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Abstract

The energy transition requires substantial amounts of metals, including copper, nickel, cobalt, and lithium. Are these metals a key bottleneck? We identify metal-specific demand shocks with an "anchor" variable, estimate supply elasticities, and pin down the price impact of the energy transition in a structural scenario analysis. Metal prices would reach historical peaks for an unprecedented, sustained period in a net-zero emissions scenario. The total production value of these four metals alone would rise more than four-fold to USD 13 trillion for the period 2021 to 2040, rivaling the estimated total value of crude oil production. These metals could potentially become as important to the global economy as crude oil.

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

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

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1 Introduction

This paper quantifies the impact of the energy transition on metals markets. 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 key building blocks for the energy transition (World Bank, 2020; IEA, 2021b). 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 model the impact of the energy transition on metals prices as a sequence of metals-specific demand shocks in separate structural VAR models for copper, nickel, cobalt and lithium. To avoid any *ex-ante* assumptions about the effects of the energy transition on the economy, we distinguish metal-specific from aggregate demand shocks. While a metal-specific demand shock, like the energy transition, leaves the demand for other commodities unaffected, an aggregate demand shock affects demand for all commodities due to, for example, higher than expected global growth. To disentangle these two types of shocks, we propose a novel identification strategy: We augment the standard three-variables commodity market model (e.g., Kilian, 2009, Baumeister and Peersman, 2013, Jacks and Stuermer, 2020, and others) with an "anchor" variable.

More precisely, each structural VAR model includes four endogenous variables, namely a measure of global economic activity, the global production of the respective metal, its real price, and the anchor variable. In our case, the anchor variable is an additional commodity price (e.g., for cotton), which we assume to be affected by the aggregate commodity demand shock but not by the metal-specific demand shock on impact. 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.

This identification relies on the assumption that the anchor variable is not a substitute for the analyzed metal.[1] Finally, the exclusion restrictions imposed on the anchor variable are complemented by traditional and narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018).

In modelling the energy transition, we take metal consumption scenarios from the IEA (2021a,b) as given, assuming that global consumption equals production over the long-term. We conduct a structural scenario analysis following Antolín-Díaz et al. (2021) to derive a sequence of exogenous metal-specific demand shocks that match the global metal consumption scenarios from 2021 to 2040. 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 structural scenario analysis allows us to deal with the limits of reduced-form condi-

[1] 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).

tional forecasts from VAR models, namely that a missing causal mechanism confounds the interpretation. The methodology 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. Modelling the energy transition as a series of metals-specific demand shocks is also in line with the iterative and highly uncertain nature of policy making and technological change.

Results show that the supply of all metals, except lithium, is quite inelastic over the short term, but is 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 3.5 percent, nickel by 7.1 percent, cobalt by 3.2 percent, and lithium by 16.9 percent. After 20 years, the same price shock raises output of copper by 7.5 percent, nickel by 13.0 percent, cobalt by 8.6 percent, and lithium by 25.5 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.

We find that the four metals are potential bottlenecks for the energy transition. Inflation adjusted metal 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 more than 60 percent. 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.

We estimate that the four metals could become as important to the macro-economy as crude oil. In the net-zero emissions scenario, the demand boom could lead to a more than fourfold increase in the value of metals production—totaling US$ 13 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 2020-2040. This implies that the markets of these four metals alone may become more important for inflation, trade, and output globally. Metals producing countries could benefit from significant windfalls due to the energy transition.

There is high uncertainty around the underlying metals consumption scenarios. Demand will depend, first, on technological change that is hard to predict, but which may allow for more possibilities to substitute certain metals. Note that innovation cycles are quite long. For example, the development and commercialization of lithium-ion batteries took 30 years. The IEA already assumes rapid technological innovation in its scenarios, faster than historical benchmarks. Second, the speed and direction of the energy transition depends on heterogeneous policy decisions, which are equally difficult to forecast. Finally, we take the consumption scenarios as exogenously given and do not model how they would endogenously react to higher prices.

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.

We also contribute to the literature by computing supply elasticities at long horizons that account for the lagged nature of the opening up of mines. This addresses a major drawback of the existing literature (see Dahl, 2020). We exploit a long historical dataset, which partly starts in 1879 and captures a long series of commodity boom and bust periods. We assume that supply elasticities remain constant over time, as technological change offsets the depletion of high quality mineral deposits in line with Stuermer and Schwerhoff (2015).

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 discusses the results and Section 5 documents sensitivity analyses. Finally, Section 6 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 wellestablished 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.[2]

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

[2]We do not consider graphite or vanadium as one of the four metals, 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. 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.

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.

Moreover, we use historical data on cotton prices since 1879. Cotton is a major non-metal 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. 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 in early 2021 and IEA (2021a) 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).

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 four endogenous variables $\mathbf{y}_t = (\mathbf{REA}_t, \mathbf{\Delta Q}_t, \mathbf{P}_t, \mathbf{P}_t^C)'$, 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 $\mathbf{\Delta Q}_t$, the log of the real price of the respective metal $\mathbf{P}_t$, and the log of the real price of cotton $\mathbf{P}_t^C$. We estimate

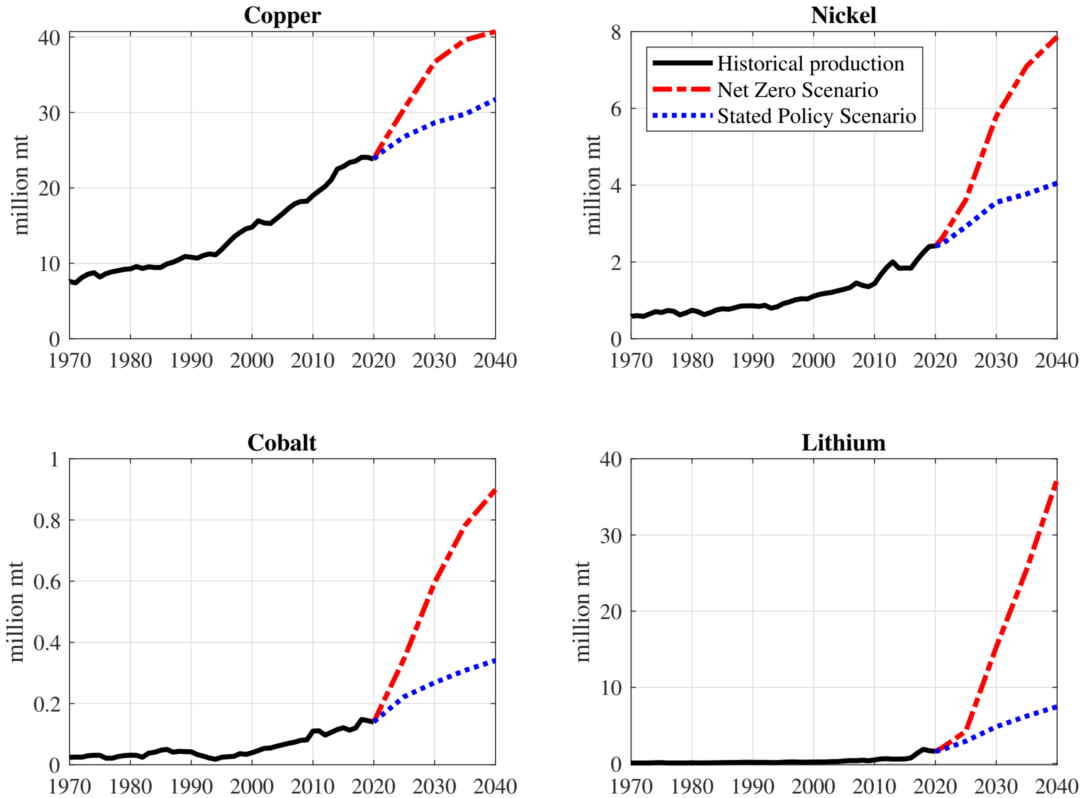

Figure 1: Metals consumption in the IEA's net-zero emissions scenario and the stated policy scenario.

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

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 as we can employ reasonably long samples for these two metals in contrast to cobalt and lithium. 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 four 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, for instance 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) and zero impact restrictions on the elements in $\mathbf{B}_0^{-1}$, i.e., we assume that the structural shocks have either a positive, negative or no instantaneous 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.

Table 1: Sign and zero restrictions on impact effects

	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

We interpret the first shock as an aggregate commodity demand shock that is related to the global business cycle and affects demand for all commodities simultaneously. A positive shock increases global economic activity, the global production of the respective metal, and the prices of both the respective metal and cotton on impact.[3]

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. As it is specific to metal supply, it should have no effect on the price of cotton on impact.

We interpret the third shock as a metal-specific demand shock. A positive shock increases the production and price of the respective metal, but unlike the aggregate commodity demand shock we assume that the metal-specific demand shock has zero effect on the cotton price on impact. We do not make an *a-priori* assumption on its effect on global economic activity, as the direction could go either way: The energy transition could

[3]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.

increase energy costs, thus dampening growth. However, it could also foster economic growth by lowering energy costs in the long-term depending on technological change and policies.

Using the price of cotton as an ”anchor” variable allows an agnostic approach on the metal-specific demand shock's effect on economic activity and provides a clear distinction between the aggregate commodity demand and the metal-specific demand shock. Compared to the aggregate demand shock, the metal-specific demand shocks is “anchored” on this variable, the cotton price, via the zero (or exclusion) restrictions displayed in Table 1.

This method can be applied more generally to disentangle aggregate (demand, supply, or financial) from sectoral (demand, supply, or financial) shocks. For example, it could be used to identify demand shocks that are only specific to one industry or an economic sector with the “anchor” variable chosen appropriately to react to the aggregate shock but not the sector-specific shock.

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 shocks on impact, while the relevance condition must hold for the aggregate demand shock.

We assume that the metal specific demand shock characterizes most closely the energy transition in our structural scenario analysis. It raises the demand for specific metals but not for other commodities. Note that this shock may also include anticipation shocks due to changes in expectations about metal-specific future demand and supply.[4] This is important, because the energy transition may also affect metal markets through this anticipation channel.

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. 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 restriction shocks displayed in Table 2 from historical market accounts from USGS (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.

[4]For our historical sample period there is no data on global metal inventories available. Thus, we cannot follow studies like Kilian and Murphy (2014), which include inventories as a fourth variable to identify flow demand, storage demand and other oil demand shocks.

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	1930/31	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

Note: 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.

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, 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 adjusted quite strongly to demand and increased by over 80% in the same year.

3.2 Computation of Supply Elasticities

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 $n = 4$ 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 $(n \text{ x } n)$ 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 η_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 $\eta_S = (\boldsymbol{\Theta}_0)_{MD,Prod} / (\boldsymbol{\Theta}_0)_{MD,Price}$.[5]

Demand shocks shift the metal demand curve along the metal supply curve, thereby

[5]This elasticity concept 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). Baumeister and Hamilton (2021) propose an alternative approach and obtain the impact elasticity directly from the structural $\mathbf{B}_0$ matrix. 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 alternative concept.

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 and are calculated as

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

3.3 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 $\mathbf{y}_{T+1,T+h}$ 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 $\varepsilon_{T+1,T+h}$, 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 forecasts $\mathbf{y}_{T+1,T+h}$. 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, the metal price and the cotton price are left unspecified. Concerning the paths of future shocks, we constrain the aggregate commodity demand shock, the metal supply shock and the residual 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.

In the case of no restrictions, the endogenous variables' unconditional forecast for periods $T+1$ to $T+h$ is given by

$$\mathbf{y}_{T+1,T+h} = \mathbf{b}_{T+1,T+h} + \mathbf{M}'\boldsymbol{\varepsilon}_{T+1,T+h} \ , \tag{4}$$

where $\mathbf{y}_{T+1,T+h} = (\mathbf{y}_{T+1}...\mathbf{y}_{T+h})$ and $\mathbf{b}_{T+1,T+h}$ represent the deterministic part of the forecast, which depends on past observables, the reduced-form VAR parameters $\mathbf{A}_i$ for $i = 1, .., p$ and the deterministic part $\mathbf{D}_t$. The matrix $\mathbf{M}$ represents the effects of the structural shocks on future values of the endogenous variables as a function of the structural parameters in $\mathbf{B_i}$ and the reduced-form parameters in $\mathbf{A}_i$ (see Antolín-Díaz et al., 2021 or Waggoner and Zha, 1999 for further details). The unconditional forecast is independent of the structural parameters. It is distributed according to $\mathbf{y}_{T+1,T+h} \sim \mathcal{N}(\mathbf{b}_{T+1,T+h}, \mathbf{M}'\mathbf{M})$, where $\mathbf{M}'\mathbf{M}$ depends only on the reduced-form parameters.

To answer the question of how the prices of energy transition metals fare in a net-zero emission scenario, we perform a restricted forecast of the endogenous variables $\widetilde{\mathbf{y}}_{T+1,T+h}$, for which we place restrictions both on parts of the future observable variables and future shocks. Hence, the future observables are restricted as

$$\overline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} = \overline{\mathbf{C}}\mathbf{b}_{T+1,T+h} + \overline{\mathbf{C}}\mathbf{M}'\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\overline{\mathbf{f}}_{T+1,T+h}, \overline{\boldsymbol{\Omega}}_f) \tag{5}$$

where $\overline{\mathbf{C}}$ is a (k_0 x nh) pre-specified selection matrix, including k_0 restrictions. The (k_0 x 1) vector $\overline{\mathbf{f}}_{T+1,T+h}$ denotes the mean of the constrained endogenous variables and the

$(k_0 \text{ x } k_0)$ matrix $\overline{\mathbf{\Omega}}_f$ denotes the covariance restrictions, i.e., the uncertainty around the restrictions on the observables. In our baseline case, we restrict the path for metal output according to the IEA scenarios and set $\overline{\mathbf{\Omega}}_f = \mathbf{0}_{k_0}$, thus assuming no uncertainty around the scenarios.

Secondly, we restrict k_s elements of the future shocks via the $(k_s \text{ x } nh)$ selection matrix Ξ expressed as $\Xi\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\mathbf{g}_{T+1,T+h}, \mathbf{\Omega}_g)$. The $(k_s \text{ x } 1)$ vector $\mathbf{g}_{T+1,T+h}$ denotes the mean and $\mathbf{\Omega}_g$ the covariance restrictions on the shocks in the conditional forecast.[6] Under invertibility of the VAR, the restricted shocks can be related to restrictions on the observables starting from equation (4) for the restricted future observables $\widetilde{\mathbf{y}}_{T+1,T+h}$ via

$$\mathbf{M}'^{-1}\widetilde{\mathbf{y}}_{T+1,T+h} = \mathbf{M}'^{-1}\mathbf{b}_{T+1,T+h} + \widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h}, \tag{6}$$

$$\Xi\mathbf{M}'^{-1}\widetilde{\mathbf{y}}_{T+1,T+h} = \Xi\mathbf{M}'^{-1}\mathbf{b}_{T+1,T+h} + \Xi\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \ , \tag{7}$$

yielding

$$\underline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} = \underline{\mathbf{C}}\mathbf{b}_{T+1,T+h} + \Xi\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\underline{\mathbf{f}}_{T+1,T+h}, \underline{\mathbf{\Omega}}_f) \ , \tag{8}$$

where $\underline{\mathbf{C}} = \Xi(\mathbf{M}')^{-1}$ and $\underline{\mathbf{\Omega}}_f = \mathbf{\Omega}_g$. We would like to explain a pre-specified path in metal output (one component of $\widetilde{\mathbf{y}}_{T+1,T+h}$) via the metal-specific demand shock. The other shocks should occur according to their unconditional distribution. In other words, we would like to restrict these non-driving shocks, while leaving the metal-specific demand

[6] When implementing the algorithm in Matlab, we also impose an upper absolute bound of 5 standard deviations on all future shocks.

shock unspecified. Thus, we impose $\boldsymbol{\Xi}\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\mathbf{0}_{k_s}, \mathbf{I}_{k_s})$ such that equation (8) becomes

$$\underline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} \sim \mathcal{N}(\underline{\mathbf{C}}\mathbf{b}_{T+1,T+h}, \mathbf{I}_{k_s}). \tag{9}$$

The restrictions in equations (5) and (9) can then be stacked according to

$$\widehat{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} \sim \mathcal{N}\left(\underbrace{\begin{bmatrix} \overline{\mathbf{f}}_{T+1,T+h} \\ \underline{\mathbf{C}}\mathbf{b}_{T+1,T+h} \end{bmatrix}}_{\widehat{\mathbf{f}}_{T+1,T+h}}, \underbrace{\begin{bmatrix} \overline{\boldsymbol{\Omega}}_f & \mathbf{0}_{k_0 \mathrm{x} k_s} \\ \mathbf{0}_{k_s \mathrm{x} k_0} & \mathbf{I}_{k_s} \end{bmatrix}}_{\widehat{\boldsymbol{\Omega}}_f}\right), \tag{10}$$

where $\widehat{\mathbf{C}}' = [\overline{\mathbf{C}}', \underline{\mathbf{C}}']$ such that the upper part relates to the conditions on observables and the lower part to the conditions on the shocks.

Antolín-Díaz et al. (2021) show how to solve for the restricted forecast of the observables $\widetilde{\mathbf{y}}_{T+1,T+h}$ such that the restrictions in equation (10) hold. In our baseline application we place $k_0 = 20$ restrictions on the observables, i.e., future metal output is constrained to the IEA's scenario output in each of the forecasted $h = 20$ periods. Moreover, we place $k_s = 3 \cdot 20 = 60$ restrictions on the non-driving shocks, i.e., all shocks, except the metal-specific demand shock, are restricted to their unconditional distributions for the forecast horizon. Thus, the total number of restrictions k is equal to nh, the length of $\widetilde{\mathbf{y}}_{T+1,T+h}$. For the case $k = nh$, there exists a unique solution of the restricted forecast (see Antolín-Díaz et al., 2021).

3.4 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

$$p(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+|\mathbf{y}^T, \mathbf{IR}(\mathbf{B_0}, \mathbf{B}_+), \mathbf{R}(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+)) \ , \tag{11}$$

where $\mathbf{y}^T$ is the historical sample, $\mathbf{B'}_+ = [\mathbf{B'}_1 \ldots \mathbf{B'}_p \, \mathbf{\Gamma}]$ 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 (10).

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.[7]

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 parameters from this randomly picked draw to then draw the scenario paths of the two price

[7]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, the metal supply shock and the residual shock).

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.[8] 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) 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 set-identified structural VAR models, as it is common in the literature.

[8]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.

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.

We note that our results are not based on a large sample and we use a large number of different sign restrictions. We still recognize that 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 are based on the impulse responses of metal production and prices to a metal-specific demand shock, as shown in Figure 2.[9] The impulse response functions show a significant increase in the prices of the four metals as a response to the metal-specific demand (MD) shock. The impact of that shock on production is 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 the supply elasticities for copper, nickel, cobalt, and lithium. Supply is quite inelastic over the short term, as it can only be expanded through 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 3.5 percent, nickel by 7.1 percent, cobalt by 3.2 percent, and lithium by 16.9 percent.[10]

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

[10] Following the alternative concept by Baumeister and Hamilton (2021), we obtain the following impact elasticities directly from the $\mathbf{B}_0$ matrix (with 68% pointwise): copper: 0.23 [0.18, 0.30]; nickel: 0.62 [0.49, 0.79]; cobalt: 0.28 [0.21, 0.37] and lithium: 1.51 [0.89, 2.37]. These are broadly in line with the elasticities in Figure 3. The supply elasticities based on the Bayes estimator are also in line with the baseline results.

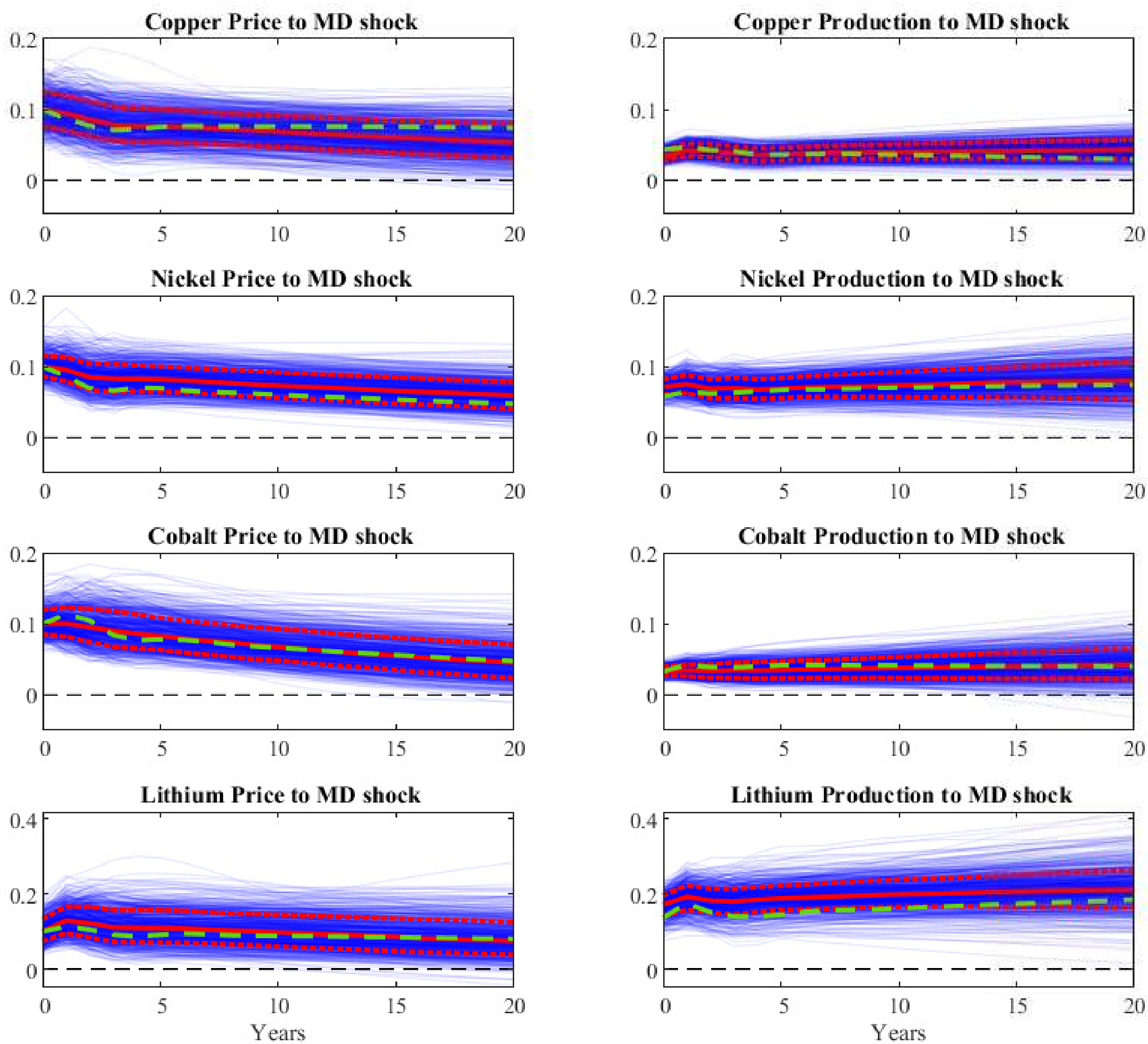

Figure 2: Impulse responses of metal production and price to a metal-specific demand (MD) shock. The shock is normalized to increase the metal price by 10% on impact. The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the 68% joint credible set under quadratic loss (blue lines). The responses are derived from four different VAR models, one for each metal. The y-axes for lithium differ from the others. The full set of impulse responses is in the online-appendix.

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 7.7 percent, nickel by 13.0 percent, cobalt by 8.6 percent and lithium by 25.5 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.

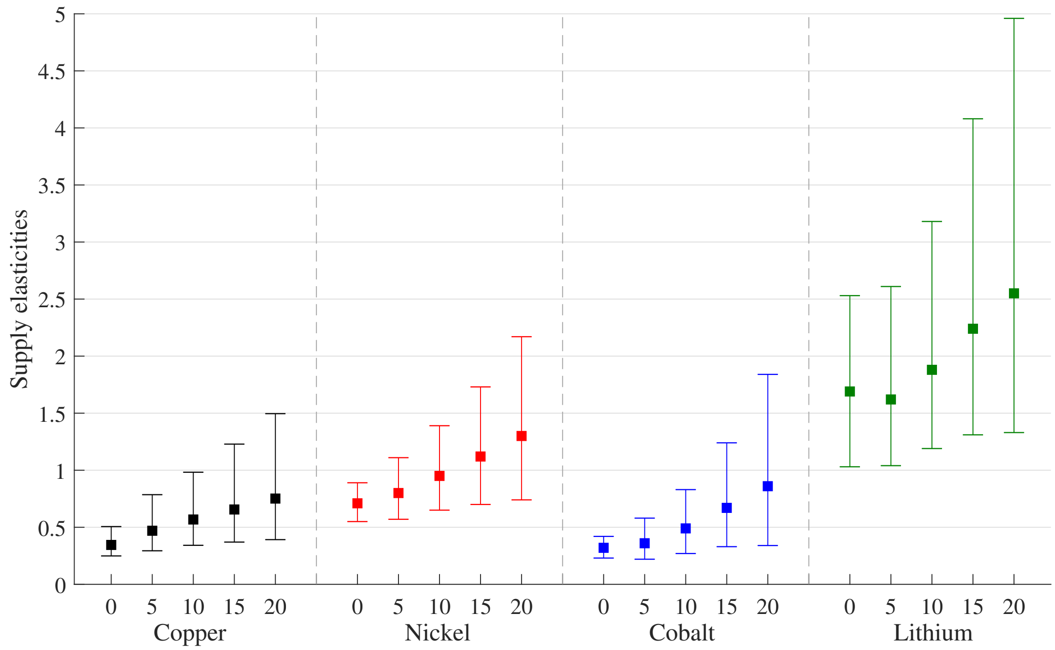

Figure 3: Supply elasticities at annual horizons based on the metal-specific demand (MD) shock. We calculate the elasticities via equation (3) for each of the 1,000 draws to construct the median and the 68 % pointwise credible sets.

4.2 Price Forecasts

Results in Figure 4 show that the four metals are potential bottlenecks for the energy transition.[11] 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 60%, as it would face more moderate consumption increases. Inflation adjusted prices of the four metals would reach peaks roughly similar to previous historical price peaks. However, prices would stay at these high levels for more than a decade, far

[11]We present the following results based on the pointwise 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 pointwise median impulse responses and mostly lie within the 68% pointwise credible sets.

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.

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 forecasts are subject to high uncertainty, reflected in the large, implied bounds. Large confidence bands (we represent 40% highest posterior density credible sets) 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 (we show the distributions of future shocks in the online-appendix), and the uncertainty around the structural impact effects of the different shocks. 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, which we do not model directly, 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.

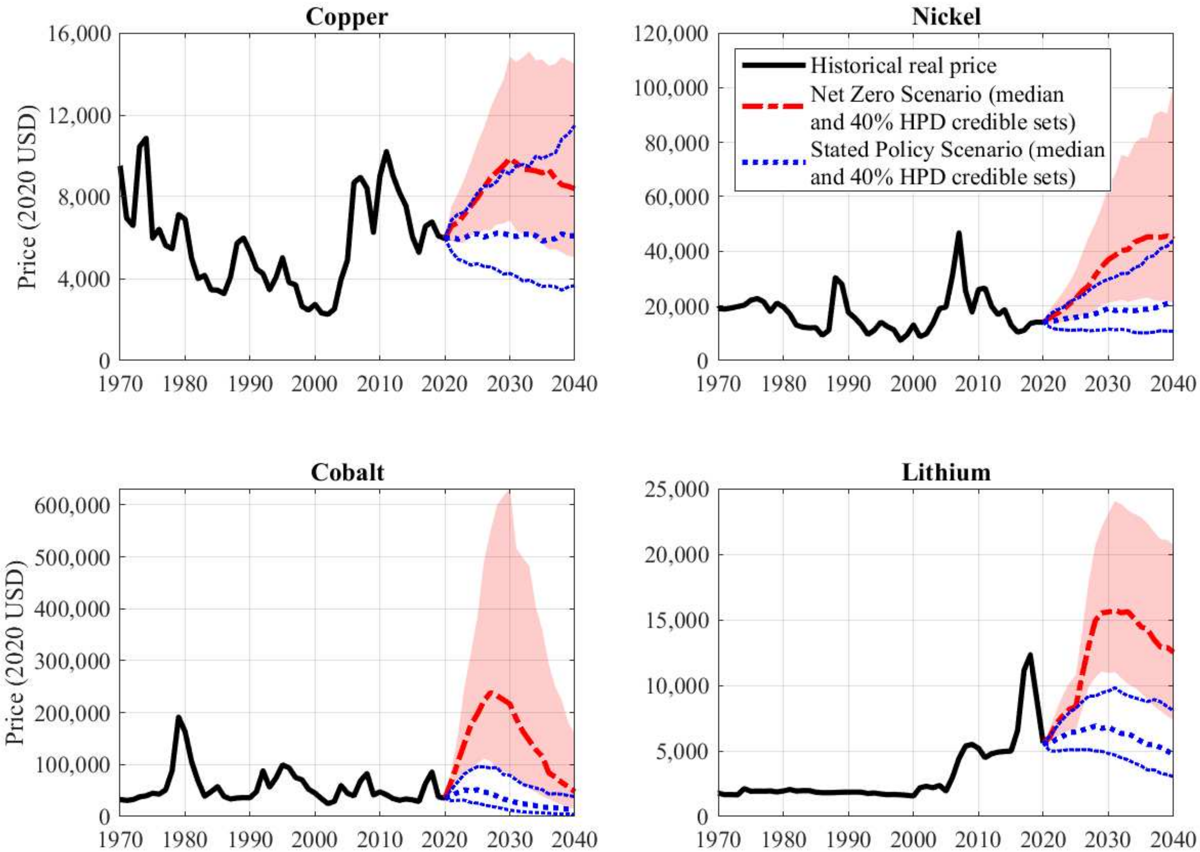

Figure 4: Price scenarios for the stated policy scenario and the net-zero emissions scenario based on the median and 40% pointwise credible sets.

4.3 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$ 13.0 trillion accumulated between 2021 and 2040 for the four energy transition metals alone, providing potentially significant windfalls to commodity producers (see Table 3). 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	4,974	13,007
Copper	2,382	3,456	6,135
Nickel	563	1,225	4,147
Cobalt	80	152	1,556
Lithium	18	18	1,170
Fossil Fuels	70,090		19,101
Crude Oil	41,819	-	12,906
Natural Gas	17,587	-	3,297
Coal	10,684	-	2,898

Table 3: 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 3). 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 5 shows that the revenue would strongly increase during the 2020s but then either flatten out, or if not reverse, in the 2030s, as supply adjusts for all metals except lithium. Annual copper revenues would more than double from around 150 USD billion in 2020 to more than 350 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 129 billion USD in 2030 in the net-zero emissions scenario. Cobalt production revenues could decline afterwards due to the decreasing scenario price from 2027 on-wards as supply re-adjusts. Annual lithium revenues would steadily increase by a factor of 50, reaching 117 billion USD in 2040. In the stated policy scenario, estimated revenues would increase moderately to historical highs.

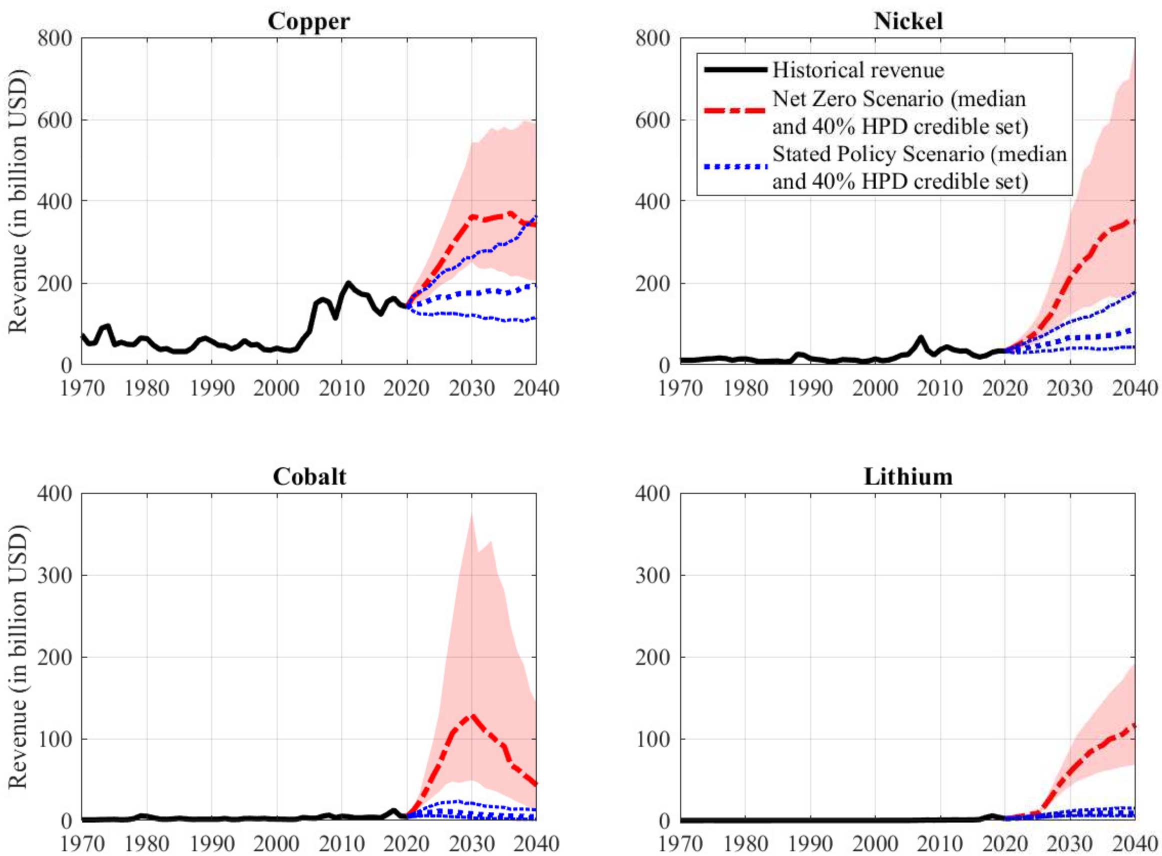

Figure 5: Annual revenues (in real US$) in the stated policy and the net-zero emissions scenario with 40% pointwise credible sets.

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 4 and 5 and compare them to our baseline. The online-appendix contains the analogous tables with sensitivity analyses for nickel and cobalt.

5.1 Alternative Anchor Variable

We replace the real cotton price with real prices for barley and coffee, respectively (both sourced from Jacks and Stuermer, 2020), as well as historical US equity total return series from Jordà et al. (2019). Results are robust, showing no large deviations, not for the estimated elasticities, the maximum prices, or for the estimated revenues compared to our baseline.

	Elasticities		**Scenario Analysis**	
	Impact	20 Years	Max Price USD per mt	Total Revenue Tril. USD
Baseline	0.35	0.75	9,861	6.1
Altern. 4th variable				
Barley	0.33	0.79	8,534	5.2
Coffee	0.33	0.75	8,760	5.5
Equity Index	0.27	0.66	9,545	5.7
Altern. Econ. Act. Var.				
Global Real GDP	0.23	0.23	21,794	12.0
Altern. Sample & Trend				
1880-2020, no trend	0.40	0.81	8,164	5.2
1955-2020, with trend	0.18	0.27	20,520	11.7
1955-2020, no trend	0.19	0.28	18,200	9.6
3 Variables Model	0.36	0.89	8,301	5.1

Table 4: Sensitivity: Copper model. Note: US Dollar (USD) refers to real 2020 prices, adjusted for inflation based on the US-CPI.

	Elasticities		Scenario Analysis	
	Impact	20 Years	Max Price USD per mt	Total Revenue Tril. USD
Baseline	1.69	2.55	15,724	1.2
Altern. 4th variable				
Barley	1.54	2.30	14,475	1.0
Coffee	1.57	2.53	14,930	1.0
Equity Index	1.46	2.32	15,629	1.1
Altern. Econ. Act. Var.				
Global Real GDP	1.75	2.82	13,119	0.9
Altern. Sample & Trend				
1955-2020, trend	1.69	2.59	19,227	1.5
3 Variables Model	1.57	2.41	15,030	1.1

Table 5: Sensitivity: Lithium model. Note: US Dollar (USD) refers to real 2020 prices, adjusted for inflation based on the US-CPI.

5.2 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. Unlike the freight rate index, it is also not a leading indicator of metals demand. 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 one 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.

We chose the results based on the freight rate index as 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 this alternative variable for economic activity.

5.3 Alternative Trend Specification

We chose to include linear trends in the copper and nickel regressions due to their relatively long sample periods. 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 for both nickel and cobalt. While yearly production growth averaged 7.1% for nickel since 1900 and 6.5% for cobalt since 1925, yearly average growth rates decreased to 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 change in average growth rates over the years, we report the baseline cobalt model without a trend.

5.4 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.

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.

5.5 The Three-Variables Model

Finally, we compare our baseline four-variables model to the standard three-variables commodity-market model without the anchor-variable (e.g., Kilian, 2009, Kilian and Murphy, 2012, Baumeister and Peersman, 2013, Jacks and Stuermer, 2020), using the same narrative sign restrictions (as in Table 2). Results are very robust for the estimated supply elasticities based on the metals-specific demand shock as well as maximum prices and total revenues.

Table 3 in the online-appendix displays the sign restrictions used to identify an aggregate metal demand shock, a metal supply shock, and a metal-specific demand shock. The disadvantage of the three-variables model is that we need to assume that there is a negative impact on global economic activity within the first year, which is not fully grounded in economic theory of the energy transition. On the one hand, the energy transition might be interpreted as a negative supply shock (cost-shock) that makes parts of the capital stock obsolete and sees workers reallocate to renewable energy sectors. On the other hand, technological change makes renewable energies significantly cheaper (Acemoglu et al., 2012) and in the long-term global economic activity may benefit. However, the identification restriction of a negative effect of the metals-specific demand shock on economic activity is necessary to differentiate between the aggregate and the metal-specific demand shock in the three variable VAR.

The impulse responses are shown in the online-appendix. The effect of the metal-specific demand shock on economic activity is slightly stronger and more persistent in the three variables model. Here, the shock significantly reduces economic activity, while the shock is less persistent and, in most cases, only borderline statistically significant (for nickel, cobalt, and lithium) in our baseline model.

6 Conclusion

We examine to what extent metals 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. Based on metal-specific demand shocks identified using an "anchor" variable we conduct 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 as the oil market to the global economy in a net-zero emissions scenario.

Our analysis offers a novel identification approach using an "anchor" variable to identify commodity-specific demand shocks that resemble the demand shock from the energy transition. This "anchor" variable allows us to clearly differentiate aggregate commodity demand from metal-specific demand shocks shocks. The "anchor" variable is assumed to be highly correlated with the global business cycle but uncorrelated with the metal-specific demand fluctuations. Such an "anchor" could also be used in other econometric applications and aid identification of specific shocks.

Our model assumes that supply elasticities stay constant in the future, incorporating the average technological change in extraction technology over the long sample period. 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. We believe that this is 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 (see IEA, 2021a). For example, the development and commercialization of lithium-ion batteries took 30 years. Finally, the IEA net-zero emissions scenario already incorporates that innovations in clean energy technologies are much more rapid than what has typically been achieved historically.

We provide a significant improvement over reduced form conditional models. We identify the underlying shock driving the energy transition. By this we avoid confounding demand and supply shocks, which would lead to misleading price scenarios. For example, higher metal consumption could also be driven by positive metal supply shocks, implying a lower price scenario.

We model the energy transition as a series of global metal-specific demand shocks over a twenty year horizon. A more micro-founded model that specifies the underlying energy transition process would be appealing, but we leave it to future research. It is, indeed, possible that a shift in the distribution of metal-specific demand shocks could induce agents to change their decision rules partly anticipating the increase in metals demand. This, 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 anticipation of the metals demand induced by the energy transition extremely unlikely.

A credible, globally coordinated climate policy with slow but predictably rising commitments could lower uncertainty, increase investment and lower the price effect.

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.

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