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Understanding the future of critical raw materials for the energy transition: SVAR models for the U.S. market

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Abstract

We examine the impact of energy transition policies on the U.S. markets of three critical minerals used for batteries, namely cobalt, lithium and nickel. To achieve this, we estimate three Structural Vector Autoregressive models, disentangling supply and demand shocks at the aggregate and mineral-specific level. We then perform a structural forecast analysis to study mineral price patterns under various demand and supply scenarios up to 2030. Specifically, we investigate the implications of the U.S. Inflation Reduction Act (IRA) and the associated policies aimed at boosting the domestic production of these critical minerals, combining them with various demand projections. Our findings suggest that, whereas cobalt and lithium prices could decrease conditional on the successful implementation of energy transition policies in the U.S., nickel price most likely will remain high.

Keywords: Energy transition, critical minerals, Structural Vector Autoregressive models, conditional forecasting, Inflation Reduction Act.
JEL Classification: C53, Q02, Q31, Q4, Q54

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2 Introduction

To address the issue of global warming – and all the related risks in terms of economic output reduction (Dell et al., 2014), environment degradation (Piguet, 2022) and worldwide increase in migration flows (Marotzke et al., 2020) – there is widespread consensus on the necessity to drastically reduce global greenhouse gas emissions. One of the challenges in fighting climate change is to limit the increase in global temperatures to no more than 1.5°C, implying a consequent reduction of CO_2 emissions till the reach of net zero by half century.

In order to achieve the Net Zero Emission (NZE) target by 2050, raw materials inputs for the energy transition will need to increase by approximately five times. The shift towards materials related to the energy transition is mainly triggered by clean energy technologies, which require minerals and metals in much greater quantities than their fossil fuels-based counterparts.[1]

Critical raw materials are becoming rapidly dominant in the development of different technologies and several countries have already studied plans to secure access to them. In fact, many of these resources are concentrated in few geographical areas, often subject to geopolitical tensions and mostly in developing countries. Two notable policies for boosting access to clean technologies are the U.S. 2022 Inflation Reduction Act, affecting the entire North America with energy and climate subsidies, and the European 2023 Critical Raw Materials Act, aimed at increasing and diversifying the EU's critical raw materials supply.[2] It is clear that governments have been acknowledging the importance of mineral requirements for the energy transition, as well as of strengthening domestic supply chains given the increasing dependence on foreign sources for many processed versions of critical minerals. Focusing on the U.S., the White House has been favoring an expansion of domestic mining, production, processing, and recycling of critical minerals and materials.[3]

Particular attention is devoted to a selection of battery minerals, namely cobalt, lithium and nickel. These materials are key ingredients for the energy transition, as they are extensively used in rechargeable lithium-ion batteries, and are strategic for the development of electric vehicles (EVs) and grid-scale energy storage. Given their importance, they are included in the U.S. classification of critical minerals by the U.S. Geological Survey (USGS) and in the Inflation Reduction Act.

In this article, we want to investigate the impact that the energy transition will have on the selected U.S. mineral markets in the forthcoming years. We focus on the three aforementioned battery minerals and develop three separate structural VAR (SVAR) models, one for each mineral market. The objective is to study the impact of selected policies related to the energy transition, considered as a mix of mineral-specific demand and supply shocks, on the future trajectories of minerals' prices. In fact, for each battery mineral market, we identify four separate structural shocks, distinguishing between aggregate supply and demand shocks, concerning the whole U.S. business cycle, and between mineral-specific supply and demand shocks, which are driven solely by the commodities'

[1] IEA Report, "The Role of Critical Minerals in Clean Energy Transitions".

[2] See H.R.5376 - Inflation Reduction Act of 2022, 117th Congress (2021-2022) for the U.S., while refer to: proposal for a regulation of the European Parliament and of the Council establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending Regulations (EU) 168/2013, (EU) 2018/858, 2018/1724 and (EU) 2019/102, for the European case.

[3] U.S. Department of Energy, "America's Strategy to Secure the Supply Chain for a Robust Clean Energy Transition" and "Inflation Reduction Act - Energy Security and Climate Change Investments".

market fundamentals.

The extreme importance of the nexus between energy shocks and economic activity is well documented within the literature, usually with a focus on the oil market. Studies disentangling oil supply and demand shocks in the global economy employ different identification schemes, such as exclusion restrictions (e.g. Kilian, 2009), sign restrictions (e.g. Baumeister and Peersman, 2013), sign restrictions complemented with bounds on the impact price elasticity of oil supply (e.g. Kilian and Murphy, 2012) or with narrative sign restrictions (as in Antolin-Diaz et al., 2021). An alternative Bayesian approach is proposed by Baumeister and Hamilton (2019), who impose priors on the structural parameters rather than on the structural impulse responses.

On the contrary, focus on the relationship between the energy transition and critical minerals is still limited, even if rapidly growing, due to the increasing relevance of the topic (see e.g. Srivastava and Kumar, 2022, for a review on the topic). Narrowing the focus down to minerals prices, Bastianin et al. (2023) assess the high degree of connectedness among the different markets of energy transition metals. Boer et al. (2023) develop separate global SVAR models for selected battery minerals disentangling metal-specific demand and supply shocks. They further study price trajectories within a structural scenario analysis focusing on the material requirements of the energy transition. Considine et al. (2023) quantify the effects of shocks driven by selected critical mineral prices on global oil price and macroeconomic variables, such as inflation.

Our article is the first to focus on the U.S. critical minerals market, and to consider both mineral-specific and aggregate supply and demand shocks. In this regard, we are able to advance a model particularly suitable for the evaluation of the U.S. policies of the energy transition. In fact, we also conduct a structural forecast exercise to quantify the effects of selected energy transition-related U.S. policies on the evolution of prices in battery minerals markets.

By combining different policy analyses and comparing them with other institutions' scenarios (i.e. S&P), we attempt to model the future impact of the energy transition on the prices of the studied minerals. To do so, we condition forecasts of the selected minerals prices on different sequences of structural shocks up to 2030. The comparison of the different outcomes provides a useful indication of the range of possible future price evolution under different policy mixes.

The rest of the article is structured as follows. Section 3 presents the dataset and some stylized facts on the critical minerals markets. Section 4 describes the econometric framework, with a focus on the identification of the model and structural forecasts. Section 5 presents and discusses the empirical results. Section 6 concludes. An Appendix completes the paper, divided in three sections. Appendix A further deepens the discussion on the U.S. markets of cobalt, lithium and nickel, with a short historical account of the price and production dynamics. Appendix B presents details on the selected U.S. policies on critical minerals. Finally, Appendix C provides the results of some robustness analyses.

3 Data

We focus on three metals, namely cobalt, lithium and nickel. These are all *i*) battery-related materials, *ii*) classified by the U.S. Government as critical minerals and *iii*) subject of several U.S. policies aimed at securing domestic supply chains, IRA included.

We estimate three SVAR models – one for each mineral of interest – based on yearly data. For each SVAR model, we collect four variables, namely $y_{g,t} = [x_t,\ \pi_t,\ q_{g,t},\ p_{g,t}]'$ where $t = 1, \ldots, T$ denotes the time index and $g = 1, \ldots, 3$ selects the mineral of interest among cobalt, lithium and nickel. The variables x_t and π_t are the U.S. industrial production growth and the inflation rate, respectively, whereas $q_{g,t}$ expresses the percent change in U.S. production of mineral g and $p_{g,t}$ its corresponding U.S. real price. We also include an exogenous variable, x_t^*, namely the world industrial production index (WIP) with the exclusion of the American one, in order to isolate the U.S. economy from the other ones. The U.S. does not export a significant amount of the analyzed commodities. For instance, in 2022 U.S. total exports accounted for only 2.9%, 2.01% and 0.95% of the global consumption of cobalt, lithium and nickel, respectively. Nevertheless, the U.S. is 76% import-reliant for cobalt, 56% for nickel and 25% for lithium, which highlights the importance of accounting for the global business cycle.[4]

The variables are constructed from the following annual time series spanning from 1958 to 2022. We collect the U.S. Industrial Production index from OECD and construct x_t as the first difference of log-transformed series.[5] Similarly, to construct x_t^* we aggregate the log-differenced Industrial Production indexes of all the countries considered in the WIP index developed in Baumeister and Hamilton (2019), with the exception of the U.S., and use the same weighting scheme.[6] U.S. inflation is obtained as the log-difference of the Consumer Price Index, also used to deflate mineral prices.[7] The variables $q_{g,t}$ and $p_{g,t}$ are the log-differenced transformations of the production and price of cobalt, lithium and nickel. The production and price series are sourced from the USGS (see Kelly et al., 2005). Note that for cobalt and nickel we consider both primary and secondary production. Moreover, data are incomplete for the lithium production series, since USGS withholds some in order to avoid disclosing company proprietary data. We therefore proxy missing U.S. production levels by subtracting imports and adding exports to the domestic lithium consumption. The reliability of this method is confirmed by checking the obtained variable against the one of Miatto et al. (2020), providing a complete dataset for the American lithium market.

Table A1 in Section A of the Appendix reports the summary statistics of the key variables, both in levels and log differences. The choice of using log-differenced series is justified by the need to rule out unit roots (see Table A2 in Section A of the Appendix, showing that most of them are non-stationary in levels and all of them are stationary when considered in differences) and to obtain direct estimates of minerals elasticities.

Figures 1 and 2 plot the time series of production and prices, respectively, both in levels and in logarithmic transformation. From these figures we can infer patterns and highlights about the history of these markets in the U.S., which is briefly outlined in Section A of the Appendix. What emerges is a price scenario characterized by spikes and high volatility, which clearly constitute an issue in terms of affordability, i.e. the provision of resources at stable prices (see Yergin, 2006, for a detailed discussion).

[4]Data come from USGS (2023). The specification without the inclusion of the exogenous variable provides similar results. However, including global industrial production as a control helps in identifying the shocks.

[5]Source: https://data.oecd.org/industry/industrial-production.htm.

[6]We refer the reader to Appendix E of Baumeister and Hamilton (2019) for the list of included countries and to the OECD Composite Leading Indicators for the weights, available at: https://www.oecd.org/sdd/leading-indicators/oecd-composite-leading-indicators-clis.htm.

[7]CPI, all items for the United States: https://fred.stlouisfed.org/series/CPIAUCSL.

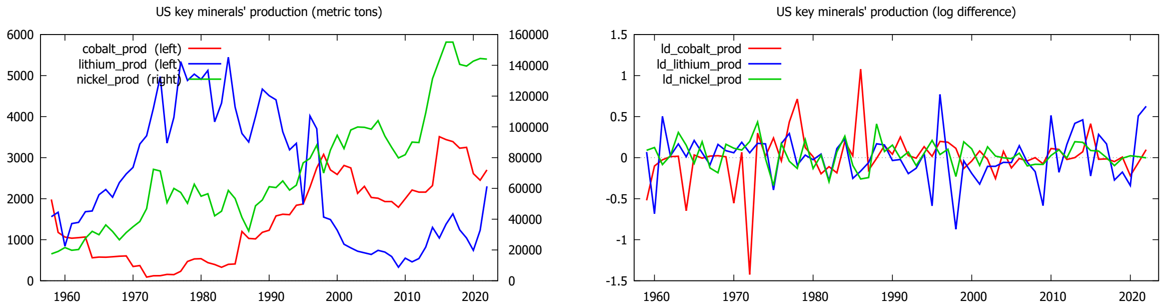


Figure 1: U.S. production of cobalt, lithium and nickel, expressed in levels, metric tons (left panel) and log difference (right panel)

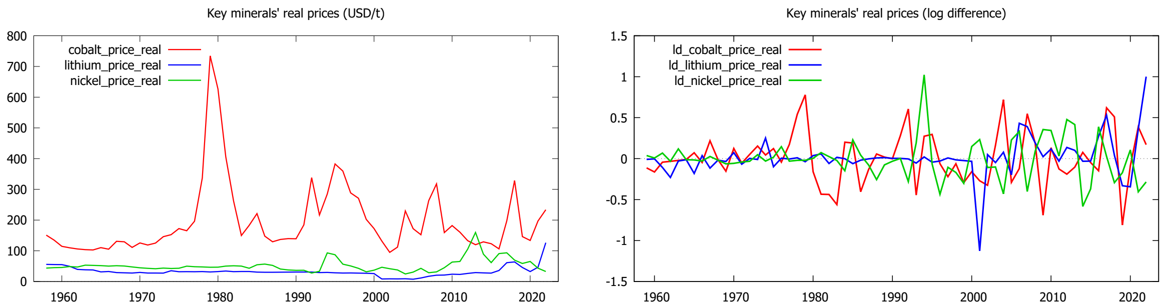


Figure 2: U.S. real prices of cobalt, lithium and nickel, expressed in levels (left panel) and log difference (right panel)

4 Econometric framework

To disentangle the shocks driving minerals production and price dynamics, we rely on a model which builds on – and extends – the standard three variables commodity market SVAR model including commodity-specific production, its price and real economic activity (see, e.g. Kilian, 2009). A specification of this kind is adopted also by Kilian and Murphy (2012) for the oil market, which allows to disentangle oil supply shock, aggregate demand shock and oil-specific demand shock by assuming the sign of each variable response to every structural shock. We follow the authors by complementing short-run sign restrictions with elasticity bounds, but enhance the model with the inclusion of U.S. inflation. This allows us to distinguish between aggregate demand and supply shocks instead of modeling a generic economic activity shock.[8] A similar assumption is adopted, in the context of energy shocks, in Casoli et al. (2022).

To the best of our knowledge, only Boer et al. (2023) has built a SVAR model for specific critical minerals' global market fundamentals, namely for cobalt, copper, lithium and nickel. Their specification differs from ours in that they do not include inflation but a generic other commodity price as an anchor variable, and identification is achieved without the inclusion of elasticity bounds.

Our analysis consists in the estimation of three mineral-specific SVAR models and a consequent exercise of structural forecasting.[9] Considering mineral g, a VAR model in

[8] This shock is sometimes called an aggregate demand shock, but this definition is misleading since by the only inclusion of economic activity it is hard to establish if such shock is in fact determined by aggregate supply or demand factors.

[9] We acknowledge the market interconnections among the different battery minerals, as documented

its reduced-form representation of order $p = l$ can be written as:

$$y_{g,t} = \mu_g + \sum_{p=1}^{l} B_{g,l} y_{g,t-l} + \theta_g x^*_{g,t} + u_{g,t}, \tag{1}$$

$y_{g,t} : (n\times 1) \quad \mu_g : (n\times 1) \quad B_{g,l} : (n\times n) \quad \theta_g : (n\times m) \quad x^*_{g,t} : (m\times 1) \quad u_{g,t} : (n\times 1).$

As shown in Section 3, the vector $y_{g,t}$ collects the $n = 4$ endogenous variables of the system and $x^*_{g,t}$ the $m = 1$ exogenous ones. $B_{g,l}$ are the matrices of lagged coefficients and $u_{g,t}$ collects white noise error terms such that $E(u_{g,t}) = 0$ and $E(u_{g,t}, u'_{g,t}) = \Omega_{g,u}$.[10] These shocks lack a structural interpretation, implying that additional information is required to retrieve economically meaningful shocks.

Specifically, the structural representation of the VAR in Equation (1) is given by:

$$A_{g,0} y_{g,t} = \alpha_g + \sum_{p=1}^{l} A_{g,l} y_{g,t-l} + C_g x^*_{g,t} + v_{g,t}, \tag{2}$$

where $A^{-1}_{g,0}\alpha_g = \mu_g$, $A^{-1}_{g,0}A_{g,l} = B_{g,l}$, $A^{-1}_{g,0}C_g = \theta_g$ and $A^{-1}_0 v_{g,t} = u_{g,t}$. The impact multiplier matrix $A^{-1}_{g,0}$ contains the contemporaneous effects of the structural shocks $v_{g,t}$ on each endogenous variable of the system. The vector of serially and mutually uncorrelated structural shocks implies a diagonal variance matrix such that $E(v_{g,t}, v'_{g,t}) = \Sigma_{g,v}$, which is further normalized to be an identity matrix.

Under appropriate restrictions on $A^{-1}_{g,0}$, it is possible to achieve identification of the model and therefore to get economically interpretable structural shocks. Once $v_{g,t}$ is identified, it is straightforward to compute the impulse response functions and historical decompositions by writing the Vector Moving Average representation of the model. At this point, the structural forecasts are simply constructed as a forward iteration in time of the historical decompositions, conditional on some hypothetical future events (see Kilian and Lütkepohl, 2017).

Conditional forecasts are a key tool for policymakers to predict and compare possible future outcomes under hypothetical scenarios. For example, they can be used to study the path of selected variables under different policy regimes or to fix a policy target and observe the responses of the system. A unified framework exploring conditional forecasting (i.e. imposing given dynamics to the structural shocks) and structural scenarios (i.e. conditioning together the path of one or more variables and a combination of structural shocks) is provided in Antolin-Diaz et al. (2021); Chan et al. (2023). The idea of imposing a path on the observables dates back to Waggoner and Zha (1999), whereas the approach of conditioning on future sequences of structural shocks is based on Baumeister and Kilian (2014). Within this work, we will focus on the latter procedure, that is, conditioning on shocks. It is relevant to stress that, unlike the conventional forecasts, structural or conditional forecasting do not aim at predicting the most likely outcome given the information set, but rather at studying possible paths under the hypothesis that some specific structural shocks are allowed to deviate from the unconditional distribution.

in Bastianin et al. (2023), but prefer to focus on separate models. Estimating a single large SVAR model would imply increasing the number of endogenous variables and related parameters, which we find hazardous given the relatively short sample.

[10] In our analysis, we set $p = 1$ in all the three models, as suggested by the Schwarz Bayesian and Hannan-Quinn Information Criteria.

Denoting with $M_{g,i}$ the dynamic multipliers for a g mineral, i.e. the impulse responses at a specific forecast horizon i, with $i = 1 \dots, h$, it is possible to write the projection in the future of a variable as the sum of two components:

$$y_{g,t+h} = \sum_{i=0}^{\infty} M_{g,i} v_{g,t+h-i} = \sum_{i=0}^{h-1} M_{g,i} v_{g,t+h-i} + \sum_{i=h}^{\infty} M_{g,i} v_{g,t+h-i}, \tag{3}$$

in which the first term relates to the effect of future shocks from time $t+1$ to $t+h$ and the second to past shocks.[11] Since the latter term is already known at time t, the common practice when computing conditional forecasts is to set it at zero, whereas the former term of Equation (3) reflects the forecast of $y_{g,t+h}$ at time t and can be used to construct different forecast scenarios. The starting point is to define a "baseline scenario", which corresponds to the point unconditional forecast and is simply obtained by setting all the structural shocks from $v_{g,t+1}$ to $v_{g,t+h}$ to zero. The intuition is that their unconditional expectation is zero by definition. Then, point conditional forecasts are created by feeding in a sequence of future structural shocks which deviate from zero. The sequences of structural shocks we input in the conditional forecast are specific to the energy transition and related U.S. policies (see Section 4.2). After hypothesizing specific shock sequences, we check how they will contribute to the future path of a generic endogenous variable relative to the baseline scenario. The difference between the two paths provides the effect of energy transition shocks in the forthcoming years.

4.1 Identification

Within our model, we disentangle four different structural shocks for each mineral market: mineral-specific supply and demand shocks, and aggregate supply and demand shocks. Given the low frequency of our data, we prefer to depart from recursive identification approaches and rely on static sign restrictions to identify the three SVAR models in (2).[12] This approach, developed by Canova and De Nicolò (2002); Faust (1998); Uhlig (2005) implies to: *i*) set the expected signs of the coefficients in the structural impact multiplier matrix, grounded on economic theory; *ii*) obtain many candidates for this matrix (note that sign restrictions allows to achieve set – and not point – identification) and *iii*) retain only the set of solutions that provide a matrix $A_{g,0}^{-1}$ coherent with the specified sign restrictions. Specifically, in our case the algorithm keeps drawing models until 100 admissible draws are reached. Note that our model is not fully identified, as some impact responses are left unrestricted without any sign specification.

Furthermore, following Kilian and Murphy (2012, 2014), we combine sign restrictions with bounds on the magnitude of the short-run mineral supply and demand elasticities.

Estimation of conventional sign restricted models and models mixing zero and sign restrictions – which we use in some robustness exercises – is based on the algorithms proposed by Arias et al. (2018); Rubio-Ramirez et al. (2010).[13]

Within our identification strategy, the four shocks have the following effects.

[11]Note that $M_{g,0} \equiv A_{g,0}^{-1}$.

[12]We remind that imposing zero restrictions in the production equation implies a vertical supply curve at the first horizon. Although this is plausible in determined settings – for instance with monthly data – we believe that a similar assumption is too strong to hold for an entire year.

[13]We refer the reader to Kilian and Lütkepohl (2017); Lucchetti (2015) for technicalities of the computational workflow.

Mineral-specific supply shock: a positive mineral-specific supply shock will by construction increase that mineral's production and decrease its price. At the same time, it instantaneously increases the domestic industrial production, while the impact on U.S. inflation is left unrestricted;

U.S. aggregate demand shock: this positive shock is driven by unexpected variations in the American business cycle driven by the demand side, hence affecting the demand for all commodities. A positive aggregate demand shock stimulates U.S. industrial production, mineral production, domestic real price of the mineral and inflation;

mineral-specific demand shock: a positive demand shock specific to the mineral's market raises on impact the real price of that mineral and stimulates its production. Further, it decreases industrial production, as standard within the energy shocks literature. This restriction implies that the mineral-specific demand shock is driven by a speculative component (see Kilian and Murphy, 2014). The impact on U.S. inflation is left unrestricted, both to maintain a more agnostic perspective and because, unlike crude oil, the three analyzed mineral prices have a negligible weight in the total Consumer Price Index. This choice is coherent with the results of Considine et al. (2023), finding that a positive shock to critical mineral prices does not have a significant impact on U.S. inflation;

U.S. aggregate supply shock: this is defined as an unexpected positive shock raising U.S. industrial production and lowering domestic inflation. Decreasing inflation also reduces the mineral price, whereas we do not assume any restriction in the impact response of mineral production. In fact, decreasing mineral prices should discourage suppliers to increase production, but at the same time, the industrial production stimulus could push the production of individual commodities.

The set of imposed sign restrictions is summarized in Table 1.

Table 1: Identification strategy with sign restrictions

Variables	Mineral specific supply shock	Aggregate demand shock	Mineral specific demand shock	Aggregate supply shock
Mineral production	+	+	+	
Industrial production	+	+	-	+
Real price of mineral	-	+	+	-
Inflation		+		-

Furthermore, we combine these restrictions with short-term bounds on the elasticity of minerals demand and supply. This further narrows down the range of admissible structural models, helping in achieving economically meaningful structural shocks.

The impact elasticity of mineral g supply with respect to its price is defined as $\frac{[A_{g,0}^{-1}]_{1,3}}{[A_{g,0}^{-1}]_{3,3}}$, that is the ratio between the mineral production response to a mineral-specific demand shock and the price response to the same shock. Conversely, $\frac{[A_{g,0}^{-1}]_{1,1}}{[A_{g,0}^{-1}]_{3,1}}$, the ratio between the mineral production response to a mineral-specific supply shock and the price response to the same shock, is the impact elasticity of mineral g demand with respect to its price.

The bounds we impose on these short-run elasticities are at the same time economically plausible and, given the limited amount of literature on the topic, relatively soft. A survey by Dahl (2020) reports that an average of the estimated values of the short-run demand elasticity of cobalt is -0.165, of lithium -0.540, of nickel -0.032. Boer et al. (2023) document a short-run global supply elasticity of cobalt is 0.4, of lithium 1.7, of nickel 0.7. We adopt a conservative approach in imposing short-run supply elasticity to be lower than 1 and short-run demand elasticity to be greater than -1.

4.2 Conditional forecasting

The final step is to model the future impact of the energy transition on the prices of the minerals of interest.

In terms of modeling the energy transition, we depart from Boer et al. (2023), who consider mineral consumption scenarios as given, and then find a series of exogenous mineral-specific demand shocks that match those scenarios. We decide to follow an alternative approach. Specifically, this is necessary because their study is about global mineral markets, and hence the authors can make the assumption of equality between global consumption and production. Within our U.S. model, we prefer to acknowledge the role of imports and exports, hence using consumption scenarios for determining production paths becomes less trivial. Moreover, we consider structural forecasts on the assumption that the energy transition will be driven by demand and supply structural shocks. While Boer et al. (2023) acknowledge that the global energy transition can be considered as a result of a shock on the demand side, we believe that, from a country perspective, it originates from a combination of demand and production pushed shocks. In fact, the U.S. is developing a massive effort to expand domestic supply precisely to decrease foreign dependence, within a broader plan of industrial policies.

We employ different strategies for constructing future paths of demand and supply shocks up to 2030. They are based on hypothetical sequences reflecting thought experiments, backed as much as possible with empirical evidence (either from the authors' calculations, or referring to other sources' forecasts). Specifically, we ask ourselves what would happen to mineral prices if mineral demand shocks impacted prices themselves more or less strongly, and supply shocks increased domestic minerals' production just enough to alleviate import dependency, versus the IRA-induced stronger increase in production.

We build specific scenarios to address those questions, and feed them into Equation (3) as future flow shocks (of supply or demand), while setting all other future structural shocks equal to their zero expected value. The cases we consider are listed below.

a) *Historical demand increase:* to reconstruct the energy transition dynamics which lead to positive mineral-specific demand shocks, we select the sequence of shocks of the years 2010-2015 and suppose that the same path will continue in the following years.

b) *Higher demand increase:* we assume that the biggest demand increase will happen in the following two years, hence we modify the previous scenario by imposing a higher increase in 2023 and 2024, setting their growth rates equal to the average of the last five years' price growth.

c) *Ambitious supply increase:* we compute the expected increase in domestic minerals' production driven by government funding. In order to map the U.S. extraction and processing projects of cobalt, lithium and nickel that will be developed in the years to come, we review their development studies and releases. We compile a list of these projects, which highlights the target year and the targeted annual production (see the policy analysis in Appendix B for more details). By cumulating each mineral's annual exceptional production across projects, we calibrate the expected supply shock matching with the desired production driven by public policies up to 2030.

d) *Lower supply increase:* we conjecture the expected increase in U.S. production driven by the government's stated goal of import independency. Official U.S. documents define import reliance as imports (M) being greater than 50 percent of annual consumption (C), for most of the minerals designated as critical, including cobalt, lithium and nickel. Considering this approximation: $C = P + (M - X)$ (consumption equals the sum of domestic production and net imports) and that imports cannot exceed 50 percent of the consumption, we calculate the new production capacity necessary to maintain the same level of consumption $P^* = C - (M^* - \overline{X})$, with $M^* = C/2$. In this manner we are able to compute an approximation of the production increase which would allow the U.S. to stop being import reliant. We therefore compute a supply shock compatible with this production approximation.

We compare each conditional forecast obtained with the five hypotheses listed above with a benchmark scenario, defined from *S&P* Global Market Intelligence.[14] Specifically, we use the U.S. price forecasts for lithium (2023-2027) and cobalt (2023-2030) concerning the demand in passenger plug-in electric vehicles. Note that the demand for passenger plug-in electric vehicles accounted for more than 70% of the overall total battery demand in the last two years. As for nickel, we consider the primary nickel prices forecasts (2023-2030).

5 Empirical results

5.1 Impulse responses

In this section we illustrate the structural impulse responses of the minerals' real prices and production, as well as the CPI and the industrial production of the U.S., to each structural shock. Figures 3, 4 and 5 report the cumulated responses of all the 100 accepted models identified by sign restrictions and elasticity bounds, for cobalt, lithium and nickel markets respectively.

A mineral-specific supply shock (first columns of Figures 3, 4 and 5) positively affects mineral production, with no persistent effects for all the three markets. Conversely, this shock has a negative and persistent effect on mineral prices of lithium and nickel, while for cobalt the effect vanishes after 3 years . All the three mineral supply shocks positively affect industrial production, but the effect reverts to zero after one year for a substantial number of models. The effect of a positive and unexpected supply shock on the Consumer Price Index, which is left unrestricted, is uncertain for all the three markets.

Aggregate demand shocks (second columns of aforementioned figures) have positive impacts on both market-specific and aggregate variables. The effect on cobalt production reverts to zero after three years, whereas it is still persistent after 5 years for cobalt prices. The effects on lithium and nickel production and price is less persistent and becomes indistinguishable from zero after 1 year. As expected, in all the three cases the effects of increasing aggregate demand on CPI are very persistent for all the accepted models.

[14] Data accessed in January 2023.

Mineral-specific demand shocks (third columns of Figures 3 to 5) display stronger and more persistent effects on the prices rather than the production of all the three minerals. The effect on industrial production becomes insignificant right after the first horizon, while the effect on CPI is unclear.

Finally, an aggregate supply shock (displayed on the fourth column of each figure) positively affects industrial production while decreasing the CPI. For each market, we do not detect a clear effect on mineral production, while the effect on prices is negative and not particularly persistent.

Comparing the effects of different shocks on minerals production, it emerges that aggregate demand shock is the major driver in the cobalt and lithium markets, while nickel production is equally affected by mineral-specific supply shocks. This reflects nickel's importance as a strategic commodity in a multitude of industries, with a well developed and long-established market. On the contrary, U.S. lithium and cobalt markets have historically been more marginal and are thus more subject to broad macroeconomic conditions. Looking at metals prices, mineral-specific and aggregate demand shocks, together with mineral-specific supply shocks, are all equally important drivers for the dynamics of cobalt prices, whereas lithium and nickel prices are particularly and persistently affected by own market specific supply shocks.

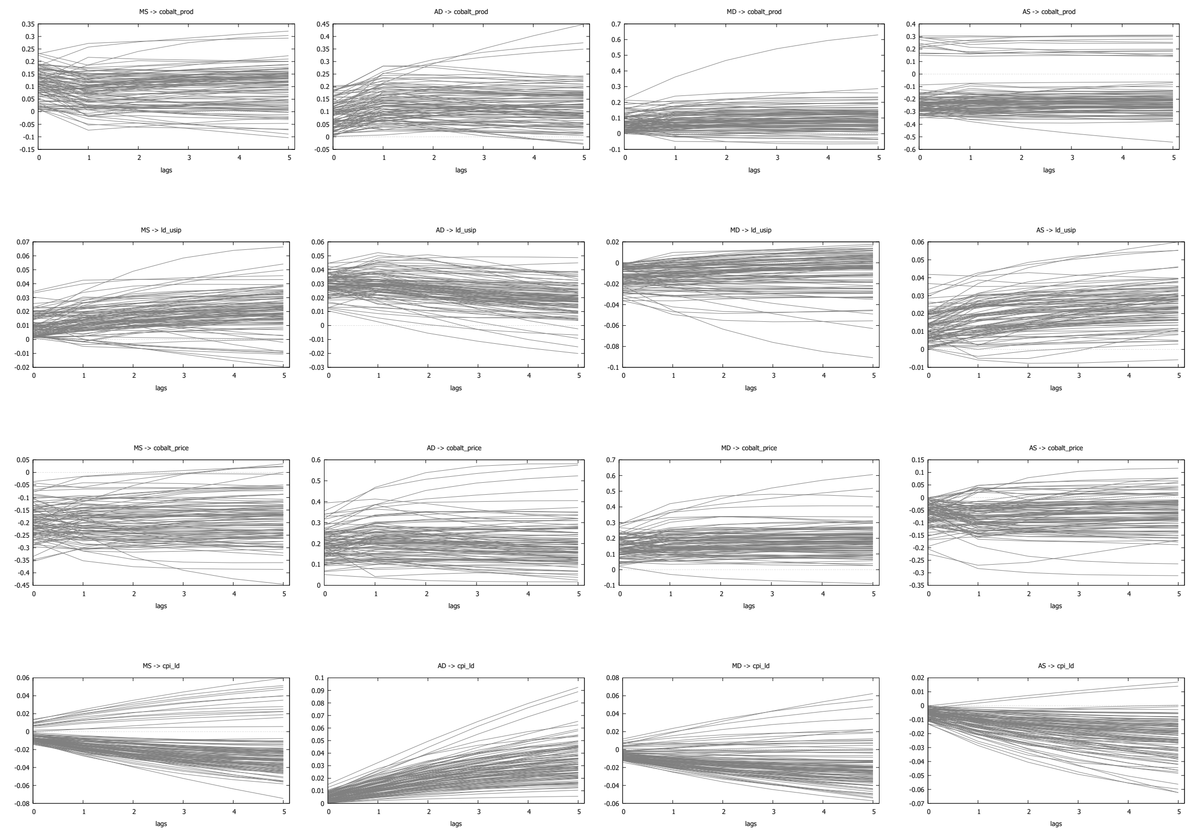


Figure 3: Cumulated Impulse Response Functions for cobalt

Notes: MS, AD, MD and AS denote a mineral-specific supply shock, an aggregate demand shock, a mineral-specific demand shock and an aggregate supply shock, respectively. The variables `cobalt_prod`, `ld_usip`, `cobalt_price` and `cpi_ld` represent cobalt production growth, the growth rate of U.S. industrial production, cobalt price growth and U.S. inflation. The above definitions hold also for Figures 4 and 5, with the required modifications for price and production labels.

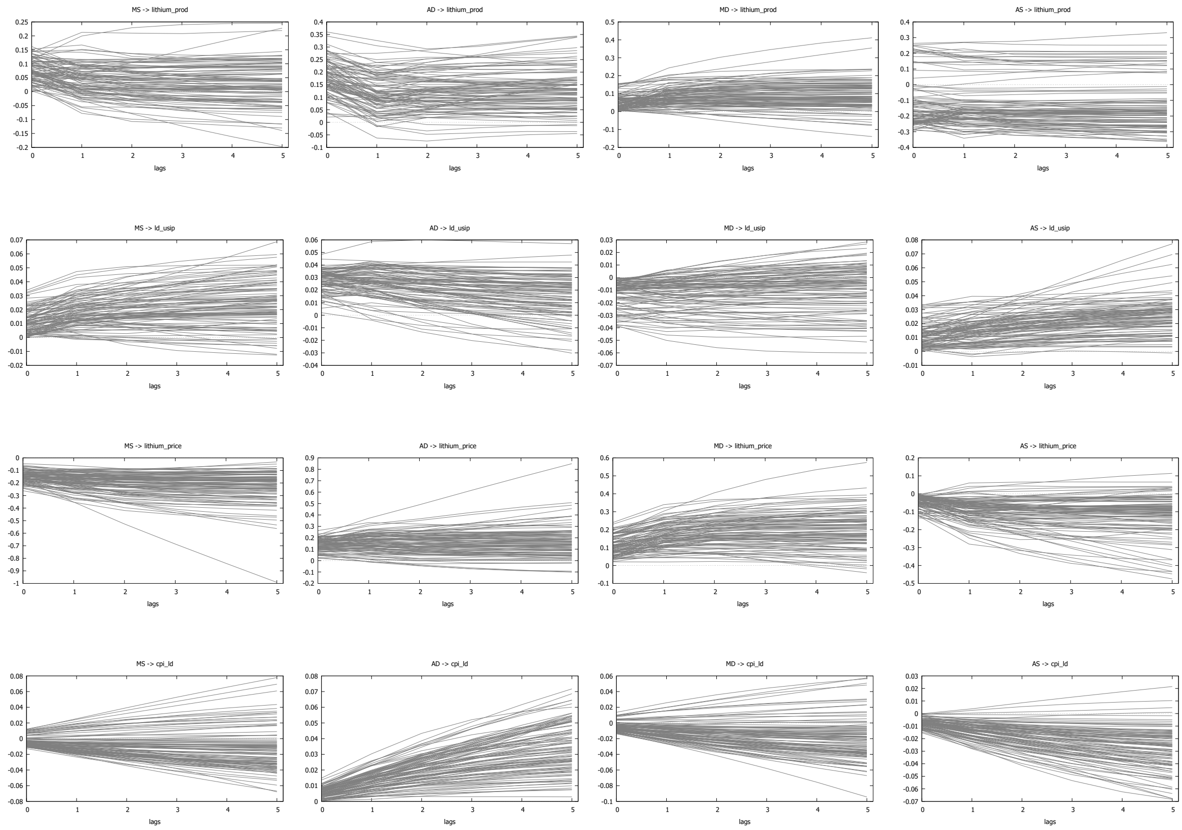


Figure 4: Cumulated Impulse Response Functions for lithium

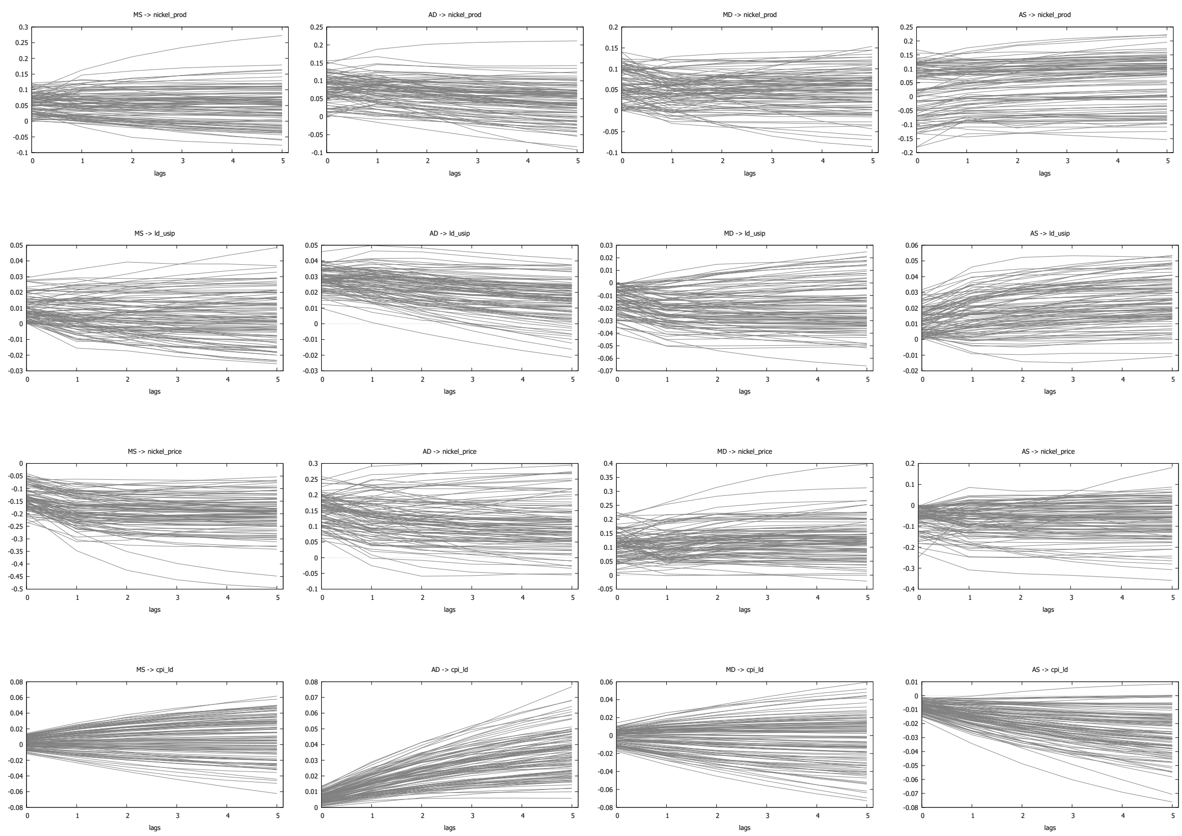


Figure 5: Cumulated Impulse Response Functions for nickel

Finally, from the impact responses of each mineral production and price to mineral-specific shocks, we can compute the short-run supply and demand price elasticities. The results are reported in Figure 6, where it is shown that the three minerals markets do not exhibit strong differences in terms of estimated supply elasticities, whereas elasticities of demand vary across markets. The medians of the short-run supply elasticities are 0.512, 0.526 and 0.504 and the ones of the short-run demand elasticities are -0.610, -0.442 and -0.487 for cobalt, lithium and nickel, respectively. These elasticities imply quite elastic supply curves if compared with those of markets of other energy commodities such as crude oil.

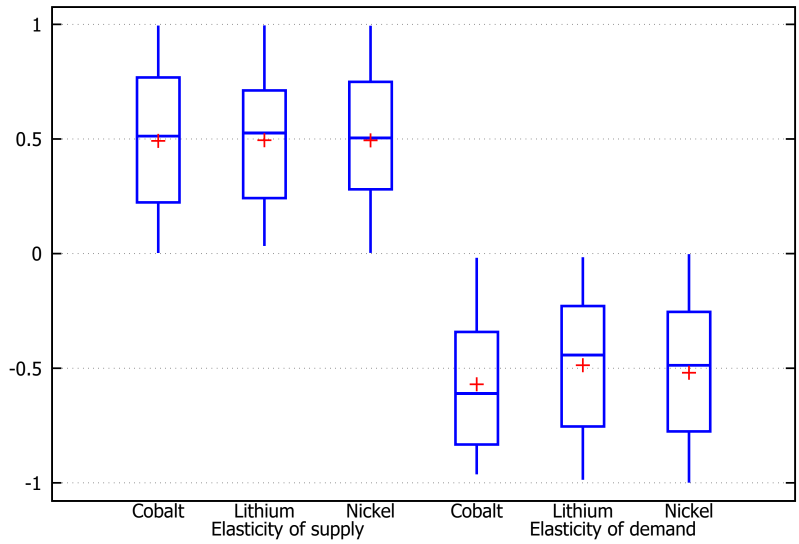


Figure 6: Short-run demand and supply elasticities: cobalt, lithium and nickel prices

Notes: The box represents the middle 50 percent of the data, while each whisker extends for 1.5 times the interquartile range. The median is represented by the line, while the mean by the red "+" .

5.2 Robustness analysis

The results reported above can be compared with those of some robustness checks in which we change the sample period, the included variables or the identification scheme in order to assess the validity of our main specification. In the first exercise, we substitute the American Industrial Production Index with U.S. GDP, which is a broader measure of economic activity.[15] The second robustness exercise focuses on a relaxed version of the identification strategy presented in Section 4, Table 1, which consists in the same sign restrictions set without the inclusion of elasticity bounds. The third analysis restricts the time interval by focusing only on the last 50 years (i.e. 1972 to 2022). This sub-sample includes the period in which the first oil shocks were affecting the U.S. economy, but discharges the precedent years in which the overall economic context was particularly different. The fourth robustness analysis considers a model without the inclusion of the inflation variable and adopts the sign restrictions identification strategy reported in Table 2, in line with Kilian and Murphy (2012).

[15]Sources: World Bank and OECD National Accounts data files: `https://data.worldbank.org/indicator/NY.GDP.MKTP.CD` and `https://stats.oecd.org/index.aspx?queryid=60705`.

Table 2: Alternative identification strategy: sign restrictions, three-variables model without U.S. inflation

Variables	Mineral specific supply shock	Aggregate demand shock	Mineral specific demand shock
Mineral production	+	+	+
Industrial production	+	+	-
Real price of mineral	-	+	+

This specification implies that a positive mineral-specific supply shock instantaneously increases that mineral production, decreases its price, and increases industrial production; a positive aggregate demand shock, affecting the demand for all the commodities, raises minerals' production, stimulates industrial production and increases the real price of minerals on impact; finally, a positive mineral-specific demand shock raises the real price of that mineral and stimulates its production, but lowers industrial production.

Finally, as a last robustness check, we consider the model developed in Boer et al. (2023) by replacing the inflation variable with an additional commodity price which should behave as an "anchor". The intuition is that the domestic real price of this commodity is contemporaneously affected by aggregate demand shocks, but not by the mineral-specific supply and demand shocks. In other words, the selected commodity is not a substitute good for the critical minerals under study. By combining zero and sign restrictions as presented in Table 3, this specification does not assume any sign on the impact of a mineral-specific demand shock on industrial production, which is left unrestricted. We select as potential anchor variables the U.S. domestic prices of cotton, sugar and wheat, sourced from MacDonald and Meyer (2018).

Table 3: Alternative identification strategy: mix of sign and zero restrictions, four-variables model without U.S. inflation and with cotton price as anchor variable

Variables	Mineral specific supply shock	Aggregate demand shock	Mineral specific demand shock	Anchor shock (residual)
Mineral production	+	+	+	
Industrial production	+	+		
Real price of mineral	-	+	+	
Real price of anchor	0	+	0	+

We report the results obtained with each robustness exercise in Figures C1, C2, C3, C4 and C5 of Section C of Appendix C. These figures focus on the lithium market only and display the responses of mineral's production and price to all the structural shocks of interest.[16]

Overall, the identification strategy we propose appears robust to each additional analysis. In particular, Figure C1 shows that substituting the Industrial Production Index with GDP results in a slightly better identification of the aggregate supply shock on lithium price. However, we find that with the baseline specification we obtain a narrower set of responses of lithium price and production to mineral-specific supply and mineral-specific demand shocks, which are the main focus of this analysis. As for the second robustness exercise, relaxing the additional constraint on short-run elasticities, we find that the main differences compared to the baseline results are, as expected, on the responses of lithium production to mineral-specific supply and demand shocks, which are enclosed in a narrower set. We therefore conclude that the inclusion of elasticity bounds enhances the identification of the structural shocks. As reported in Figure C2, the other

[16]Results concerning cobalt and nickel alternative models are available from the authors upon request.

responses are in line with the main results. Figure C3 shows that no particular differences emerge when restricting the sample, with the exception of a sharper identification of the effect of a mineral-specific supply shock on lithium price. In Figure C4, in which we compare the baseline specification with an alternative model excluding inflation, we can assess the importance of disentangling aggregate supply and demand shocks for the U.S. economy. In fact, with the specification including three variables we cannot properly infer the nature of an economic activity shock, thus obtaining interesting comparative results.[17] First, with the baseline specification we better identify the effect of an aggregate demand shock on lithium production, while the alternative model without inflation restricts the set of admissible responses of lithium price. Second, the response of lithium price to mineral-specific demand shocks identified with the alternative model presented in Table 2 is permanent and positive, whereas the baseline results become more uncertain after 3 years. Third, the inclusion of inflation in the model and the disaggregation of economic activity shock into demand and supply-driven components improves the identification of mineral-specific supply shocks, especially for what concerns the response of price. Finally, we compare impulse responses obtained with the baseline model and the one inspired from Boer et al. (2023) in which identification of the structural shocks is reached with the inclusion of an anchor variable. Figure C5 shows that, using cotton price as anchor variable, the resulting responses of lithium production and prices to all the structural shocks are consistent with those referring to the main model.[18] Nevertheless, we note that with our specification a mineral-specific demand shock has a positive effect on prices that is absorbed only after 3 years, whereas in model identified following Table 3 the price response becomes immediately uncertain.

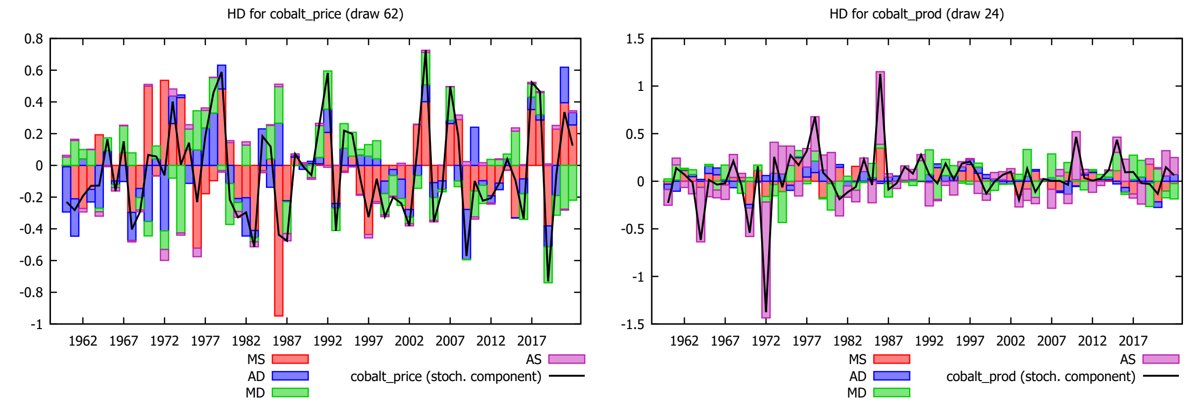
Since the results are robust to the several alternative specifications presented, we proceed with the rest of the analysis focusing on the baseline model.

5.3 Historical decompositions

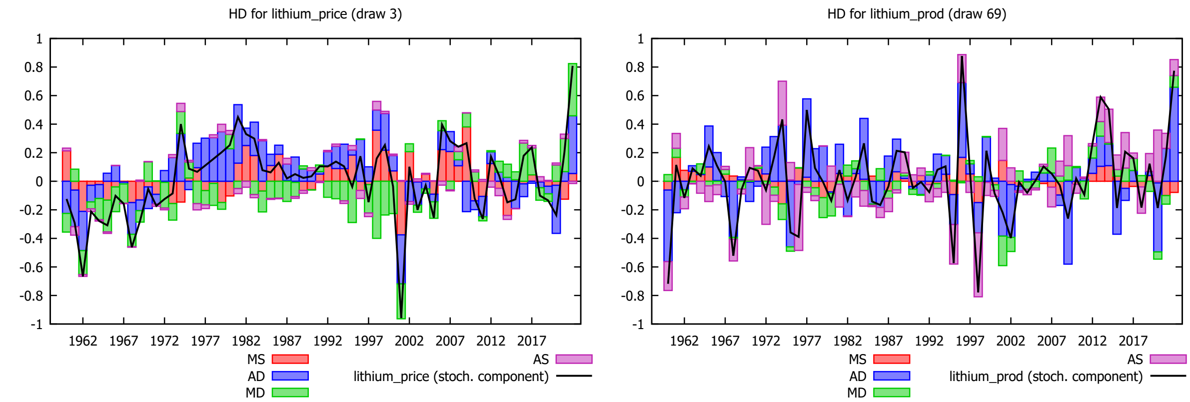
As common among practitioners, we perform the historical decompositions considering the single impulse response functions that minimize the distance to the pointwise median (see Fry and Pagan, 2011). We therefore analyze the closest-to-median historical decomposition, that is the cumulative effect of all structural shocks on minerals price and production growth over time. The outcome is displayed in Figure 7, depicting the single structural shocks contributions to the selected variables as colored histograms and the stochastic component of the variables as continuous lines.

[17]For the sake of simplicity, the shock is denoted as an aggregate demand shock (AD) as often assumed within the literature.

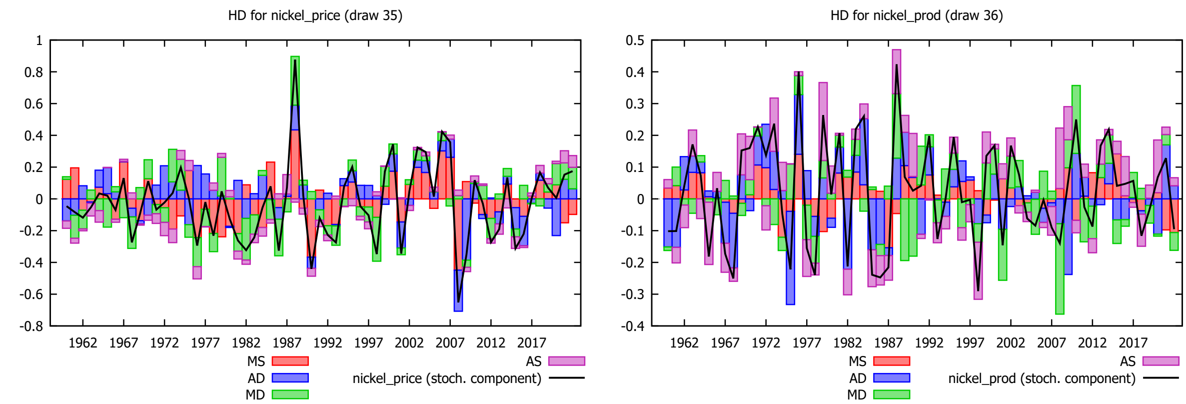
[18]Results obtained using wheat and sugar prices report negligible differences.



(a) Historical decompositions of cobalt price (left) and production (right) rates of growth



(b) Historical decompositions of lithium price (left) and production (right) rates of growth



(c) Historical decompositions of nickel price (left) and production (right) rates of growth

Figure 7: Historical decompositions of minerals' prices and production

Notes: MS, AD, MD and AS denote a mineral-specific supply shock, an aggregate demand shock, a mineral-specific demand shock and an aggregate supply shock, respectively. The variables `cobalt_price` , `lithium_price` and `nickel_price` represent the price growth of the three minerals, while `cobalt_prod`, `lithium_prod` and `nickel_prod` their production growth.

The evolution of the mineral markets and the main historical events highlighted in Appendix A provide interesting information to understand the prices and production historical decompositions.

The left-hand side of Figure 7a represents the closest-to-median historical decomposition of the cobalt U.S. price growth. Overall, mineral-specific supply and demand shocks are the most important drivers of price growth dynamics. Aggregate demand shocks are also crucial especially in explaining some of the price drops (e.g. the 2008 negative peak), whereas the role of aggregate supply shocks is marginal for the whole analyzed sample.[19] Moreover, in recent times the role of mineral-specific supply shocks in explaining price peaks has slightly increased, whereas in the past aggregate demand shocks were relatively more important. This reflects the fact that the U.S. supply of cobalt was entirely based on secondary materials production until recent years, and more importantly that previous price drops and spikes were mainly driven by events happening in the Democratic Republic of Congo (e.g. the DRC cobalt crisis in 1975), a dominant cobalt producer worldwide as highlighted in Appendix A. The right-hand side of Figure 7a represents instead the historical decomposition of the U.S. cobalt production growth. In this case, aggregate supply shocks are the predominant driver of cobalt production growth for the whole sample.

The left-hand side of Figure 7b depicts the historical decomposition of the U.S. lithium price growth. While in the past aggregate demand shocks were positively contributing to lithium price growth, the low domestic lithium-specific demand was balancing this upward push. This is observed from the beginning of the sample to the 1990s, when the U.S. was the leading producer and user of lithium worldwide (see Appendix A). As for cobalt, also in the lithium case aggregate supply shocks contribution is almost negligible to explain price growth, while more important in explaining production growth (right panel). The most recent upward trends in price growth are associated with mineral-specific demand shocks, in line with the increased interest towards lithium-ion batteries during the last years. In terms of production growth, it emerges the important role of aggregate demand shocks. The U.S. lithium production declined notably starting from the 1980s and throughout all the 1990s, not because of a lithium supply shock but rather due to industrial policies shifting the production to countries with cheaper labor (e.g. Chile).

Figure 7c represents the historical decompositions of the nickel price (left-hand side) and production growth (right-hand side). Overall, price and production growth fluctuations are driven by a balanced mix of shocks. A detailed explanation of the U.S. nickel market main episodes is reported in Appendix A, where it is outlined that the price peak registered in 1987-88 is a combination of increased demand for stainless steel and a drop of production. This is consistent with the results of the historical decomposition, which relates the price growth sudden increment to a combination of aggregate demand, nickel demand and nickel supply shocks. Looking at the production growth historical decomposition, the most interesting result is the irrelevance of mineral-specific supply shocks in explaining the overall dynamics from 1999 to 2012. This period coincides with the years in which the U.S. has not produced any primary nickel. Starting from 2013, corresponding to the start of production in the nickel-copper Eagle Mine, mineral specific supply shocks gain more importance.

Finally, some considerations hold for all the three mineral markets, as they are related to U.S. economic conditions in general. Specifically, we observe price and production growth drops after 9/11/2001, especially in the case of lithium and nickel markets. These drops presumably reflect the high uncertainty characterizing the period and are explained,

[19]As shown in Figures 3, 4 and 5, the effect of aggregate supply shocks on minerals production is not properly identified. Therefore, we center our discussion on the other structural shocks and acknowledge the fact that this residual may capture other external factors.

with the exception of cobalt market, by aggregate demand shocks in a considerable portion. Aggregate demand shocks also play a relevant role in explaining the 2007-8 financial crisis, accompanied with a drop in both production (especially lithium and nickel) and prices (mostly cobalt and nickel). Aggregate demand shocks contribute to lower prices and production growth also in 2020, due to Covid-19 trade and production restrictions.

5.4 Structural forecasts

As anticipated in Section 4.2, we can construct conditional point forecasts corresponding to particular hypothetical scenarios.

As discussed, it is convenient to define a baseline forecast (i.e. the unconditional forecast in which all future structural shocks are set to zero) and plot the difference between each conditional forecast and the baseline scenario. In Figure 8, we plot the percent deviations from the baseline forecast for scenarios a to d up to 2030, as outlined in Section 4.2, for cobalt, lithium and nickel prices growth. Positive demand shocks clearly imply an immediate price growth increase, while positive supply shocks lead to decreasing prices. By construction, demand scenarios (a and b) lead to similar results in terms of forecast variations among mineral prices, while production scenarios (c and d) produce results which differ across the three selected markets. Specifically, lithium price growth deviation is remarkably different with respect of nickel's, with the former being considerably affected in both scenarios and the latter only slightly. This result reflects the strong emphasis that the strategic U.S. policies for the energy transition are placing on lithium in particular. For instance, as reported in Appendix B, out of the 11 projects selected for this analysis, 7 are focused on lithium production. Nickel is quite at the opposite side of the spectrum: the U.S. is already producing important quantities of this mineral (especially from secondary production), reason for which government policies are not particularly targeting production increments (scenario c), nor a strong increase is needed in order to reduce the domestic import dependency (scenario d).

Additionally, Figure 9 illustrates different combinations of supply and demand scenarios. Specifically, the increase in production driven by U.S. policies such as the IRA is matched with historic or higher demand increases (left panel). In parallel, the increase in production necessary to address the issue of import dependency is matched with historic or higher demand increases (right panel). The effect on prices of the production increase resulting from IRA policies is particularly pronounced for lithium and cobalt, which exhibit negative percentage changes in prices with both historic (top-left quadrant) and high (bottom-left quadrant) demand increases. Instead, nickel price's growth fluctuates more around zero. As already anticipated, this suggests that neither the goal of import-independence, nor the IRA-related policies are strong enough to drive nickel's price down. For all the minerals, the impact on price growth is almost negligible when production increases just enough to alleviate import dependency and demand increases more than the historical trend (bottom-right quadrant). This means that these two hypothetical shocks balance each other. By contrast, the production increase driven by import independency coupled with lower demand growth (top-right quadrant) drives nickel's price up in 2023 (mostly due to the demand increase scenario), while it lowers the prices of cobalt and mostly of lithium.

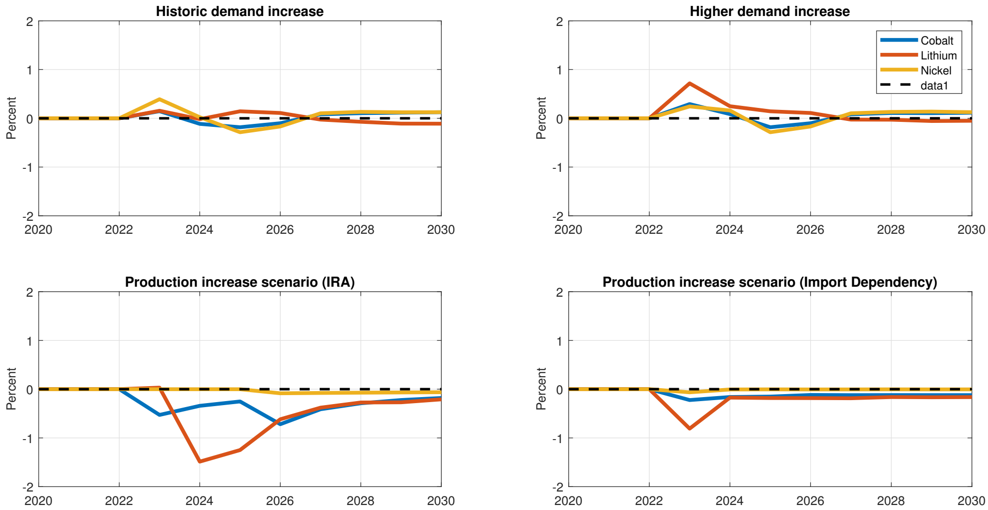


Figure 8: Forecast scenarios for minerals' prices: percent deviations from baseline forecast.

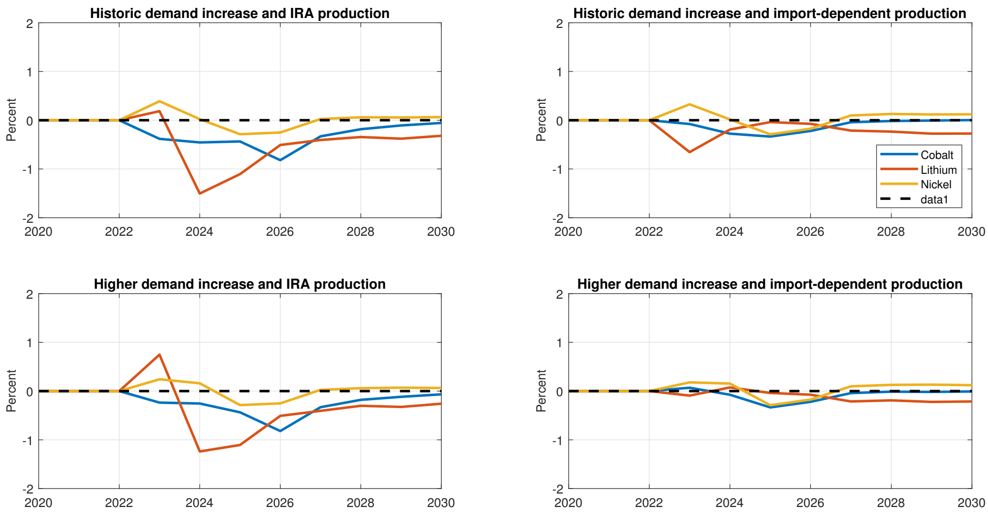
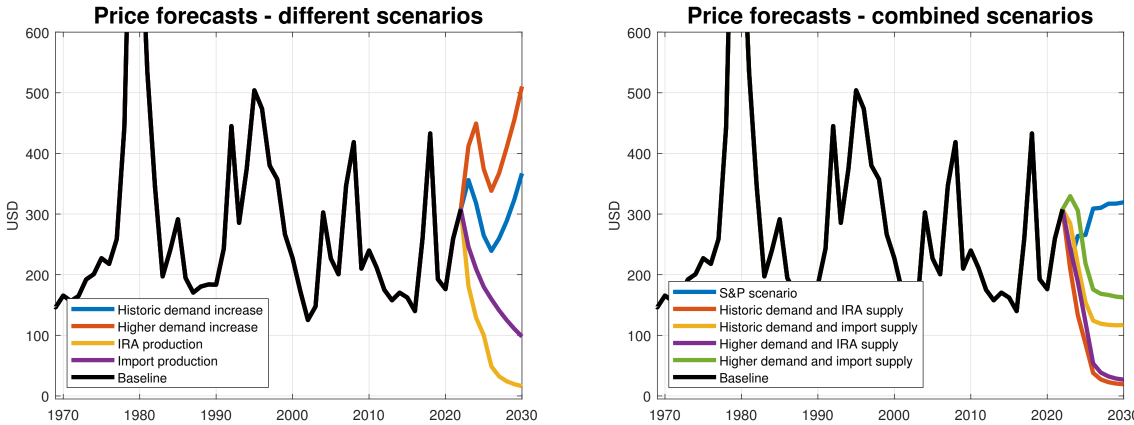


Figure 9: Combinations of forecast scenarios for minerals' prices: percent deviations from baseline forecast

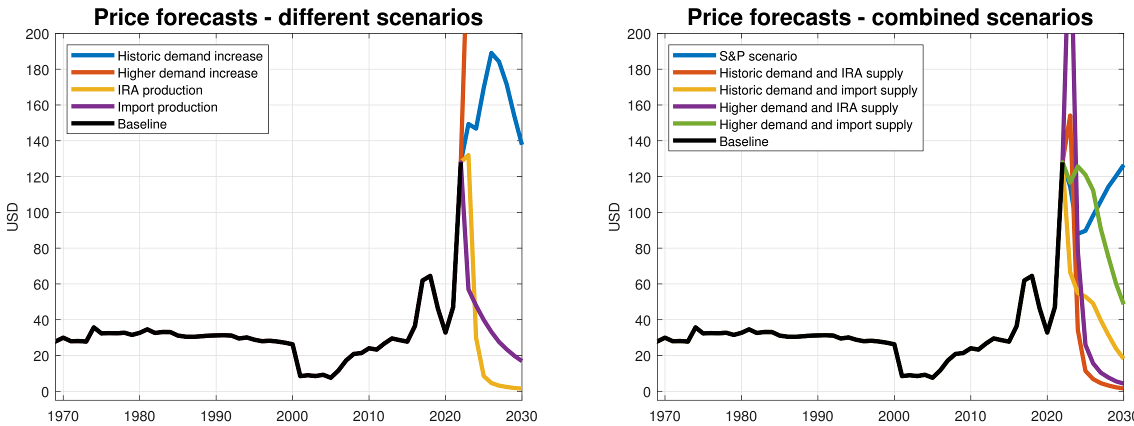
Finally, Figure 10 displays the historical series along with the structural forecasts up to 2030 for the prices of the three minerals. The left panel presents the projections based on individual scenarios, namely *(a)* historical demand increase, *(b)* higher demand increase, *(c)* increasing production driven by U.S. government policies such as the IRA, and *(d)* increasing production driven by the goal of achieving import independence. Both demand scenarios result in peaking prices, particularly pronounced in the case of lithium. Specifically, with the higher demand increase scenario, lithium price "explodes". This is caused by the fact that lithium price in the most recent years (i.e. 2021 and 2022, when the conditional forecast begins) is already exhibiting an exploding behavior, reaching unprecedented levels. Supply scenarios also have particularly pronounced effects on lithium prices, pushing them close to zero, and to a lesser extent on cobalt prices. Nickel price, instead, is less affected by production scenarios, due to the marginal attention the U.S. government is devoting to this market development.

Despite considering these scenarios in isolation presents an interesting picture, a more realistic situation would involve a combination of supply and demand forces. For instance, a significant supply increase without a corresponding demand request is unlikely For this reason, the right panel of Figure 10 displays combinations of demand and supply scenarios together as already presented in Figure 9, and compares the different matches with the S&P projections. In the case of cobalt market, supply rather than demand scenarios have the most significant effect on price, which, as a consequence, keep decreasing quite steadily, especially with IRA-driven production. Lithium price, already peaking in 2022, has an extended peak in 2023, particularly pronounced in the case of higher demand and IRA-driven supply scenario, and reverts to more credible levels starting from the subsequent year. This is likely explained by the fact that, according to the funded projects, additional lithium domestic production will not start until 2024. In contrast, as predicted, the structural forecast of nickel prices is only moderately influenced by supply scenarios. Given that the additional investment in the domestic production of the mineral is quite restricted in both the IRA- and import-independency-driven production scenarios, nickel price exhibits a path which follows more the demand-side scenarios.

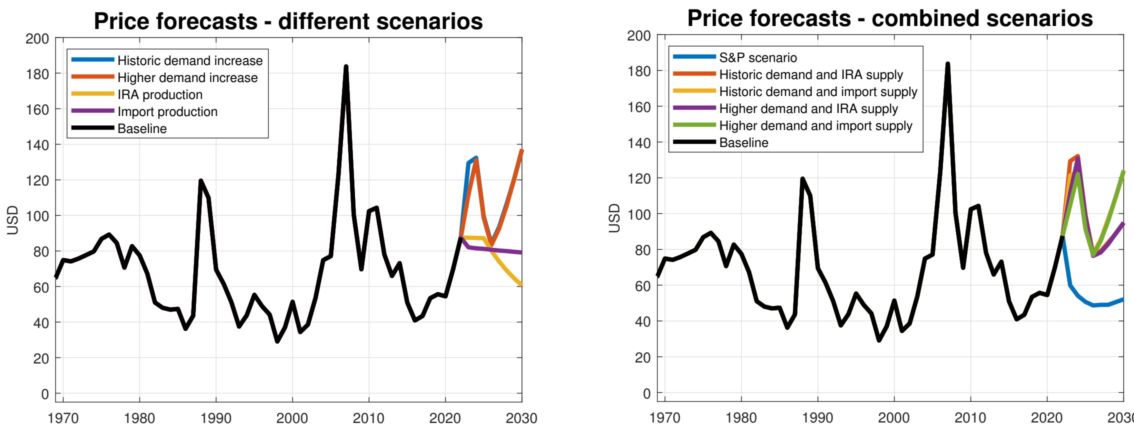
Our structural forecasts are remarkably different from the S&P projections. It is important to stress that S&P scenarios are unconditional, and hereby aim to offer the price path which is most likely to happen in the future. Therefore, these forecasts provide a suitable benchmark for comparing what would happen in the business-as-usual case versus a successful implementation of the U.S. balanced policy mix targeting the energy transition. Specifically, the implementation of the listed policies would keep the price of cobalt and lithium relatively low in the forthcoming years. Instead, nickel price would increase more with respect to the unconditional forecast, reflecting the lower interest in financing development projects for this market.



(a) Forecast of cobalt prices, according to individual (left panel) and combined (right panel) scenarios



(b) Forecast of lithium prices, according to individual (left panel) and combined (right panel) scenarios



(c) Forecast of nickel prices, according to individual (left panel) and combined (right panel) scenarios

Figure 10: Forecast of minerals' prices (USD/t) up to 2030, according to different scenarios

6 Concluding remarks

In this study, we have delved into the dynamics of some critical raw materials' markets – specifically cobalt, lithium, and nickel – within the evolving energy transition landscape of the United States. The urgency to address global warming, environmental degradation, and greenhouse gas emissions, as well as the ambitious goal of achieving Net Zero Emissions by 2050, has driven a significant surge in the demand for raw materials crucial for clean energy technologies. This shift towards greener alternatives is contingent on securing a sustainable supply of selected minerals and metals, thus driving the U.S. government to a strategic implementation of *ad hoc* policies. Among these, of particular relevance is the 2022 Inflation Reduction Act (IRA), which demonstrates the U.S. commitment to strengthening domestic production and diversifying supply chains for critical minerals through expanded mining, production, processing, and recycling.

Within this context, we have developed three distinct Structural Vector Autoregressive models, one for each mineral market, to assess the impact of energy transition-related policies on each mineral price. We have identified four distinct structural shocks, differentiating between mineral-specific supply shocks, aggregate demand shocks, mineral-specific demand shocks and aggregate supply shocks. To the best of our knowledge, this is the first structural exploration of the U.S. critical minerals market, accounting for both mineral-specific and aggregate economic shocks. We have also conducted a structural forecasting exercise, quantifying the effects of selected energy transition-related U.S. policies on the trajectory of battery mineral prices. Our forecasts are conditioned on various sequences of structural shocks up to 2030, corresponding to defined scenarios, providing a comprehensive spectrum of potential futures. Specifically, we have examined four different scenarios, and some combinations of them: *(a)* historical demand increase, *(b)* higher demand increase, *(c)* increasing production driven by U.S. government policies, e.g. the IRA, and *(d)* increasing production driven by the goal of achieving import independence.

Our research yields two key takeaways. Firstly, different mineral markets exhibit distinct dynamics, emphasizing the need to treat them as separate entities rather than a homogeneous group. Secondly, different policy combinations lead to heterogeneous price patterns over the forthcoming years. Our price forecasts are, by definition, conditional on the chosen scenarios. This follows from the definition of a structural forecast, which can be framed in the form of: "what would happen, if...?" and therefore does not provide the most likely outcome. For example, if the U.S. experiences an increase in demand which follows the historical trends, coupled by the ambitious production boost driven by U.S. public investments, prices of cobalt and lithium will decrease steadily. Conversely, nickel price is expected to remain high. This reflects the aim of U.S. policies, focused on strengthening the domestic production of cobalt and lithium, whereas less effort is devoted to nickel market expansion.

More research effort should be invested around the development of country-specific scenarios. In fact, most of the studies – including IEA technical reports – provide demand (and to a lesser extent, supply) estimations only at the global level (Calvo and Valero, 2022; Hund et al., 2023). Moreover, we acknowledge the importance of focusing on conditional forecasts targeting specific national policies, thus providing a useful tool for the evaluation of government strategies.

As the U.S. navigates the path toward cleaner energy, the insights around price dynamics gained from this study could provide valuable guidance for policymakers and industry stakeholders.

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A Descriptive statistics

Table A1: Summary statistics for the U.S. market variables

	Level					Log Difference				
Variable	Mean	Median	S.D.	Min	Max	Mean	Median	S.D.	Min	Max
USIP	65.31	61.20	26.86	20.17	102.20	0.03	0.03	0.04	-0.12	0.11
WIP minus USIP	44.34	48.98	18.75	7.916	71.161	0.034	0.03	0.052	-0.11	0.26
Cobalt prod.	1518.00	1580.00	1014.00	89.00	3510.00	0.00	0.01	0.30	-1.43	1.08
Lithium prod.	2460.00	2036.00	1569.00	329.00	5448.00	0.01	0.02	0.30	-0.87	0.77
Nickel prod.	71679.00	62100.00	37898.00	17420.00	155100.00	0.03	0.03	0.15	-0.34	0.43
Cobalt price	196.10	152.30	116.40	95.07	734.30	0.01	-0.03	0.32	-0.81	0.78
Lithium price	32.34	30.35	16.50	7.48	126.40	0.01	0.00	0.24	-1.13	1.00
Nickel price	52.05	47.27	21.44	24.51	159.70	0.00	-0.02	0.25	-0.58	1.02

Notes: Industrial production (for both U.S. and the entire world) is an index set at 100 in 2017. Minerals' production data are expressed in metric tons, while price data in dollar per ton, inflation adjusted.

Table A2: Test statistics (first line) and associated P-values (second line) of the Augmented Dickey-Fuller unit root test.

Variable	Level			Log Difference		
	ADF C	ADF CT	ADF CTT	ADF C	ADF CT	ADF CTT
USIP	-1.13	-2.88	-1.70	-6.07	-7.08	-7.02
	0.71	0.17	0.91	0.00	0.00	0.00
WIP minus USIP	-2.29	-1.65	-3.22	-5.04	-3.00	-0.09
	0.18	0.77	0.20	0.00	0.13	0.99
Cobalt prod.	-0.88	-3.38	-2.67	-4.63	-4.62	-4.82
	0.80	0.05	0.47	0.00	0.00	0.00
Lithium prod.	-1.72	-2.69	-0.12	-8.62	-8.53	-7.29
	0.42	0.24	1.00	0.00	0.00	0.00
Nickel prod.	-0.56	-2.46	-3.51	-8.12	-8.09	-6.98
	0.88	0.35	0.11	0.00	0.00	0.00
Cobalt price	-3.93	-3.91	-4.19	-7.50	-7.44	-4.23
	0.00	0.01	0.02	0.00	0.00	0.02
Lithium price	-0.21	0.74	-0.12	-2.94	-3.34	-5.32
	0.93	1.00	1.00	0.04	0.06	0.00
Nickel price	-3.04	-3.25	-3.96	-4.24	-4.21	-4.21
	0.03	0.08	0.04	0.00	0.00	0.02

Notes: The test is performed with inclusion of a constant (ADF C), constant and trend (ADF CT) and constant and quadratic trend (ADF CTT) testing down from 12 lags, for the seven level variables and the first differences of the natural log values.

We present a brief historical account of the evolution of U.S. production and price patterns of cobalt, lithium and nickel through time, in order to provide additional context for Figures 1 and 2, as well as the historical decompositions in Section 5.3.

Regarding cobalt, the U.S. has not produced primary cobalt since 1972, when the Missouri lead belt mines were shut down, until 2013, when the nickel-copper Eagle Mine in Michigan began production. The positive trend displayed in the aforementioned Figures relates to cobalt secondary (scrap) materials production, which accounts for most of the

U.S. cobalt production. From a pricing perspective, it is fundamental to keep in mind that the Democratic Republic of Congo (DRC) is the dominant producer, and, historically, prices have been influenced by political and civil events in this country. The "cobalt crisis" begun in 1975, the civil unrest in 1991, and the concerns about cobalt supply in 1996 all contributed to the several observed price spikes. A quick price collapse occurred in 2002-03 due to lower demand given weak economic conditions and high uncertainty following 9/11, as well as increased production in the previous years. In 2004, a decrease in cobalt production caused a new price peak. The last huge negative peaks happened in 2008-09 and 2019, driven by the increased demand for lithium-ion batteries, political instability in DRC, global financial turmoils, and the Covid-19 outbreak (only concerning the second peak). The current situation shows prices peaking right in 2022, due to an increasing demand. According to Benchmark Mineral Intelligence, cobalt market conditions have been weakening throughout 2023, with the growing global production (especially in DRC and Indonesia) contributing to lower prices.[20] For what concerns the current U.S. cobalt production, cobalt-bearing nickel has been produced in Michigan, and nickel-copper-cobalt concentrates in Missouri. In October 2022, commissioning began at a cobalt-copper-gold mine and mill in Idaho, where cobalt concentrate was expected be the principal product, but the operations were halted in April 2023, presumably due to the declining prices.

For what concerns lithium, the U.S. has been producing the metal since 1898 and was among the dominant producers up to the 1990s, when new significant operations came online in Chile and Argentina. Lithium demand was very low until the potential use of lithium in batteries for electric vehicles was first discussed in the 1970s, causing prices to begin rising, albeit only slightly.[21] After 2010, when lithium's use in battery applications greatly increased, prices have been trending upward, with a particularly steep pace in recent years. In terms of production, the United States went from being the largest primary producer and user of lithium in the world, to relying on imports of lithium in chemicals and industrial products (notice the significant decline in domestic production starting in the 1980s). This shift did not occur due to the exhaustion of domestic lithium resources but rather as a direct consequence of U.S. corporations' decision to move production to countries with cheaper labor and more relaxed environmental regulations, such as Argentina (Miatto et al., 2020). As of today, there is only one active lithium mine in the U.S., that is the Silver Peak Mine in Nevada. However, other companies are starting exploring lithium deposits in the U.S. and could potentially ramp up production in the future, especially thanks to the opportunity offered by geothermal brines.

In contrast to cobalt and lithium, nickel is produced in larger quantities in the United States. It is important to consider that nickel, besides being a key metal in the energy transition, is also a critical commodity for a broader set of applications, including its use as a fundamental resource in wartime. In fact, nickel is employed to produce super-alloys for engines propelling jet aircraft, guided missiles, and some space vehicles, as well as high-performance batteries. Consequently, during war periods (e.g. the Korean Conflict), U.S. nickel happened to be under government allocation, resulting in a relatively

[20] Benchmark Mineral Intelligence, 2023 in review: `https://source.benchmarkminerals.com/article/cobalt-price-rout-deepens-in-2023-as-oversupply-weak-ncm-demand-looms-2023-in-review?mc_cid=2a16054797&mc_eid=99397ec972`

[21] Before that, lithium was mainly used as an additive in the aluminium smelting process, as an ingredient in pharmaceutical products to treat manic depression, and in the manufacture of high-strength glass-ceramic products.

flat price trend (e.g. during 1953-1961). Domestic production has historically followed an upward trend, thanks to the continuous opening of new production facilities, which has also helped to keep prices relatively low and stable over time. However, in 1987-1988, increased demand for stainless steel, coupled with a decrease in production, caused a sudden increase in prices. Subsequently, increased production of both primary and secondary (scrap) nickel during the following years, due to the discovery of new deposits and the development of novel technologies, kept prices stable and low. However, from 1999 to 2012, U.S. primary production of nickel was zero, with all the reported production resulting from secondary (scrap) materials. During this period of stagnating production, prices peaked especially in 2007-09 when increasing global production of stainless steel created a temporary nickel supply deficit. After 2012, the U.S. resumed nickel production, thanks to the opening of a greenfield underground operation in Michigan (the nickel-copper Eagle Mine, which was further expanded in 2019). Nevertheless, prices peaked again in 2021. In terms of future developments, an important project is currently approaching the environmental review and permitting phase. A new underground mine would extract nickel ore in Minnesota, which would then be processed in another new plant in North Dakota.

B US policies on critical minerals

The Inflation Reduction Act (IRA) represents the largest federal response to climate change to date. The whole energy sector is potentially affected by IRA incentives, from the mining of raw materials, to end-users purchasing EVs. In many instances, IRA extended and expanded existing programs (e.g. the Department of Energy's Loan Guarantee Program or the Defense Production Act). In some cases, it introduced entirely new programs. Among the fiscal costs of the climate-related provisions ($392 Billion), 2/3 will be in the form of tax credit, and the remaining 1/3 will be direct expenditures. Tax credits include investments in clean electricity generation and storage, clean energy and efficiency incentives for individuals, clean vehicles, and clean energy manufacturing. Direct expenditures will cover energy loans and initiatives for energy efficiency and industrial decarbonization.

The IRA will have direct and indirect impacts on the domestic mining landscape. On the one hand, a direct push will come from subsidies and production incentives (e.g. Minerals Security Partnership, Infrastructure Law). On the other hand, support for clean energy and national EV manufacturing is also contingent on using at least partially US-made minerals, battery components, and vehicles themselves. This market pull mechanism will indirectly influence domestic production.

One notable example of market pull mechanism is the provision of clean vehicle tax credits (Section 13401). The IRA allows taxpayers to claim credits up to $7,500 for purchasing a new electric or hydrogen fuel cell vehicle, subject to several specific conditions. These conditions include the requirement that the final assembly of the vehicle takes place in North America, and a portion of both the critical minerals and the battery components must originate from North America, with this share escalating over time after 2024.[22] This creates a pathway for growing EV demand (and consequently, demand for critical minerals), while also necessitating an increased use of domestically sourced

[22]In the case of critical minerals, after 2026, 80% of their market value in the EV battery has to be extracted or processed in the U.S. or any of the 20 free-trade countries.

critical minerals in the batteries of such EVs.

Among the direct incentives, we highlight the following:

- Advanced manufacturing production credit (Section 13502). Starting from 2023, this provides a 10% tax credit on production costs to any miner/producer of critical minerals in the United States. The Congressional Budget Office (CBO) estimated that this tax credit will result in tax expenditures of approximately $30 billion.

- Up to $500 million for the "Enhanced use" of the Defense Production Act (DPA) to strengthen the U.S. supply chain of critical minerals. This enables the Department of Defense to use DPA funds to support: (1) feasibility studies for mature mining, beneficiation, and value-added processing projects; (2) by-product and co-product production at existing mining, mine waste reclamation, and other industrial facilities; and (3) mining, beneficiation, and value-added processing modernization to increase productivity, environmental sustainability, and workforce safety.

- Additional $40 billion to the Department of Energy (DOE) Loan Guarantee Program, to accelerate the deployment of innovative clean-energy projects, including critical minerals projects and processing. The Loan Programme Office (LPO) has already facilitated the deployment of innovative clean energy, advanced transportation, and tribal energy projects, having closed more than $30 billion of deals over the past decade.

The IRA is coupled with the grants provided through the bipartisan Infrastructure Investment and Jobs Act (P.L.117-58), mostly known as Bipartisan Infrastructure Law. Specifically, the DOE has selected more than 20 projects to receive almost $3 billion in total funding through the BIL - Battery Materials Processing and Battery Manufacturing, "to make more batteries and components in America, bolster domestic supply chains, create good-paying jobs, and help lower costs for families".

With this in mind, we selected projects under development in the U.S. that received significant public funding from the programs described above. The underlying rationale is that these projects became feasible specifically thanks to the U.S. government's support, and by aggregating their expected production, we gain insight into the promised production increase for constructing an IRA-centered scenario.

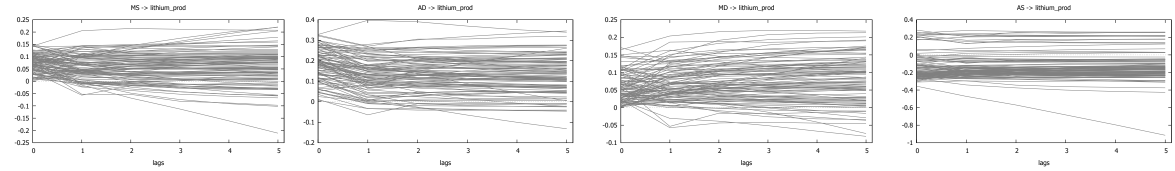
Out of a total of 182 projects being developed (note, not already operating) in the U.S. related to the EV supply chain (Turner, 2022), we selected 32 that involve the extraction or processing (note, not recycling) of either cobalt, lithium or nickel. Among these, 11 received either public funding or public support (for example, directly mentioned in the DOE's "Securing a Made in America Supply Chain for Critical Minerals" document). The majority of the selected projects concerned lithium production, with 2 dedicated to cobalt, and 2 to nickel. The full list is reported in Table B1.

Table B1: Minerals projects financed by the U.S. Government

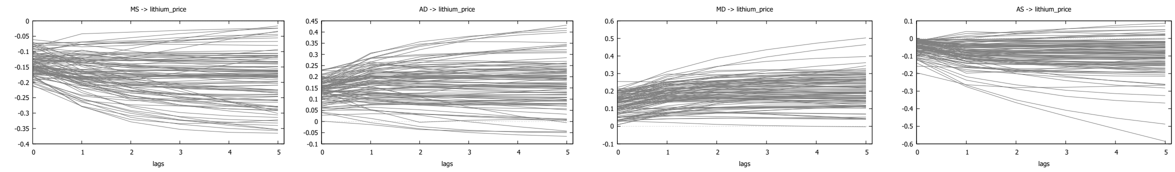
Key Mineral	Target Year	Facility/ Project Name	Company	City	Total (public) Investment ($M)	Gov.t Programme	Target annual production (tons)
Co	2022	Idaho Cobalt Operations	Jervois	Lemhi County (ID)	107.5 (15)	DPA	1,900
Li	2024	Texas Lithium Refinery	Tesla	Corpus Christi (TX)	375	Announced post-IRA	2,000
Li	2025	Hell's Kitchen Project	Controlled Thermal Resources	Imperial County (CA)	(4.46)	DOE[a], CEC[b]	25,000
Li	2025	Rhyolite Ridge Lithium-Boron	Ioneer	Rhyolite Ridge (NV)	785 (700)	LPO	22,000
Li	2025	Project ATLiS	Energy Source Minerals	Imperial County (CA)	660	DOE[c]	19,000
Li	2025	Tennessee Lithium	Piedmont Lithium	Etowah (TN)	600 (141)	BIL	30,000
Li	2026	Tonopah Flats Lithium	American Battery Technology	Tonopah (NV)	115 (57)	BIL	5,000
Co	2026	Ev. En. Cobalt Processing Plant	Evelution Energy	Tacna (AZ)	200	Announced post-IRA	7,000
Ni	2026	Battery Minerals Processing Facility	Talon Metals	Mercer County (ND)	433 (114)	BIL	12,500
Li	2029	Kings Mountain Lithium Processing Plant	Albemarle	Kings Mountain (NC)	374 (149)	BIL	50,000

[a]Securing a Made in America Supply Chain for Critical Minerals
[b]California Energy Commission
[c]Securing a Made in America Supply Chain for Critical Minerals

C Robustness checks

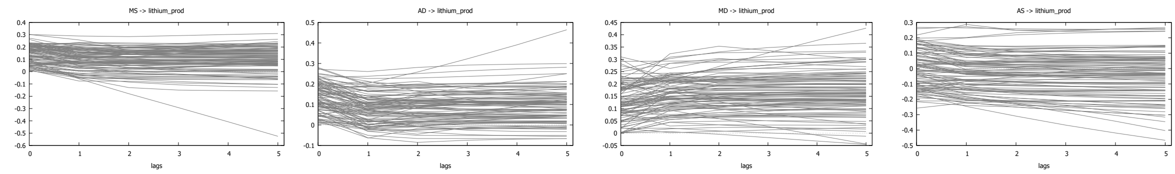


(a) Shocks impacts on lithium production

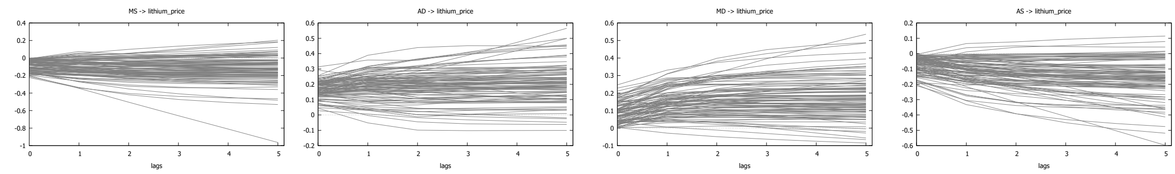


(b) Shocks impacts on lithium price

Figure C1: Cumulated IRFs, lithium market, identification strategy with U.S. GDP instead of Industrial Production Index

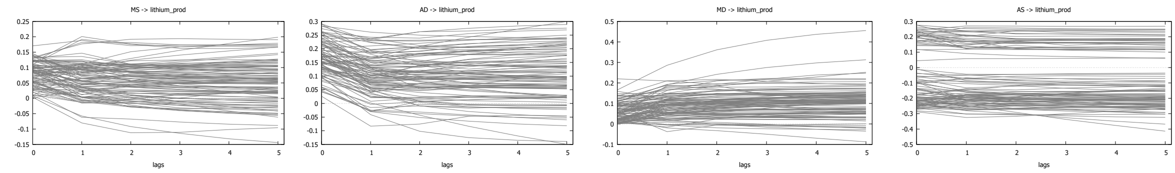


(a) Shocks impacts on lithium production.

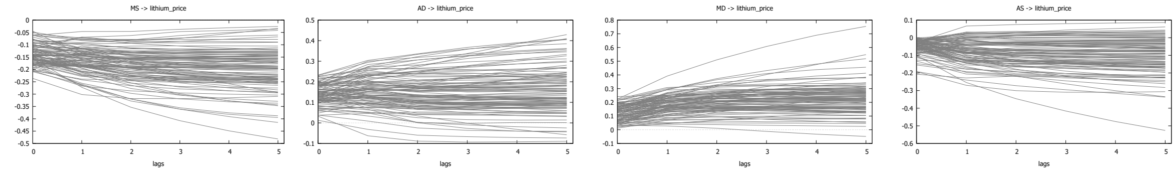


(b) Shocks impacts on lithium price

Figure C2: Cumulated IRFs, lithium market, identification strategy without elasticity bounds

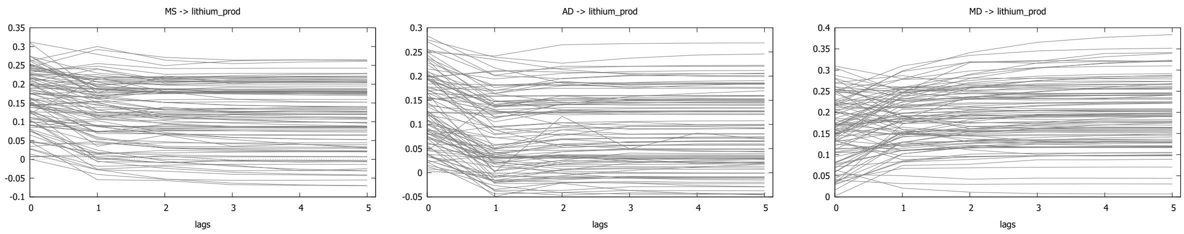


(a) Shocks impacts on lithium production.

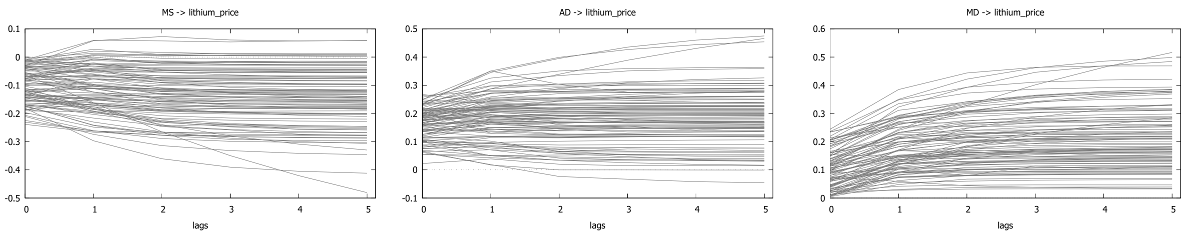


(b) Shocks impacts on lithium price

Figure C3: Cumulated IRFs, lithium market, identification strategy with shorter time interval (1972-2022)

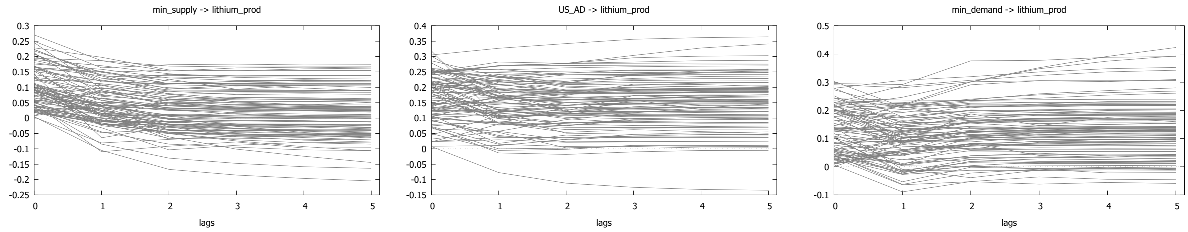


(a) Mineral supply, aggregate demand and mineral demand shocks on lithium production

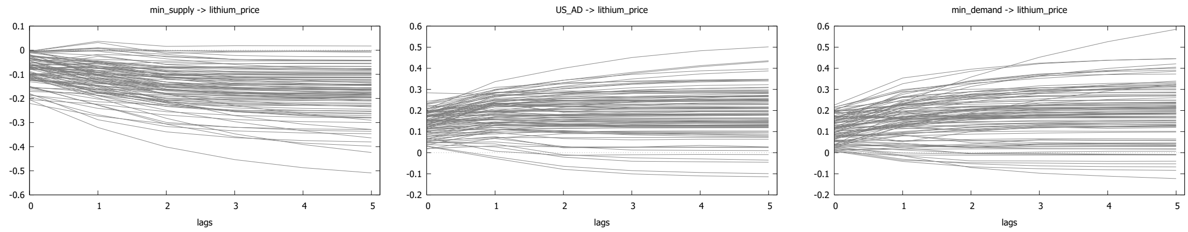


(b) Mineral supply, aggregate demand and mineral demand shocks on lithium price

Figure C4: Cumulated IRFs, lithium market, identification strategy: sign restrictions, three-variables model without U.S. inflation



(a) Mineral supply, aggregate demand and mineral demand shocks on lithium production



(b) Mineral supply, aggregate demand and mineral demand shocks on lithium price

Figure C5: Cumulated IRFs, lithium market, identification strategy: mix of sign and zero restrictions, four-variables model without U.S. inflation and with cotton price as anchor variable

Contact.

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