# CHAPTER 1 ONLINE ANNEX

## Annex 1.SF.1.

### A1. Metals and Minerals

The special feature mentions the following metals:

Aluminum (Al), chromium (Cr), copper (Cu), cobalt (Co), graphite, lead (Pb), lithium (Li), manganese (Mn), molybdenum (Mo), nickel (Ni), platinum group metals (PGM), rare earth elements (REE) silicon (Si), silver (Ag), vanadium (V), zinc (Zn) and the mineral: graphite (C).

Rare earth elements (REE) and platinum group metals 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.

We do not consider graphite or vanadium as one of the four representative 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 their usage in the energy transition.

### A2. Methodology for Effects of Metal Price Shocks on Exporters and Importers

To evaluate the effects of metal price shocks on countries' GDP and government revenues, we estimate a panel VAR model with each country's real GDP growth, its government balance-to-GDP ratio, current account-to-GDP ratio, the Commodity Research Bureau's real metal price index (year-on-year growth rate), and with world GDP growth and real oil prices (year-on-year growth rate) as additional control variables. To reduce multicollinearity, oil prices and metal prices were orthogonalized vis-à-vis world GDP growth prior to the VAR estimation (although the results were very similar without such filtering), as metals and oil prices tend to correlate with world GDP (as a proxy for the global business cycle).

We use generalized impulse responses following Pesaran and Shin (1998), to estimate the effects of a 1 standard deviation shock to real metal prices (which amounts to about 15 percentage points) on GDP growth and the government balance-to-GDP ratio. Doing so gives an orthogonal set of innovations that do not depend on the VAR ordering. Figure 1.SF.7 shows the differences of the impulse responses for the 15 largest metals exporters and the 15 largest metals importers in 2020.

Data are from the IMF WEO and cover the period 1960-2020 (annual data). The 15 largest metals exporters (in trade value, from UN Comtrade statistics, consistent with the extended list listed in A1) included in the sample are Australia, Brazil, Chile, Peru, South Africa, Canada, Mexico, United States, Ukraine, Guinea, Sweden, Kazakhstan, Mongolia, Indonesia, and Russian Federation". The 15 largest metals importers in the sample are China, Japan, Korea, Germany, Taiwan POC, Spain, United Kingdom, France, Finland, Netherlands, Austria, Vietnam, Bulgaria, Italy, Malaysia. In another iteration, the group of importers also included Poland, Egypt, Czech Republic, Bahrain, and Slovak Republic.

## A3. Methodology for Long-term Demand, Supply and Price Projections

We set up separate VAR models for each metal. Each reduced form model includes three endogenous variables $y_t = (\Delta Y_t, \Delta Q_t, \log(P_t))'$, namely the percentage change of global real GDP $(\Delta Y_t)$, the percentage change of global production of the respective metal $(\Delta Q_t)$, and the log of the real price of the respective metal $(P_t)$. We estimate

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \Pi^* D_t + u_t \tag{1}$$

where $A_i$ are the reduced-form VAR coefficients and $u_t$ the reduced-form forecast errors. These errors have no economic interpretation. The matrix of deterministic terms $D_t$ consists of a constant and dummies for the years around the world wars. For copper and nickel, we add a linear trend to the regression. The analysis is performed at annual frequencies. The reduced-form VAR can be expressed in a structural form given by

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \Pi^* D_t + \epsilon_t. \tag{2}$$

In equation *(2)*, $\epsilon_t$ are independent structural shocks with an economic interpretation, e.g., aggregate metal demand and metal supply shocks. The structural shocks are related to the reduced-form errors via the linear transformation $u_t = B_0^{-1}\epsilon_t$. Thus, $B_0^{-1}$ contains the impact effects of the structural shocks on the three endogenous variables in $y_t$. By assuming a unit variance for the uncorrelated structural shocks, i.e., $E(\epsilon_t\epsilon_t')$ is an identity matrix, the reduced-form covariance matrix $\Sigma_u$ is related to the structural impact multiplier matrix as $\Sigma_u = E(u_t u_t') = B_0^{-1}E(\epsilon_t\epsilon_t')B_0^{-1'} = B_0^{-1}B_0^{-1'}$.

Without further information it is not possible to identify $B_0^{-1}$ and thereby the structural form in *(2)*. The literature has come up with different restrictions that can be assumed to solve this identification problem. We apply sign restrictions (e.g., Faust, 1998, Canova and Nicolo, 2002, and Uhlig 2005) on the elements in $B_0^{-1}$, i.e., we assume that the structural shocks affect the endogenous variables either in a positive or negative way based on economic intuition as specified in Table 1: The first shock increases global real GDP, the global production of the respective metal, and the respective metal's real price on impact. We interpret it as an aggregate demand shock that is related to the global business cycle. The shock also includes periods of industrialization, which drive up the demand for copper and other metals. We assume that this is the type of shock that characterizes most closely the energy transition in our structural scenario analysis.

The second shock is assumed to drive up global real GDP and global production of the respective metal, but to decrease the real price. We interpret this shock as a metal supply shock, capturing for example, strikes or other production outages. We assume that the third shock increases metal production and price, similar to the aggregate metal demand shock, but decreases global real GDP. We interpret it as a metal inventory-demand shock, capturing unexpected changes in inventories due to shifts in expectations about future metal demand or supply.

***Annex 1.SF.Table 1. Sign Restrictions on Impact Effects***

| | Global Real GDP | Global Metal Production | Real Metal Price |
|---|---|---|---|
| Aggregate metal demand shock | + | + | + |
| Metal supply shock | + | + | – |
| Metal inventory demand shock | – | + | + |

Our object of interest is a conditional forecast $y_{T+1,T+h}$ 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 $y_{T+1,T+h}$ and a subset of the future shocks $\epsilon_{T+1,T+h}$, thereby linking the path of future variables directly to certain shocks. Antolin-Diaz, Petrella, and Rubio-Ramirez (2021) provide a formal framework of this structural scenario analysis. We briefly lay out the underlying intuition tailored to the IEA's scenarios.

We take the IEA's scenarios for each metal as given, thus prespecifying the future metal production in the conditional forecasts $y_{T+1,T+h}$. We set global consumption equal to global metal production in the IEA's forecast, assuming that there are no short-term changes in inventories. The levels of future GDP growth and the metal's price are left unspecified. Concerning the path of future shocks, we constrain the metal supply shock and the inventory demand shock to their unconditional distributions. The algorithm then finds a series of aggregate metals demand shocks that incentivizes the metal production path needed for the energy transition. From these shocks we derive the implied price and revenue paths.

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

Estimation and inference are based on standard Bayesian techniques laid out in Waggoner and Zha (1999), Rubio-Ramirez, Wagonner, and Zha (2010), and Antolin-Diaz, Petrella, and Rubio-Ramirez (2021). We use a standard Minnesota-type prior in combination with a sum-of-coefficients prior (Doan, Litterman, and Sims 1984) and a dummy-initial-observation prior (Sims 1993) to estimate equation *(1)* and the conditional forecasts. Identification via sign restrictions does not yield point estimates but instead sets of possible parameter intervals for the different elements in $B_0^{-1}$. We obtain a set of 1000 admissible draws, where each draw consists of a conditional forecast, future shocks, and an associated $B_0^{-1}$ matrices that satisfies the sign restrictions. These draws are also used for inference, i.e., they yield an indication of the uncertainty around the point-wise median estimates. It is common to report point-wise median and percentiles of impulse responses for set-identified structural VAR models (Antolín-Díaz and Rubio-Ramírez, 2018), although the median does not represent one of the structural models.

Finally, we obtain the supply elasticities from the $B_0^{-1}$ matrix of structural impact effects and the reduced-form parameters $A_i$ from equation *(1)*. The responses of the variables in $y_t$ to the structural shocks $\epsilon_t$ can be traced over time via $\Theta_h = \Phi_h B_0^{-1}$ for *h = 1,2,…* where $\Theta_h$ is an (*n x n*) matrix of structural impulse responses for the horizon *h* and $\Phi_h = \sum_{j=1}^{h} \Phi_{h-j} A_j$ and $\Phi_0$ is an identity matrix (Lütkepohl 2005, chapter 2). The impact supply elasticity $\eta_S$ is calculated as the ratio of the metal production response to an aggregate metal demand shock (*AD*) relative to the price response to the same shock written as $\eta_S = (B_0^{-1})_{AD,Prod} / (B_0^{-1})_{AD,Price}$. Demand shocks shift the metal demand curve along the metal supply curve and thereby trace 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 $\eta_{S,h} = \sum_{i=1}^{h} (\Theta_i)_{AD,Prod} / \sum_{i=1}^{h} (\Theta_i)_{AD,Price}$. The 1000 different draws again allow for the construction of credible sets by estimating an elasticity for each draw and then calculating percentiles.

## A4. Data Descriptions

We use historical annual data for global real GDP, global production and real prices of the respective four metals. Employing long sample periods, partly going back to 1840 for copper, 1900 for nickel, 1925 for cobalt and 1955 for lithium, allows us to estimate the long-run relationships between the variables. This is particularly 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 market data. These commodities were not traded on public exchanges for a long time. Its 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 market. We attribute some of the relatively broad sets of admissible draws in our results to some remaining measurement errors.

### *A4.1 Global Real GDP Data*

We construct a series for global real GDP data by using data for 1840 to 2007 from Schwerhoff and Stuermer (2020), which build on Maddison (2010). We expand the data to 2020 based on growth rates of global real GDP from the International Monetary Fund's World Economic Outlook database.

### *A4.2 Copper Market Data*

Copper has a long track record of trade and production. We use annual price data from the London Metal Exchange, which has been and still is the major exchange for the global price settlement of the metal. The data for the period from 1840 to 2014 is sourced from Stuermer (2018) and the one from 2015 to 2020 from the US Geological Survey (2021). We use the U.S. all urban consumers price index to adjust prices for inflation.

Production data refer to refined copper production, including production from recycled materials. We source the data from Stuermer (2018) for the period 1840 to 2010. For 2011 to 2019, we obtain data from the International Copper Study Group (2021) and for 2020 from the World Bureau of Metals (2021). Note that the data points for 2019 and 2020 are preliminary.

### A4.3 Cobalt Market Data

Cobalt has a far shorter history than copper and was not traded on metal exchanges for a long time. For the period from 1925 to 2015, we use price data from the US Geological Survey (2017) computed based on the quantities and value of US import data. Starting in 2016, we use U.S. spot price data for cobalt cathodes from the US Geological Survey (2021). As cobalt has a relatively high value compared to weight and can be traded relatively freely, we assume that changes in US prices are a good approximation for global price movements.

Cobalt production data refer to the cobalt content of mine or refined production depending on the producing country and year.  Recycling does not play an important role in cobalt supply. We source the data for the period from 1925 to 2017 from Schwerhoff and Stuermer (2020) and for 2018 to 2020 from the US Geological Survey (2021).

### A4.4 Lithium Market Data

Lithium is the least mature market across the four metals. Price data from 1955 to 2000 refer to lithium carbonate and from 2001 to 2015 to prices derived from U.S. import data by the US Geological Survey (2017). For 2016 to 2020, we use battery grade lithium carbonate for large contracts as provided in US Geological Survey (2019, 2021). We have made sure that the price series are consistent across time by splicing series on each other and using adjustment factors. As lithium has a relatively high value compared to weight and can be traded relatively freely, we assume that US price changes are a good approximation for global price movements.

We source world mine production data for the years 1955 to 2017 from Schwerhoff and Stuermer (2020). The data are in metric tons of gross product of lithium minerals and brine. For the years 1967 to 2015 it is reported as gross product of ore and ore concentrates from mines and lithium carbonate from brine deposits. For the years 2017 to 2020, the U.S. Geological Survey (2019, 2021) reports lithium content of mine production. This data series is spliced on the earlier lithium ore series to come up with a consistent series over time. The source for the data from 2018 to 2020 are US Geological Survey (2020, 2021).

### A4.5 Nickel Market Data

Nickel price data refer to US prices until 1978 and from 1979 onwards to U.S. dollar prices at the London Metal Exchange. The data from 1900 to 2017 is sourced from Stuermer and Schwerhoff (2020) and from 2018 to 2020 from the US Geological Survey (2021).

Global nickel production data is mine production data from 1900 to 1962 from the US Geological Survey (2017). From 1963 to 2020, the data are from the World Bureau of Metal Statistics (2021) and are described as refined production data, including recycled materials.

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