DIW BERLIN

1976

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2021

Energy Transition Metals

Lukas Boer, Andrea Pescatori and Martin Stuermer

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
https://www.diw.de

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
https://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
https://ideas.repec.org/s/diw/diwwpp.html
https://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html

Energy Transition Metals*

Lukas Boer[†], Andrea Pescatori[‡] and Martin Stuermer[§]

October 12, 2021

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, 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 value of metals production would rise more than four-fold for the period 2021 to 2040, rivaling the total value of crude oil production. Metals are a potentially important input into integrated assessments models of climate change.

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

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

---

*We are grateful to Christiane Baumeister, Christian Bogmans, Petya Koeva Brooks, Lutz Kilian, Christoffer Koch, Helmut Lütkepohl, Lukas Menkhoff, Philipp Mattner, Ervin Prifti, Gregor Schwerhoff and Nico Valckx for helpful suggestions, and to Juan Antolin-Diaz, Juan Rubio-Ramirez and Ivan Petrella for sharing their code with us. We thank participants at the IMF RES Commodities Unit Seminar for their valuable comments and feedback. We are grateful for excellent research assistance by Rachel Brasier, Wenchuan Dong and Piyusha Khot. The views in this paper are those of the authors and do not necessarily reflect the views of the International Monetary Fund or the German Institute for Economic Research. The online-appendix is available here.

†German Institute for Economic Research (DIW Berlin) and Humboldt-Universität zu Berlin, Email: lboer@diw.de.

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

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

1 Introduction

This paper quantifies the impact of the energy transition on metals prices. 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 shocks 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).

We also contribute to the literature on estimating supply elasticities by being the first to use a long historical data-set. Our sample partly starts in 1879 and captures a long series of commodity boom and bust periods. This allows us to compute supply elasticities at long horizons that account for the lagged nature of the opening up of mines, which addresses a major drawback of the existing literature (see Dahl, 2020). 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).

In modelling the energy transition, we take metal consumption scenarios from the IEA (2021b) as given, assuming that global consumption equals production over the long-

[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).

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 conditional 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.

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 a substantially higher long-run estimate for cobalt 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 energy transition could provide significant windfalls to metals producing firms' and countries. 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, providing significant windfalls to commodity producers. This could rival the roughly estimated value of oil production in a net-zero emissions scenario over that same period.

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. Second, the speed and direction of the energy transition depends on 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.

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 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.[2]

[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

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.

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

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.

the same time, its production and consumption should be uncorrelated to the ones of the selected metals, except for movements due to aggregate demand shock, 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 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

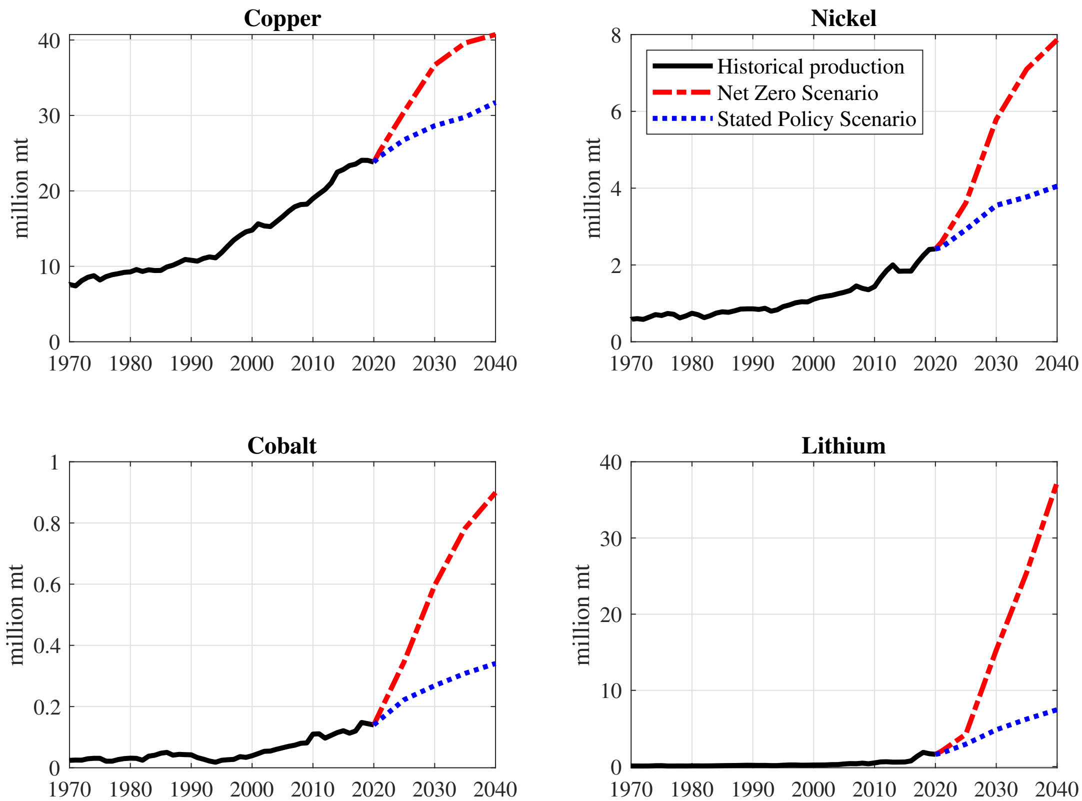

Figure 1: Metals consumption in the IEA's net-zero emissions scenario and the stated policy scenario.

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 slow 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 $\mathbf{y}_t = (\mathbf{REA}_t, \mathbf{\Delta Q}_t, \mathbf{P}_t, \mathbf{P}^C_t)'$, 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 $\mathbf{\Delta Q}_t$, 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

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

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 $\boldsymbol{\Sigma}_u$ is related to the structural impact multiplier matrix as $\boldsymbol{\Sigma}_u = \mathbb{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{B}_0^{-1}\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t')\mathbf{B}_0^{-1\prime} = \mathbf{B}_0^{-1}\mathbf{B}_0^{-1\prime}$.

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 ways: The energy transition could 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.

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

[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.

[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.

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.

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 $\mathbf{\Theta}_h = \boldsymbol{\phi}_h \mathbf{B}_0^{-1}$ for $h = 1, 2, \ldots$ where $\mathbf{\Theta}_h$ 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 $\eta_S = (\mathbf{\Theta}_0)_{MD,Prod}/(\mathbf{\Theta}_0)_{MD,Price}$.[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 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 a series of the 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 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 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 ($k_s$ 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. 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 shock unspecified. Thus, we impose $\Xi\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\mathbf{0}_{k_s}, \mathbf{I}_{k_s})$ 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

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

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 $k = nh$, Antolín-Díaz et al. (2021) show that there exists a unique solution of the restricted forecast.

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). 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.[6] 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 point-wise median estimates. Following Antolín-Díaz and Rubio-Ramírez, 2018 and Antolín-Díaz et al., 2021, we report point-wise median and percentiles of impulse responses for set-identified structural VAR models, as it is

[6]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.

common in the literature. [7] The 1,000 different draws allow for the construction of credible sets by estimating an elasticity for each draw and then calculating percentiles.

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. [8]

[7] Please find the impulse responses for the full set of admissible models in the online-appendix. For interpreting our results, it is important to take into account the recent discussion about inference in Bayesian models. 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. Hence, in interpreting our results, it is important to recognize that our inference summarizes both prior uncertainty and sampling uncertainty. We conjecture that the extent of the uncertainty attributed to the prior on Q is rather small, as our results are not based on a large sample and we use a large number of different sign restrictions. We also recognize that the posterior median response function does not represent one of the structural models (see Inoue and Kilian, 2021), but report it for illustrative purposes in line with the literature.

[8] 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).

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 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.

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 muted for all metals, except lithium.

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

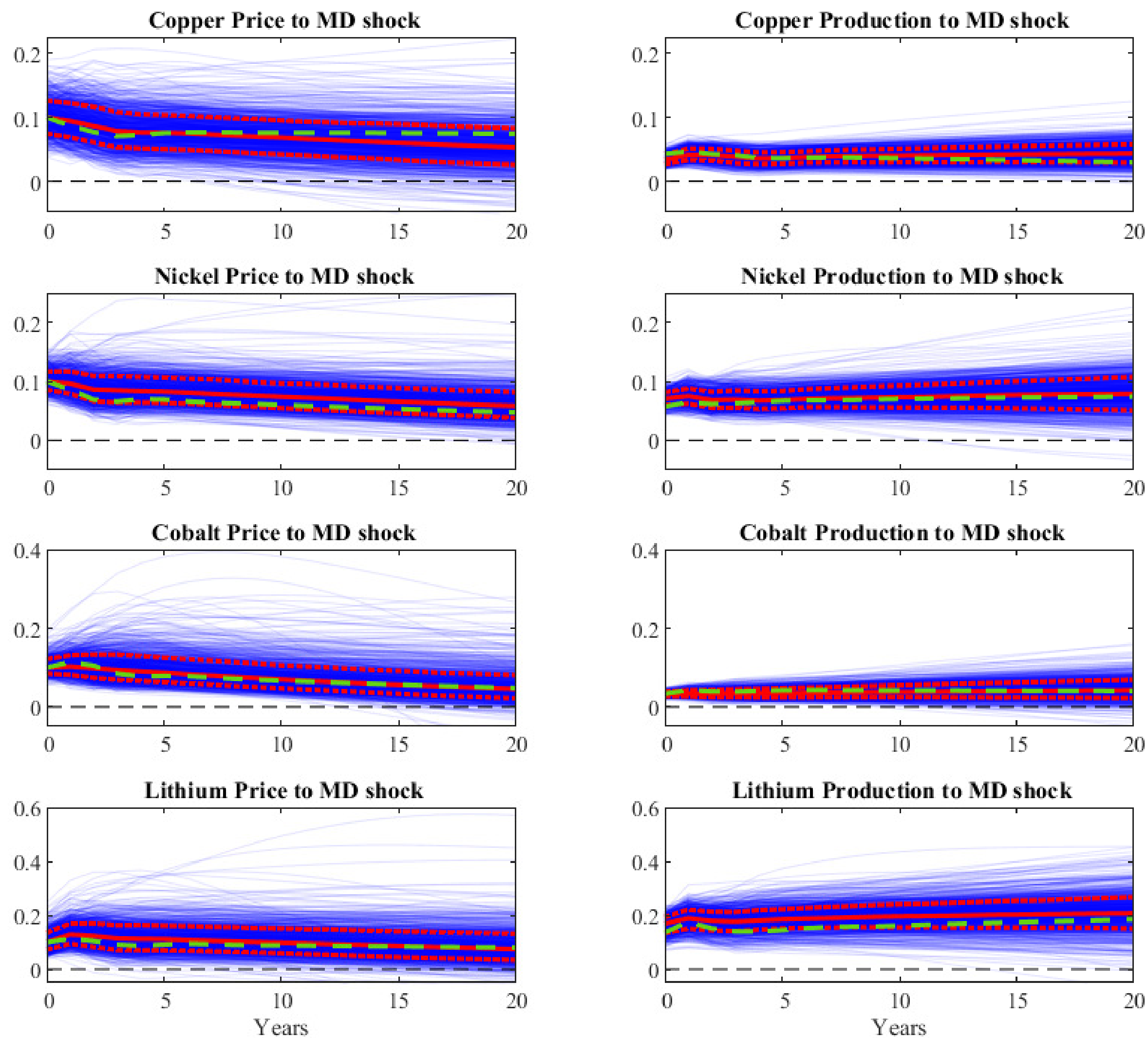

Figure 2: Impulse responses of metal production and price to a metal-specific demand (MD) shock, that increases the median and modal metal price by 10 percent on impact, for copper, nickel, cobalt, and lithium based on 1,000 draws showing the pointwise median (red solid line) and the modal model (green dashed line) with 68% point-wise credible sets (red dotted lines) among the full set of impulse response functions for each model. The impulse response functions are derived from four different VAR models, one for each metal.

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]

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.

[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% confidence bands): 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 2.

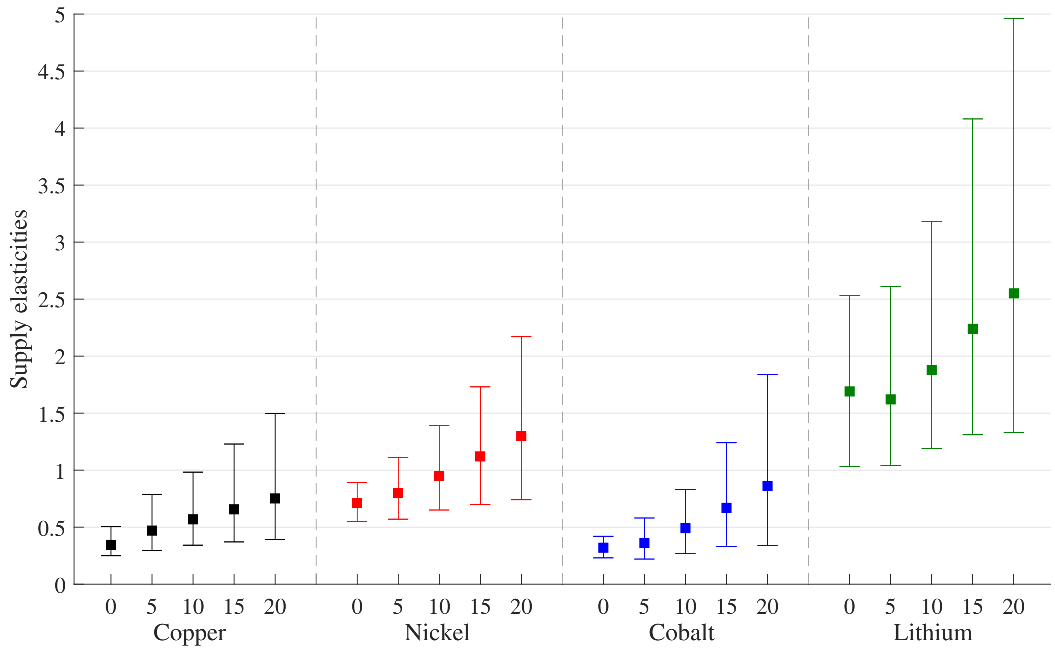

Figure 3: Supply elasticities at annual horizons based on the metal-specific demand (MD) shock with 68% point-wise credible sets. Elasticities are calculated via equation (3).

4.2 Price Forecasts

Results in Figure 4 show that the four metals are potential bottlenecks for the energy transition. 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 percent, 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 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.

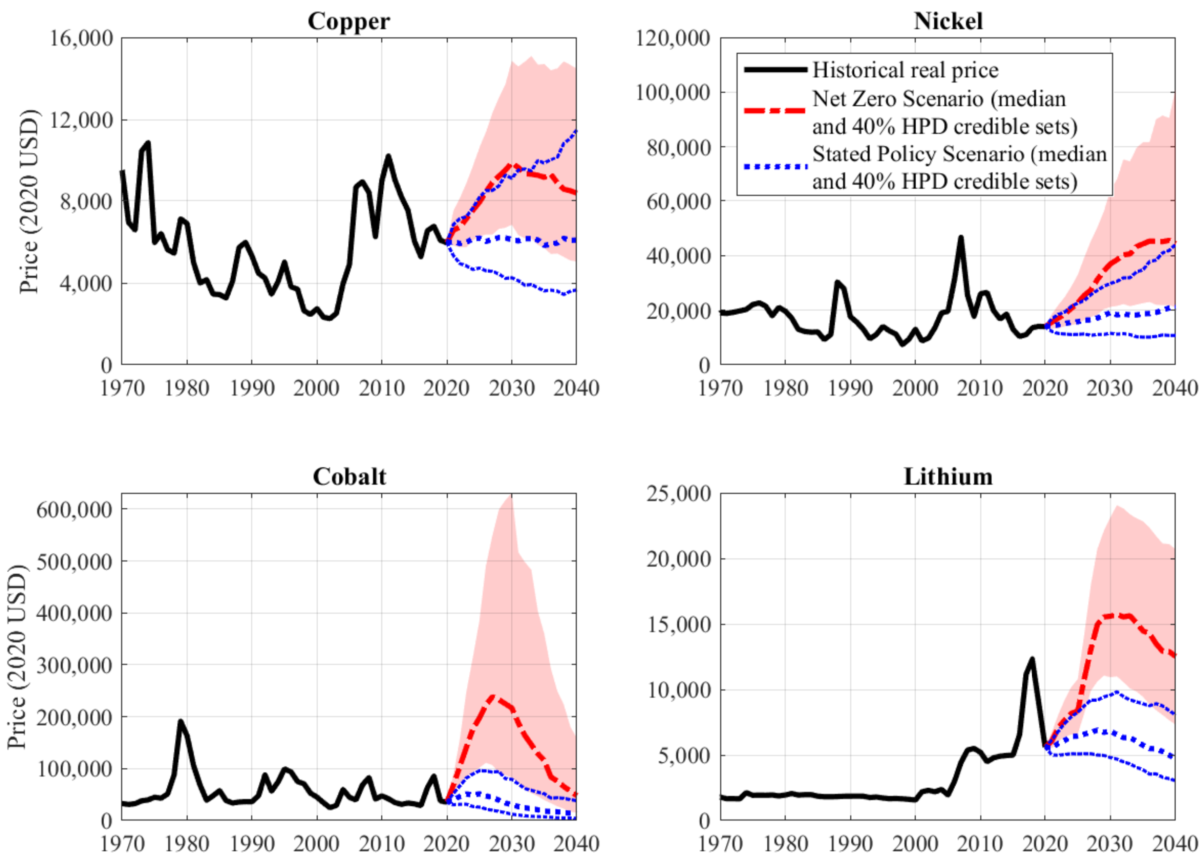

Figure 4: Price scenarios for the stated policy scenario and the net-zero emissions scenario with 40% point-wise credible sets.

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. Note: Estimates are in billion 2020 USD.

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.[11] 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

[11] To provide a yardstick for the order of magnitude of the results for the four metals, we include an illustrative back-on-the envelope calculation for the value of fossil fuel production in the net-zero emissions scenario of the IEA (2021a). In this IEA scenario, consumption of oil drops by 54 percent, natural gas by 45 percent, and coal by 80 percent between 2020 and 2040. Based on this, we assume that oil prices average 30USD per barrel (in 2020 terms) between 2021 and 2040, which is about half the average inflation adjusted price from 1970 to 2020. Similarly, coal prices are presumed to average 40USD per metric ton from 2021 to 2040, which is about half of the average real term price from 1979 to 2020. As global LNG trade will likely continue to increase in importance and there is a structural break due to the shale gas revolution, we make the assumption that natural gas prices are 1.50USD per million British units on average between 2021 and 2040, half of the average price during the year 2020.

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.

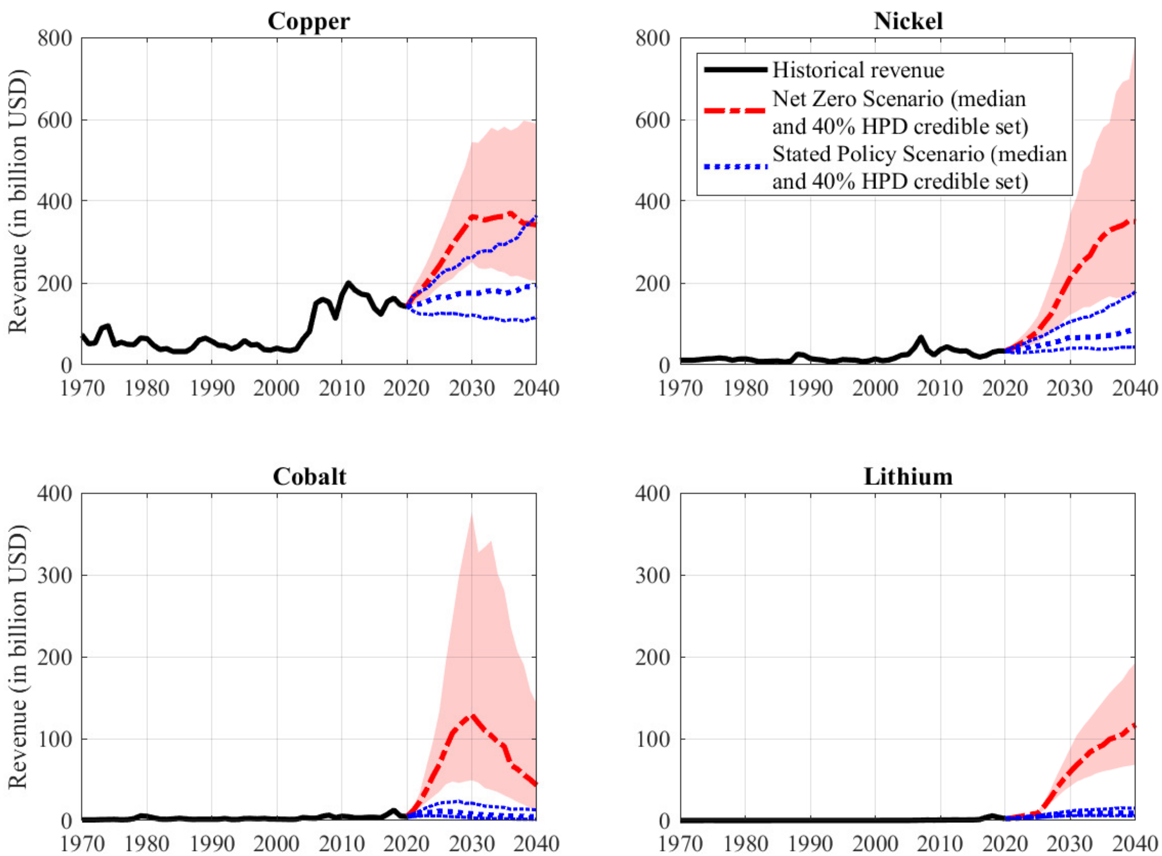

Figure 5: Annual revenues (in real US$) in the stated policy and the net-zero emissions scenario with 40% point-wise credible sets.

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	0.22	0.16	21,570	11.9
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 lower 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 embedded in a structural scenario analysis, we find that prices of lithium, cobalt, and nickel could rise 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. Robustness checks suggest that there is upside risk to net-zero emissions scenario price paths. Metals producers of these four metals alone could generate revenues similar to those of the oil sector over the next 20 years in this scenario.

In addition to contributing to the literature on metals supply elasticities, our analysis offers a novel identification approach of commodity-specific demand shocks using an "anchor" variable that increases resemblance of this shock to an energy transition induced metals' demand increase.

Our model assumes that supply elasticities stay constant in the future. These elasticities could be higher due to technological change or 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.

There are a number of potential policy implications of our results. First, if the energy transition is surrounded by high uncertainty, this could delay investment in metals production and supply may not adjust in time. Hence, a credible, globally coordinated climate policy that directs investment to sufficiently expand metals supply could play a decisive role in avoiding unnecessary cost increases in low-carbon technologies. Countries may want to announce slow but rising commitments.

Second, a substantial expansion of mining could have adverse effects on the environment, unless firms adopt mitigating technologies. Thus, stringent, high environmental, social and governance standards are important. Incentivizing recycling, reuse, and refurbishment as well as metal efficient product designs is also a vital part of the energy transition.

Third, the energy transition will create winners and losers, potentially requiring fiscal or structural policy interventions. Commodities exporting and importing countries may be affected differently by the energy transition, depending on the scenarios as well as the behavior of specific metal markets and prices. Specific guidance may be needed for countries benefiting from large windfalls (e.g., establishment or strengthening of reserve funds, frameworks on how to share the gains).

Fourth, some metals have already been subject to export restrictions as well as to subsidies for domestic mining. An accelerated energy transition may lead to additional trade restrictions, which could cause additional cost increases and hamper investments in clean energy technologies. Reduced trade barriers and more stringent multilateral rules on export restrictions would allow markets to operate efficiently.

Finally, the creation of an international institution focused on metals—analogous to the International Energy Agency for energy and the Food and Agricultural Organization for agricultural commodities—could play a pivotal role for data dissemination and analysis, setting industry standards, and be a forum for international cooperation.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1):131–66.

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. (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.

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.

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

Kilian, L. and 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.

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.

Nordhaus, W. D. and Boyer, J. (2000). *Warming the World: Economic Models of Global Warming*. Cambridge, MA, MIT Press.

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.

Stuermer, M. and Schwerhoff, G. (2015). Non-renewable resources, extraction technology, and endogenous growth. Dallas Fed Working Papers 1506 (Update 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.

USGS (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.