Empirical Analysis On Green Strategic Commodity Metal, Cobalt System Equation – 3SLS

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Contents

Abstract

The United Climate Change conferences have increasingly emphasized the urgency of addressing global warming and transitioning towards a green economy. This shift has led to a rise in the importance of strategic green metals like cobalt, lithium, and nickel, essential in electric vehicle batteries and renewable energy technologies. Cobalt, in particular, has seen a surge in demand due to its efficient energy storage capabilities. This paper aims to study the impact of macroeconomic and microeconomic indicators on cobalt, focusing on the supply and demand dynamics that global economic developments have influenced. The study employed a system of equations - three stages least square (3SLS) model to understand the outcomes obtained from the technique.

Keywords : three stages least square, cobalt price, cobalt production, GDP per capita, global sales of electric vehicles, nickel production, China's policy interest rate, and conflicts in the DRC.

1 Introduction

The United Climate Change conferences, which are held with the support of the United Nations, have hosted more recurrent meetings than ever. Over the past two decades, the number of conferences has tripled in the 21^{st} century compared to the $20^{th} century$(UNCC,2024). Several nations signed multinational agreements. For instance, the Paris Agreement, the Kyoto Protocol, Europe 2020, COP27, COP28, etc.(Atwoli et al., 2022). All are stressing the urgency of tackling the decarbonization of the global economy and achieving long-term sustainability by leveraging cutting-edge technologies. In recent years, global developments have increased greenhouse gas emissions and furthered accelerated climate change and global warming (Fu et al., 2021). While the African continent has contributed to 3% global pollution, North America and Europe have contributed to 65% of carbon dioxide emissions since the Industrial Revolution (Atwoli et al., 2022). With this in mind, the focus has been on reducing CO2 emissions. According to Our World In Data, the energy sector is the leading CO2 emitter at 24.2%, followed by transportation at 16.1%, and both industry and agriculture(Land use and forestry) sectors, respectively 12% and 18.2% (Ritchie et al., 2020). The concentration of CO2 emissions in the energy and transportation sectors clearly shows where green governmental solutions should be targeted to intensively deplete emissions production and achieve net zero emission targets in the long term.

The Energy and Electric Vehicle revolutions have been undertaken to decarbonize the global economy. To curb this phenomenon, government solutions are concentrated on energy mechanisms that emit fewer greenhouse emissions, such as battery-dominated energy by automobiles, energy grid generation infrastructure such as solar panels, wind turbines, grid storage, charging infrastructure, etc. (Glencore, 2018). Three nonferrous metals, commonly Lithium, Nickel, and Cobalt, received particular attention as they are indispensable in the new age of batteries for electric vehicles and renewable energy. These earth metals are an integral part of global consumption, such as home appliances, automobiles, aircraft, military applications, coinage, electronic devices, etc. Lithium is essentially used for its energy storage properties. Nickel has a high level of anti-oxidation and corrosion making it a vital metal for vehicle production. Cobalt is also preferred for its ability to store renewable energy efficiently. It is produced as a by-product of other base metals such as Nickel and Copper (Swarup at al., 2023). In 2030, the forecast for metals requirement expects 1.1 metric tons of Nickel or 56% supply of 2016 and Cobalt 314 kilotons or 314% of 2016 supply (Glencore,2018). The expected demand driven by the EV revolution will increase the volatility of these earth materials as governments align behind the net zero emission target. The Inflation Reduction Act, known as IRA, proposed USD 1.6 trillion to counter climate change and USD 160 billion to update infrastructure that will support the demand for Lithium, Cobalt, Nickel, graphite, and Copper by 2024. IRA is expected to increase the demand for those strategic green metals Lithium, Nickel, and Copper by 23% in 2035 (Oregon Inst., 2023). A recent study observed seven earth materials to determine whether their sensitivity or elasticity is linked to price or consumer levels and found that commodities mainly depend on income level (Fernandez, 2018). As future demand is expected to grow, the adoption of electric vehicles and reusable energy behaviors among consumers will further increase the volatility of those strategic materials.

This paper aims to study the effects of microeconomic and macroeconomic indicators on one of these commodities, particularly Cobalt. Recent global developments put pressure on the demand and supply side of these metals. Cobalt supply and demand grew from 2016 to 2022 by 94% and 490%, respectively (IEA,2023). The green transition is no longer out of the question, and the manufacturing of Lithium Electric vehicle batteries has reached an all-time high (Pistilli, 2023). According to IEA (2023), In 2022, about 60% of lithium, 30% of cobalt, and 10% of nickel demand was for EV batteries. Just five years earlier, in 2017, these shares were around 15%, 10%, and 2%. The Cobalt Institute (2021) stated that electric vehicles consumed 59,000 tons of cobalt, or 34% percent of the global supply, compared to 26,000 tons for cell phones and 16,000 tons for laptops. The report depicts the wide gap in the quantity demanded of Cobalt by sector and stresses the spike in demand for electric vehicles. The International Energy Agency identified Lithium, Nickel, Manganese, and Cobalt oxide or NMC remained dominant battery chemistry with a market share of 60%. However, other car manufacturers are looking for cheaper alternatives by making batteries without Cobalt (Carson, 2024), using Lithium, Iron, and Phosphate or LFP with a market share of 30% of batteries. For instance, electric vehicle automaker BYD makes up 50% of the demand for LFP batteries, while Tesla accounted for 15% and increased its usage of LFP to 30% in 2022(IEA, 2023). Though these alternatives hedge against the risk of relying on cobalt, they provide cheaper production costs, less energy density, and reduced long-range energy performance compared to NMC batteries (Carson,2024). Moreover, essential players in cobalt ore production are critical to maintaining global supply. The US Geological Survey (2024) identified 25 million tons of world terrestrial Cobalt resources, with the vast majority in the Democratic Republic of the Congo or Congo (Kinshasa) and Zambia. Congo (Kinshasa) accounts for more than 70% or 170,000 metric tons of world Cobalt production, followed by Indonesia with 7% or 17,000 metric tons, Russia with 4% or 8,800 metric tons, Australia 2% or 4,600 metric tons (USGS,2024). Furthermore, China is the leading consumer of Cobalt, where the Lithium Ion battery industry uses 87% of the consumption and possesses 65% of the world's cobalt refineries (USGS, 2024). According to the China Global South Project, China has 65% or 18 mining projects in the Democratic Republic of the Congo with the total transaction estimated at USD 20 billion (2022). The major Cobalt mines are Kamoto Copper Company SARL, Compagnie de traitement des rejets King Yamba, Teke Fungurume Mining, and Mutanda mining (CGSP, 2022). While the abundance of the earth metal lures global perception, the reality depicts a different picture of a robust supply chain. The concentration of supply in Congo (Kinshasa) makes the production and price vulnerable to externalities. The price volatility is caused by recent government initiatives, and historical data suggests that conflicts in the DRC mined regions harm the commodity's price (Cavelor, 2021). Human rights issues surfaced in the mining regions, such as Kolwezi, Lubumbushi territory, and Likasi, with child labor and poor mining conditions (Raleigh, 2023). Therefore, automakers are more likely to distance themselves due to those growing concerns caused by unregulated artisanal Cobalt mining, which contributes to the production in the Congo. In 2020, the local government set up a watchdog agency to regulate all the artisanal mining exchanges, but the project hasn't gotten off the ground yet (Pistilli,2024).

The post-Covid-19 pandemic era has witnessed an accelerated push to transition to a greener and more sustainable global economy, and it is attainable by the extensive use of earth metals such as Lithium, Cobalt, and Nickel in cutting-edge technologies concentrated in transportation and energy generation. The demand and supply of cobalt are the targets of this study. The focal point of this study revolves around how macro-economic and micro-economic indicators induce the price and production of this strategic green commodity.

2 Literature Reviews

Numerous thorough and tedious research series were conducted to forecast commodity prices and study the effect of exogenous variables as they are proved dependent on outside factors(Searle,1998). A study on the effects of battery recycling on the Global Cobalt market unveils intriguing findings. It stresses the importance of recycling previously mined cobalt to increase supply and further stabilize its price volatility as it is prone to conflicts in the Democratic Republic of the Congo, dependence on China's refinery processing with 65% share of the world refinery (Cavelor, 2021). The empirical study uses a three-stage least squares system equation or 3SLS to observe the effect of endogenous variables on the demand for Cobalt. According to Cavelor (2021), this study also reiterates using instrumental variables to export the covariance from the error terms and enhance the precision of the said system equation. The 3SLS estimates are more consistent, asymptotically normal, and more efficient than single equation estimates (Bakhsh, 2017). In 1993, new pressure was identified for several projects to reinvigorate the Cobalt by-product supply by redeveloping the Nickel, Copper, and Cobalt mining industries in Africa (Searle, 1998). Outside factors, as stated in the research, affect the nature of the price of the commodity, making Cobalt influenced by exogenous variables. Cavelor (2021) suggests the addition of a supply equation with proxy variables to capture the covariance in error terms to enhance coefficient estimates to capture outside factors not found in the demand equation. According to Cavelor. Tests of the endogeneity of instruments in both the supply and demand equation indicate an endogeneity problem exists in the regression; therefore, an instrumental variable is preferred over the Ordinary Least Square model (Zhu,2012). In the end, the author pointed limitation of data accessibility as some variables were not added to capture outside effects on cobalt price. As suggested, nickel production, and framing the conflicts in the DRC regions with dummy variables will be considered for the supply equation.

Within the machine learning spectrum, natural language processing models have been applied to predict price volatilities of commodities such as LSTM networks GR networks, ARMA, etc. For forecasting commodities by using price shocks and dynamics to forecast future trends. These neuron network models rely on lag values for better performance, and a gap would mean otherwise(Swarup at all, 2023). A study on forecasting evaluates the medium-term and long-term impact of crude oil on commodities Nickel and Cobalt using a Temporal Fusion Transformers neural network model, TFTs, that integrates an extra layer architecture LSTM, a class neuron network developed for natural language processing applications. The model has great attention mechanisms and focuses on the most critical data to capture long-term relationships between lag variables. The study shows dependencies of commodity prices relying on variation to perform forecasts (Swarup at al.,2023). The study undermines some outside shocks as commodities respond to exogenous variables (Cavelor,2021). The author stresses the poor performance of the forecast model as it favors key features to gauge future values. (Swarup at. Al, 2023) . Considering the remarks, the system equation model of this research will contain lag-dependent variables to capture shock dependencies.

3 Econometric Model, Hypotheses, and Methodology

3.1 Econometric model

- Demand Equation

$\ln(CB_{Price})_t = \beta_{10} + \beta_{11} GDP_(capita)_t + \beta_{12} \ln(GEV)_t + \beta_{13} \ln(CB_{prod})_t + \beta_{14} \ln(CB_{Price})_{t-1} + \mu \ln(CB_{Price})_t$

- Supply Equation

$\ln(CB_{prod})_t = \delta_{20} + \delta_{21} R_{CHN_t} + \delta_{22} \ln(NKL_{prod})_t + \delta_{23} Conflicts_{(DRC)_t} + \delta_{24} \ln(CB_{price})_t + \delta_{25} \ln(CB_{prod})_{t-1} + \epsilon \ln(CB_{prod})_t$

- Instrumental Variables

$GDP_(capita)_t$, $\ln(GEV)_t$, $\ln(CB_{Price})_{t-1}$, R_{CHN_t}, $\ln(NKL_{prod})_t$, $Conflicts_{(DRC)_t}$, $\ln(CB_{prod})_{t-1}$.

3.2 Hypotheses

Based on the above discussion, the study focuses on the effects of economic indicators on cobalt. Correctly identifying those effects is observed through a system equation in which the fundamental interaction of the demand and supply equation determines the underlying price. The global gross domestic product per capita represents global welfare advancements in one individual purchasing power that will have a significant positive impact on the price of the metal. The rise in the production of electric vehicles supported by government initiatives to tackle greenhouse gases will positively affect the commodity's price. Moreover, the China interest rate is considered the cost of financing for mining companies and is expected to impact the cobalt production level negatively. Nickel production is anticipated to positively affect Cobalt production as Cobalt is a by-product of other metals such as Nickel. Conflicts in the mining regions are expected to hinder global Cobalt production. As for the endogenous variables, the production of cobalt will have a direct effect on the price level as well as the price will positively influence the production of the commodity. The lag-dependent variable of the price of cobalt should have a positive effect on its current price, while the lag-dependent variable of cobalt production to production level should have a positive effect.

3.3 Methodology

The study implements a three-stage least Square Model or 3SLS to estimate the effects of economic variables Cobalt. The particularity of a 3SLS model lies in exporting the structural covariance matrix of the error terms of two or more equations to each coefficient. The joint estimation's main benefit permits estimating coefficients more accurately with more minor standard errors. The point of difference with a 2SLS model is that it avoids the correlation in the error term by using proxy variables, which resolves the endogeneity issue. That is, at least one independent variable is correlated with the error term, so to remediate the problem of endogeneity, instrumental variables or IV are leveraged to ensure that when $Cov(X_i, \mu_i) \neq 0$ where $Cov(X_i, Z_i) \neq 0$ and $Cov(Z_i, \mu_i) = 0$ to make $Cov(X_i, \mu_i) = 0$. Overall, a 2SLS model exports the covariance of instrumental variables to one single equation to reduce variance and estimate the coefficients of each structural equation individually (Cavallero, 2021). For the variance to be reduced, proxy variables ought to be correlated. Conversely, the 3SLS estimates equations jointly and exports the correlation of the error terms of each equation. Bakkash (2017) states that the 3SLS us more efficient than the 2SLS as the model allows correlation between unobserved disturbances across various equations. Moreover, the covariance structure is the matrix of the correlation of error terms between two or more equations.

For a system equation using a 3SLS model, suppose :

- n = the number of observations
- Y_i = dependent variables.
- X_i = exogenous variables.
- B_i = coefficients for both the demand and supply equations.
- U_i = error terms for the demand and supply equation.

The matrix is represented as follows:

Given that,

$$Y_{it} = X_{it}\beta_i + \mu_{it}$$

$$\ln(CB_{price})_t = \beta_{10} + \beta_{11} GDP_{(capita)_t} + \beta_{12}\ln(GEV)_t + \beta_{13}\ln(CB_{prod})_t + \beta_{14}\ln(CB_{price})_{t-1} + \mu_{\ln(CB_{price})_t} \quad (1)$$

$$\ln(CB_{prod})_t = \alpha_{20}+\alpha_{21}R_{(China)_t}+\alpha_{22}\ln(NKL_{(prod)})_t+\alpha_{23}Conflicts_{DRC}+\alpha_{24}\ln(CB_{price})_t+\alpha_{24}\ln(CB_{prod})_{t-1}+\epsilon_{\ln(CB_{prod})_t} \quad (2)$$

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} 1 & X_{11t} & X_{12t} & X_{13t} & X_{14t} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & X_{21t} & X_{22t} & X_{23t} & X_{24t} \end{bmatrix} \begin{bmatrix} \beta_{11} & 0 \\ \beta_{12} & 0 \\ \beta_{13} & 0 \\ \beta_{14} & 0 \\ 0 & \alpha_{21} \\ 0 & \alpha_{22} \\ 0 & \alpha_{23} \\ 0 & \alpha_{24} \end{bmatrix} + \begin{bmatrix} \mu_i t \\ \epsilon_i t \end{bmatrix} \quad (3)$$

Suppose the covariance structure in the error terms:

$$\begin{bmatrix} \mu_i t \\ \epsilon_i t \end{bmatrix} = \sum \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \quad (4)$$

where

$\sigma_{11} = Var(\mu_{\ln(CB_{price})_t})$
$\sigma_{22} = Var(\epsilon_{\ln(CB_{prod})_t})$
$\sigma_{12,21} = Cov(\mu_{\ln(CB_{price})_t}, \epsilon_{\ln(CB_{prod})_t})$

Thus the covariance matrix can be estimated by:

$\hat{\sigma}_{11} = \frac{1}{n}\sum_{i=1}^{n} \hat{\mu}_i^2$
$\hat{\sigma}_{22} = \frac{1}{n}\sum_{i=1}^{n} \hat{\epsilon}_i^2$
$\hat{\sigma}_{12,21} = \frac{1}{n}\sum_{i=1}^{n} \hat{\mu}_i^2 \ \hat{\epsilon}_i^2$

$$\begin{bmatrix} \hat{\mu}_{it} \\ \hat{\epsilon}_{it} \end{bmatrix} = \hat{\sum} \begin{bmatrix} \hat{\sigma}_{11} & \hat{\sigma}_{12} \\ \hat{\sigma}_{21} & \hat{\sigma}_{22} \end{bmatrix} \quad (5)$$

Furthermore, the covariance matrix of the error terms allows correlations between unobserved shocks between two or more equations, and the model avoids the problematic issue of endogeneity (Ren et al, 2021). The robustness of the model relies on leveraging unobserved variables. According to Zhu, under the 3SLS most of the instrumental variables are robust, indicating that most are strong and reliable (2012).

Another important concept in econometrics when dealing with time series data is its non-stationary characteristic. The usage of non-stationary variables in regression analysis can lead to the appearance of pseudo-regression (Ren et al., 2021). In this study, the chosen variables will undergo a unit root test to determine whether or not the variables are stationary before running any regression. A measure to address non-stationary problems is using a difference equation model achieved through an ARMA(p,q) model, assuming all the characteristics are within the unit root circle. if p=0 , the process suggests an autoregressive model AR(p) and if q=0, the process is a moving average MA(q). In addition, the difference equation suggests that Y_t is non-stationary in terms of the ϵ_t.

The Unit root tests are determined by performing the Augmented Dickey-Fuller or ADF test. However, the limitation in the number of observations, 33, does not satisfy unit root tests because non-stationary is a long-run property.

Under the Gauss Markov Theorem, MLR 5, requires that both homoskedasticity and serially uncorrelated errors, where the variance of the error term is all the same for all observations $Var(\mu_i|X_{i1},...,X_{ik}) = 0$ (Jeffrey et al, 2019). That is, the usual OLS standard errors, and test statistics are not valid and even asymptotically. If the serial correlation is ignored, the variance estimator will be biased. The use of the lagged differences allows for controlling for the serial correlation.

Given that :

$\delta Y_t = \gamma\ Y_{t-1} + \epsilon_t$

$\epsilon_t \sim AR_{(1)} : \epsilon_t = \lambda\epsilon_{t-1} + e_t,\ e_t \sim WN(0, \sigma^2)$

$\delta Y_{t-1} = \gamma\ \epsilon_{t-1}$

Under the assumption that $H_0(\lambda = 0) : \delta Y_t = \epsilon_t$

$$\delta Y_t = \gamma\ Y_{t-1} + \lambda\ \delta Y_{t-1} + e_t \tag{6}$$

4 Data Sources

The data ranges from 1990 to 2022 annually and originates from the following sources:

- Federal Reserve Bank of Saint Louis, **FDRS.**
- Bloomberg Terminal,**BBG.**
- British Geological Survey, **BGS.**
- United States Geological Survey, **USGS.**
- Armed Conflict Location and Event Data Project, **ACLED.**
- International Monetary Fund, **IMF.**

Table 1: Data Sources Table

Attribute	**Attribute Definition**	**Source**	**Unit**
CB_{Pr}	Global Cobalt Price	IMF	USD/ton
CB_{Prod}	Global Cobalt Production	BGS and USGS	Metric ton
NKL_{prod}	Global Nickel Production	BGS and USGS	Metric ton
GEV_s	Global Electric Vehicles sold	BBG	Million
R_{CHN}	China Interest Rate	BBG	Percentage
C_{DRC}	Congo Kinshasa Conflicts	ACLED	Dummy(0,1)
GDP_{Capita}	Global GDP Per Capita	FDRS	Percentage

Data composition is relevant to this study in exploring the effects of economic indicators on the global demand for the metal Cobalt. As shown in Table 1, On the demand side, the global cobalt ore price, the variable of interest, represents the market price an investor is willing to pay per metric ton. The global gross domestic product per capita is of interest to capture the breadth of the demand for the metal relative to global societal wealth fare per individual (purchasing power) when the global economy navigates recessionary, stationary, and expansionary phases. The variable is also used as a proxy to capture the demand for the commodity in other sectors as people's wealth increases. At the time of capture, GDP per capita is expressed in percentage change. The data novelty of the Global sales of Electric Vehicles is crucial to observe its effect on the price of the commodity as the International Energy Agency report outlined new registrations of electric vehicle car passenger sales increased 55% in 2022 relative to 2021 (2023). The data is expressed in millions of electric vehicles sold and grouped by regions capturing North America, Asia Pacific, Western

Europe, the Middle East, and other regions. Recent records show data tracking started in 2010. However, the data was overlaid to fill in data gaps. The Global Production of Cobalt is recorded in metric tons on the supply side. It encompasses the total world production from mining projects in different regions, such as Indonesia, Australia, Russia, Madagascar, Morocco, and Congo Kinshasa producing 70% of the world metal supply (USGS, 2024). Cobalt is produced as a by-product of Nickel for battery production making their prices more in synchronization. The global Nickel production is expected to amount to 37% by 2030 from its 2017 level (Swarup, 2023). As Nickel production is ramping up due to high demand for electric vehicles and batteries, it serves as a suitable attribute to track Cobalt production. As extracted from the Bloomberg terminal, China's interest rate was retrieved from the People's Bank of China, which is the 1-year loan prime rate serving as the benchmark lending rate since August 2019 (2024). The cost of capital for mining projects is the interest rate. Mining companies leverage loans to finance multiple expansionary projects, and interest rates are central when seeking financing. China owns 18 mines in the Democratic Republic of the Congo that exploit Cobalt (China Global South Project,2022). A high-interest environment rate can force companies to adopt conservative measures. The Conflict attribute is a dummy variable generated from the ACLED report. The recorded dummy variable meticulously captured conflictual events in Cobalt mining regions, such as in the Shabba, Katanga provinces, Lualaba, and Haut-Katanga regions (Raleigh, 2023). The stability in the Democratic Republic of the Congo is detrimental, especially in the mining regions, to avoid supply chain disruption, which can lead to price volatility.

Table 2: Descriptive Statistics

	CB_P	**CB_PROD**	**NKL_PROD**	**GEV**	**R_CHINA**	**GDP_PERCAP**
Mean	31563.57	82004.39	1679111	610102.3	5.600991	1.599310
Median	30580.00	59952.00	1432046.0	280869.0	5.580000	1.793330
Maximum	72632.05	197000.0	3270000.0	6450512.0	12.60000	5.311520
Minimum	6551.136	23167.00	892927.0	32.00000	0.000000	-4.030070
Std. Dev.	17360.40	51758.99	699187.6	382827.9	2.639965	1.659241
Skewness	0.965116	0.423117	0.727185	1.923443	0.053883	-1.322341
Kurtosis	3.446109	1.730923	2.370210	6.202059	4.107749	6.584906
Observations	33	33	33	33	33	33

The correlation matrix from Table 3 depicts a distinct relationship between variables. Within the realm of economics, a high correlation leads to biased estimates, which should be avoided. Multicollinearity is when

Table 3: Correlation statistics

Correlation	CB_P	CB_PROD	NKL_PROD	GEV	R_CHINA	CONFLICTS	GDPcap
CB_P	1.000000						
CB_PROD	0.482476	1.000000					
NKL_PROD	0.473871	0.907827	1.000000				
GEV	0.367087	0.399262	0.304323	1.000000			
R_CHINA	-0.017691	-0.237285	-0.162733	-0.001447	1.000000		
CONFLICTS	0.069321	0.154469	0.239880	-0.016791	-0.469057	1.000000	
GDPcap	0.345959	0.070934	0.119720	-0.073602	0.195928	-0.164973	1.000000

two or more independent variables are highly correlated and do not satisfy MLR 3 no perfect collinearity (Jeffery et al., 2019). The author outlined the inefficiency of a model where predictors are correlated with one another by clouding estimates and inflating the variance of coefficients, causing model misspecification (2019). Table 3 shows low correlation coefficients, even though CB_{prod} and NKL_{prod} have a 0.91 correlation score. However, it will not impair the model as CB_{prod} is the dependent variable of interest in the supply equation. Moreover, with acceptable correlation coefficients, there is no need to test for multicollinearity.

5 Empirical Analysis and Results

5.1 Empirical analysis

The theoretical analysis laid the foundation and structure of this research which will be applied to properly estimate the green commodity metal demand and supply equations. Through a thorough understanding of the processes, first, the ADF test of each variable should be performed to determine whether variables are stationary or non-stationary. However, a unit root process requires a large sample size because the unit root test becomes unreliable by not being able to distinguish between non-stationary and stationary as it relies on asymptotic theory which assumes large sample sizes. Second, the 3SLS model containing supply and demand equations should follow. Third, the 3SLS will undergo a serial correlation test for both equations to control for heteroskedasticity. Finally, the 3SLS model will be rerun to obtain the final model with proper estimated coefficients.

5.1.1 Serial correlation test

The residuals for the demand and supply equations from the correlogram Q-statistics are individually evaluated through a correlogram test to determine whether it is necessary to control for serial correlation. In addition, tables 4 and 5 do not indicate any serial correlation in the lag tern residuals of both the supply and demand equation for cobalt. Their p-values are respectively insignificant at 10%, 5%, and 1% significance level. Therefore, the 3SLS model does not suffer from serial correlation.

Table 4: Serial Correlation Test Results for LN(CB_price)t

Lag	**AC**	**PAC**	**Q-Stat**	**Prob**
1	-0.107	-0.107	0.4020	0.526
2	-0.333	-0.349	4.4320	0.109
3	0.151	0.076	5.2881	0.152
4	0.125	0.044	5.8940	0.207
5	-0.256	-0.187	8.5420	0.129
6	-0.044	-0.061	8.6226	0.196
7	-0.168	-0.394	9.8528	0.197
8	0.060	-0.012	10.015	0.264
9	0.086	-0.060	10.367	0.322
10	-0.061	-0.054	10.550	0.394

Table 5: Serial Correlation Test Results for LN(CB_prod)t

Lag	AC	PAC	Q-Stat	Prob
1	-0.038	-0.038	0.0502	0.823
2	-0.043	-0.045	0.1180	0.943
3	-0.120	-0.124	0.6618	0.882
4	0.046	0.034	0.7435	0.946
5	-0.152	-0.163	1.6727	0.892
6	-0.108	-0.137	2.1586	0.905
7	-0.130	-0.160	2.8947	0.895
8	-0.056	-0.144	3.0366	0.932
9	0.043	-0.022	3.1222	0.959
10	0.084	0.009	3.4753	0.968

5.1.2 Final 3SLS Model

Table 6 presents the final 3SLS model. The serial correlation test reveals that a lag adjustment is not of necessity in both the demand and supply equation. Some exogenous shifters in the supply and demand equations are significant at 5% and 10% significance levels. Notably, on the demand side, $GDP_{(capita)_t}$ is significant at 5% and 10% levels alongside with $LN(CB_{price})_{t-1}$. $LN(GEV)_t$ significant at 1%, 5%, and 10% levels. Furthermore, $LN(CB_{prod})$, the endogenous variable, does show significance at the said levels. On the supply side, the endogenous variable, $LN(CB_{price})_t$ demonstrates significance only at 10% level alongside explanatory variables $R_{(CHN)_t}$. Moreover, $Conflicts_{(DRC)t}$ and $LN(NKL_{(prod)})_t$ show significance at 5% and significance 10 % levels.

Table 6: **Eviews Output of 3SLS Regression Final Model**

VARIABLES	$LN(CB_{price})_t$	$LN(CB_{(Prod)})_t$
$LN(NKL_{prod})_t$		0.346122 **
		(0.158836)
$R_{(CHN)t}$		-0.021119 *
		(0.011437)
$Conflicts_{(DRC)t}$		-0.125600**
		(0.055544)
$LN(CB_{price})_t$		0.147941 *
		(0.082445)
$LN(CB_{prod})_{t-1}$		0.739732 ***
		(0.110188)
$GDP_{(capita)t}$	0.070130 *	
	(0.037541)	
$LN(GEV)_t$	0.080531***	
	(0.026447)	
$LN(CB_{(Prod)})_t$	0.263479 **	
	(0.122138)	
$LN(CB_{price})_{t-1}$	0.317246 **	
	(0.131740)	
Observations	32	32
R-squared	0.538453	0.953513

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2 Empirical results

Testing and modeling were performed using a 3SLS regression in Eviews. The estimated outcomes obtained from the model are of consideration as the influence of economic indicators is uncovered to determine their effect on the price and production of cobalt. The study examines time series data on a global level despite having two country-specific independent variables: China's policy interest rate and conflicts in the identified regions of the Democratic Republic of the Congo. The final model reiterates some initial claimed assumptions from the hypotheses mentioned above. Moreover, the initial assumption that global GDP per capita will positively affect the price of Cobalt has been proven significant, with a direct positive relationship with the commodity's price. With everything else constant, continuous global expansion of the economy leads to a price increase of metal erupting from the demand with recent government initiatives to reduce GHG. Fernandez (2018) confirmed that commodities are income-elastic rather than price-elastic, further supporting the significance of GDP per capita relative to price. Electric vehicles are among the leading long-term solutions for reaching the net zero emission target. Its anticipated positive effect, Ceteris Paribus, on the price of cobalt is proven in Table 6 by driving up the price of the metal. By the same token, the model indicates that the relationship between cobalt's price and production level is significant exhibiting inelasticity of demand. That is, the price of cobalt is not influenced by its production level as the coefficient is less than 1. The demand for cobalt is lagging compared to its supply, where countries mining cobalt are ramping up production while the demand is falling, potentially due to weak sales in consumer electronics such as phones and laptops, whose batteries contain cobalt (Zonebourse, 2023). As a result, there is more supply than demand. The output does align with the initial claim about the relationship between cobalt's price and production. In addition, the previous price of the commodity can predict the current price level by ceteris paribus, an increase in the previous price level leads to a positive change in today's price. In other words, previous shocks tend to influence the future price of the commodity. The relationship between the production of cobalt, and its price on the supply side demonstrates an inelastic effect. In other words, the price of cobalt has a mere impact on the production level. However, its previous production level leads to an increase of future production. A spike in demand for electric vehicles leads to an increase in demand for batteries. Lithium Nickel, Manganese, and Cobalt or NMC batteries occupy 63% of the market share(IEA, 2023). Cobalt is a by-product of nickel that makes batteries, lithium, and manganese. Empirical results prove that, with all else being constant, an increase in nickel production positively impacts cobalt production, which maintains the initial hypothesis on cobalt as a by-product of nickel. In addition, cobalt production is not risk-free due to systematic risk. As specified above, interest is the cost of financing, and based on the empirical results, a higher interest rate environment negatively impacts Cobalt's mining productions, confirming the initial interest rate hypothesis. Another systematic risk that the Cobalt supply faces are conflicts within the mining regions of the DRC; as long as instability is recurrent, the global supply chain of the metal is at risk of disruption with a negative impact on production, Ceteris Paribus, which could further lead to price volatility as Cobalt supply is concentrated in the Congo.

6 Conclusion

The empirical findings aim to uncover the effects of economic indicators on the green strategic metal, Cobalt, while the global governments are pushing towards a greener economy and net zero emissions. The research concluded that global GDP per capita positively impacts the price of cobalt. The demand for electric vehicles, driven by governmental initiatives to reduce greenhouse gas emissions, is a significant factor in the price increase of cobalt. Moreover, the quantity demanded was inelastic relative to the price level. Conversely, the quantity supplied was inelastic, which measures the responsiveness of quantity supplied to a change in price, demonstrating that a change in the price level merely affects the production level. An increase in nickel production is positively associated with cobalt production, given that cobalt is a by-product of nickel. However, the study highlights systemic risks such as higher interest rates and conflicts within mining regions, particularly in the Democratic Republic of the Congo (DRC), which disrupts the cobalt supply chain and contributes to price volatility. The findings underscore the importance of cobalt in the global shift towards a greener economy and the impact of economic indicators on its market dynamics. The metal price faces challenges with the lagging global adoption of electric vehicles, the weakening of international mobile phone and laptop sales, the concentration of supply in the Congo mined with conflicts, and growing uses of LFP batteries for electric vehicles as an alternative to MNC batteries.

This research faced roadblocks related to the number of observations, limited data availability, and data consistency. The study is conducted with 33 observations, which limits the possibility of capturing short-term trends and shocks. As mentioned, there is limited data regarding electric vehicles, which started around 2010. An unconventional technique was utilized to capture its effect on the commodity by overlaying the data. Even though the expected outcome was obtained, the model's robustness could have been hindered. Global battery production can be a good substitute for the global EV variable in the demand equation for future research reference. The model's robustness and precision can be improved. Moreover, there is reason to believe that when the sample size of a model is small, the unit root test is unreliable, Monthly or quarterly data would aid in improving model estimations with large sample sizes to minimize error residuals.

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