced by the energy transition unlikely. A micro-founded model that specifies the underlying drivers of the energy transition process would be appealing, but we leave it to future research.

Our results have important lessons for policy makers. If metals demand increased according to the net-zero scenario and prices rose to historic highs for an unprecedented long period, the energy transition would become more expensive, metal producers would benefit, and global inflationary pressures could increase for a sustained period of time. A credible, globally coordinated climate policy with slow but predictably rising commitments could lower uncertainty, increase investment and lower the price effect.

References

Antolín-Díaz, J., Petrella, I., and Rubio-Ramírez, J. F. (2021). Structural scenario analysis with SVARs. *Journal of Monetary Economics*, 117(C):798–815.

Antolín-Díaz, J. and Rubio-Ramírez, J. F. (2018). Narrative sign restrictions for SVARs. *American Economic Review*, 108(10):2802–2829.

Basher, S. A., Haug, A. A., and Sadorsky, P. (2018). The impact of oil-market shocks on stock returns in major oil-exporting countries. *Journal of International Money and Finance*, 86:264–280.

Baumeister, C. and Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica*, 83(5):1963–1999.

Baumeister, C. and Hamilton, J. D. (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. https://doi.org/10.1257/aer.20151569.

Baumeister, C. and Hamilton, J. D. (2020). Drawing conclusions from structural vector autoregressions identified on the basis of sign restrictions. *Journal of International Money and Finance*, 109(C).

Baumeister, C. and Hamilton, J. D. (2021). Estimating structural parameters using vector autoregressions. Mimeo.

Baumeister, C. and Peersman, G. (2013). The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. *Journal of Applied Econometrics*, 28(7):1087–1109.

Boer, L., Pescatori, A., and Stuermer, M. (2021). Energy Transition Metals. IMF Working Papers 2021/243, International Monetary Fund.

Canova, F. and Nicolo, G. D. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, 49(6):1131–1159.

Dahl, C. A. (2020). Dahl mineral elasticity of demand and supply database (MEDS). Working Papers 2020-02, Colorado School of Mines, Division of Economics and Business.

Doan, T., Litterman, R., and Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews*, 3(1):1–100.

Fally, T. and Sayre, J. (2018). Commodity trade matters. NBER Working Papers 24965, National Bureau of Economic Research, Inc.

Faust, J. (1998). The robustness of identified VAR conclusions about money. In *Carnegie-Rochester Conference Series on Public Policy*, volume 49, pages 207–244.

Giacomini, R. and Ragusa, G. (2014). Theory-coherent forecasting. *Journal of Econometrics*, 182(1):145–155.

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

Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.

Hassler, J. and Krusell, P. (2012). Economics and climate change: Integrated assessment in a multi-region world. *Journal of the European Economic Association*, 10(5):974–1000.

Herrera, A. M. and Rangaraju, S. K. (2020). The effect of oil supply shocks on US economic activity: What have we learned? *Journal of Applied Econometrics*, 35(2):141–159.

IEA (2021a). Net zero by 2050. A roadmap for the global energy sector. International Energy Agency. Paris, France.

IEA (2021b). The role of critical minerals in clean energy transitions. world energy outlook special report. International Energy Agency. Paris, France.

Inoue, A. and Kilian, L. (2020). The role of the prior in estimating VAR models with sign restrictions. Manuscript, Federal Reserve Bank of Dallas.

Inoue, A. and Kilian, L. (2021). Joint Bayesian inference about impulse responses in var models. *Journal of Econometrics*, forthcoming.

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

Jordà, O., Knoll, K., Kuvshinov, D., Schularick, M., and Taylor, A. M. (2019). The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics*, 134(3):1225–1298.

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(3):1053–1069.

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3):454–478.

Krebs, R. E. (2006). *The history and use of our Earth's chemical elements. A reference guide*. Greenwood Press.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125.

Leeper, E. M. and Zha, T. (2003). Modest policy interventions. *Journal of Monetary Economics*, 50(8):1673–1700.

Lucas, R. E. (1976). Econometric policy evaluation: A critique, in the carnegie-rochester conference series, the phillips curve.

Ludvigson, S. C., Ma, S., and Ng, S. (2017). Shock restricted structural vector-autoregressions. *NBER Working Paper*, (w23225).

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Cambridge Univ Press, Cambridge.

Mertens, K. and Ravn, M. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review*, 103(4):1212–47.

Nickel Institute (2022). *History of Nickel*. Nickel Institute.

Nordhaus, W. D. and Boyer, J. (2000). *Warming the world: economic models of global warming*. Cambridge, MA, MIT Press.

Rausser, G. and Stuermer, M. (2020). A dynamic analysis of collusive action: The case of the world copper market, 1882-2016. *MPRA Working Paper*, (104708).

Robertson, J. C., Tallman, E. W., and Whiteman, C. H. (2005). Forecasting using relative entropy. *Journal of Money, Credit and Banking*, 37(3):383–401.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Sims, C. A. (1993). A nine-variable probabilistic macroeconomic forecasting model, in business cycles, indicators and forecasting. *NBER Studies in Business Cycles, In J.H. Stock and M.W. Watson (eds.) University of Chicago*, pages 179–212.

Sousa, L. J. (1981). The US copper industry. problems, issues and outlook. *US Bureau of Mines: Washington DC*.

Stock, J. H. and Watson, M. (2012). Disentangling the channels of the 2007-09 recession. *Brookings Papers on Economic Activity*, 43(1 (Spring)):81–156.

Stuermer, M. and Schwerhoff, G. (2015). Non-renewable resources, extraction technology, and endogenous growth. Dallas Fed Working Papers 1506 (Updated version: August 2020), Federal Reserve Bank of Dallas.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

U.S. Geological Survey (2008). Mineral commodities summaries. Scientific investigations report, U.S. Geological Survey.

U.S. Geological Survey (2013). Metal prices in the United States through 2010. Scientific investigations report, U.S. Geological Survey.

Waggoner, D. and Zha, T. (1999). Conditional forecasts in dynamic multivariate models. *The Review of Economics and Statistics*, 81(4):639–651.

Watson, M. (2019). Comment on “The empirical (ir) relevance of the zero lower bound constraint”. *NBER Macroeconomics Annual*, 34.

World Bank (2020). Minerals for climate action: The mineral intensity of the clean energy transition. World Bank, Washington D.C.