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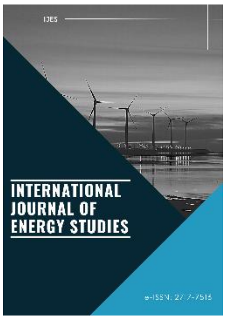

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Interplay between metal and oil markets in the renewable energy transition: An internal and external connectedness perspective

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Highlights

- Copper and aluminum act as key information transmitters in petroleum markets.
- Connectedness decomposition measures shock spillovers between metals and oil markets.
- Metal-oil market linkages strengthen during periods of economic crisis.
- The renewable energy transition increases oil prices sensitivity to metal markets.
- Granger causality reveals how critical metals influence petroleum price dynamics.

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ABSTRACT

This study investigates the information spillover between critical metals and oil markets within the context of the global transition to renewable energy. Metals such as copper, aluminum, cobalt, nickel, and zinc are essential for renewable energy technologies, and their price movements are closely linked to energy markets. Using the connectedness decomposition approach, this study analyzes internal and external information flows between metal and oil markets. The findings reveal that copper and aluminum are the strongest information transmitters, while oil prices, particularly Brent and WTI, become more sensitive to metal markets during crisis periods. As the energy transition accelerates, critical metals are playing an increasingly influential role in commodity markets, shaping energy price dynamics. These results provide valuable insights for sustainable energy policies and risk management strategies, emphasizing the growing interdependence between energy and metal markets.

Keywords: Renewable energy, Oil markets, Metal prices, Information spillover, Connectedness analysis

1. INTRODUCTION

The global energy transition aims to increase the use of renewable energy sources by reducing dependence on fossil fuels. In this transition process, many technologies, from wind turbines to solar panels, electric vehicles to energy storage systems, rely on the intensive use of specific metals [1]. With the rapid expansion of renewable energy infrastructure, metals such as copper, aluminum, nickel, and zinc are becoming increasingly important. However, these metals' price movements and supply dynamics strongly interact with energy markets [2].

This study examines the relationship between the prices of metals used in renewable energy production and oil prices. In particular, the methods used in the study reveal how metals interact with oil prices in terms of information diffusion. The results show that certain metals (especially copper and aluminum) play a driving role in global energy markets, while oil prices generally receive information. Especially in times of crisis, oil prices are found to be more sensitive to information flows from metals markets [3, 4]. These findings have important policy implications for understanding the future of energy markets.

During the renewable energy transition, the security of the supply of critical metals, price volatility, and sustainable mining practices become increasingly important. Although there are many studies in the literature on the interaction between energy and metal markets, there is limited research on how the transition to renewable energy is reflected in the relationship between metal prices and oil prices [5, 6]. Therefore, this study aims to contribute to the literature by analyzing the interactions between oil and metals markets in the context of energy transition.

The transition to renewable energy ensures environmental sustainability and plays a critical role in global energy security and economic stability. As dependence on fossil fuels decreases, the strategic importance of metals in renewable energy production increases. However, fluctuations in the supply of these metals and vulnerabilities in the global supply chain pose risks that could slow the energy transition [7, 8]. In this context, our study aims to understand the dynamics of metals markets and their interaction with oil markets during the energy transition. The results have important implications for policymakers and market actors toward a sustainable and stable energy transition.

In the following section of the study, the theoretical framework is presented, building upon the insights gained from the literature review. Section 5 introduces the data utilized in the study, accompanied by a presentation of the summary statistics. The findings are detailed in Section 6, while Section 7 provides a comprehensive discussion. Finally, Sections 8 and 9 present the conclusions and recommendations derived from the study.

2. THEORETICAL FRAMEWORK

The transition to renewable energy aims to meet the ever-increasing demand for energy from more sustainable sources by reducing dependence on fossil fuels. This transition increases the demand for critical metals and redefines their role in financialized markets. The conceptual framework of this study is based on the following four key theories for understanding the interactions between energy and metals markets: supply and demand shocks, financialization theory, information diffusion and connectedness models, renewable energy, and the role of critical metals. These theories provide a crucial framework for the methods used in our study and the interpretation of our findings.

2.1. Supply and Demand Shocks

One of the key economic dynamics for understanding the relationship between oil and metals markets is supply and demand shocks. Oil supply disruptions or demand expansions can increase the cost of industrial metals and lead to price volatility [9]. The increasing demand for renewable energy technologies in the global energy transition process affects the prices of certain metals, making their interactions with energy markets more complex. In particular, the question of how this process affects oil prices is an important area of research for researchers. At this point, understanding the nature of supply and demand shocks between oil and metals markets is essential to explain how these two markets interact.

2.2. Financialization Theory and Commodity Markets

The financialization of commodity markets has changed the relationship between investor behavior and price dynamics, strengthening the link between metals and energy markets [10]. The increasing presence of financial actors in commodity markets has increased the volatility of these markets and made price movements more susceptible to speculative factors. In this context, how metals interact with energy markets and how investors evaluate price movements between these markets is an important research topic.

This raises the question of how the financialization of oil and metals markets affects price dynamics and volatility.

2.3. Models of Connectedness and Knowledge Diffusion

Understanding information flows between markets is crucial for explaining investors' decision-making processes and price dynamics. Connectedness models are used to understand how shocks propagate in specific markets and help identify the direction of information spillovers between commodity markets [11]. To better understand the interactions between energy and metals markets, analyzing which markets are information transmitters and which markets are information receivers is necessary. Such an analysis can reveal how the connectedness between energy and metals markets changes in times of crisis.

The question to be answered is: Under what market conditions does information diffusion between oil and metals markets strengthen or weaken?

2.4. Renewable Energy and Critical Metals

Renewable energy technologies, especially electric vehicles, solar panels, and battery systems, rely intensively on certain metals [1]. Fluctuations in the price of these metals can directly impact renewable energy investments and alter their interactions with oil markets. In the transition to renewable energy, the security of supply and price volatility of critical metals are crucial for the stability of energy markets. Therefore, understanding the impact of the energy transition on metals markets will provide essential clues on how energy policies will be shaped in the future.

In this context, the main question is: How does the price volatility of critical metals affect oil markets during the transition to renewable energy?

This theoretical framework provides the necessary background to understand the dynamics of energy and metals markets and to shape future policy recommendations. Our study further aims to investigate the energy transition's impact on metal prices by supporting this framework with empirical analysis.

3. RELATED LITERATURE

The impact of the transition to renewable energy on energy and commodity markets has received increasing academic attention in recent years. The interaction between oil and metals markets has been discussed in terms of supply and demand imbalances, price volatility, and financialization. In particular, the existing literature analyzes the role of critical metals in renewable energy systems and their linkages with global energy markets.

3.1. Interaction between Oil and Metal Markets

Changes in industrial production, global economic growth, and financial markets often shape the dynamics between oil and metal markets. Kilian [3], highlighted the impact of oil prices on macroeconomic variables, but recent studies have shown that oil prices are not the only determinant. Islam et al. [12]. and Nwonye et al. [13]. examine the directional effects of metals, especially copper and aluminum, on oil prices and show that information flows between energy and metals markets can be bidirectional. Aydoğdu & Uyar examine volatility spillovers between energy commodities and precious metals using daily return data from October 1, 2012, to June 4, 2024, through a Wavelet Coherence-based Dynamic Conditional Correlation (DCC) approach. Their findings reveal long-term, mostly positive interdependencies from Brent crude to gold, silver, and platinum, and from palladium to natural gas [14].

3.2. Financialization and Price Dynamicsl

The financialization of commodity markets has led to a more complex relationship between oil and metal prices. Büyükşahin & Robe [15], highlight the increasing importance of industrial metals for financial investors and their linkages with energy markets. Tang & Xiong [10], show that speculative investment in commodity markets increases price volatility and that shocks in commodity markets are transmitted across sectors. In this context, studies such as Goutte & Mhadhbi [16], find that the link between energy and metals markets strengthens during periods of global crisis . Charteris et al. [17], investigate the interconnectedness of oil, coal, and natural gas markets during the COVID-19 pandemic and the global energy crisis. Their results indicate a temporary spike in connectedness during the pandemic and a more persistent increase throughout the energy crisis period.

3.3. Renewable Energy Transition and Critical Metals

Renewable energy technologies rely on the intensive use of certain metals, and their supply and demand balances play a critical role in global energy markets [1]. Sovacool et al., [5] and Olivetti & Cullen [18], highlight the strategic importance of critical metals for sustainable mining and energy policies. Nansai et al., analyze the long-term impact of the renewable energy transition on metals markets and show that the security of the metals supply is critical for the sustainability of the energy transition [19]. Saadaoui et al., examined the impact of geopolitical risk on the prices of critical minerals important in the clean energy transition. They find substantial evidence that the impact of geopolitical risk on the prices of critical minerals has a time-varying effect, with shocks from geopolitical threats being larger in magnitude than those from geopolitical actions [20].

The literature shows that macroeconomic, financial, and political factors influence the interactions between energy and metals markets. The growth of commodity-based financial markets and increased interconnectedness during crises show that this relationship is time-varying. Understanding the impact of critical metal price volatility on energy markets during the transition to renewable energy requires a more comprehensive design of future energy policies.

However, the literature on the interaction between metals markets and oil prices in a long-term and dynamic framework is limited. Most studies examine metal and energy markets separately but do not comprehensively analyze how they transmit information to each other, significantly how they change during crisis periods. Moreover, studies on the interaction dynamics between metal and oil prices are limited. Using the internal connectedness method, our study aims to fill this gap by identifying the dynamic connectedness between metal and oil markets. Moreover, it contributes to the literature by analyzing how oil prices respond to information flows from metal markets, how this effect changes over time, and how market connectedness is shaped during crises.

4. METHOD

In this study, two main methods are used to determine the causality between variables and to analyze the structure of interconnectedness: the Granger causality test and the connectedness decomposition method developed by Gabauer & Gupta (2018) [21].First, the Granger causality test is preferred to examine the causal relationship between time series. This test, proposed by Granger, indicates that if the past values of one time series contribute significantly to the prediction of the future of another time series, the related series causes the other series in the Granger sense [22]. Accordingly, for the two-time series X_t and Y_t the test is carried out using the following regression models:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + \varepsilon_t$$

$$X_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + v_t \tag{1}$$

Where p is the lag length, ε_t and v_t are the error terms. Hypothesis tests are conducted by evaluating whether the coefficients of the independent variables are zero or not, and if a statistically significant result is obtained, it is accepted that the related variable Granger causes the other variable.

Second, the study employs the connectedness decomposition method developed by Gabauer & Gupta (2018) [21]. This method is based on the "spillover index" methodology presented by

Diebold & Yilmaz and analyzes dynamic connectedness in a time-varying framework. The main component of the method is a vector autoregression with time-varying parameters (TVP-VAR) model [10].

4.1. TVP-VAR Model

The TVP-VAR model is used to model the dynamic nature of the time series in a flexible way and is defined as follows:

$$Y_t = A_t Y_{t-1} + \eta_t \tag{2}$$

Where Y_t is the N-dimensional vector of variables, A_t is the time-varying coefficient matrix and η_t is the error term. The time-varying variable structure of the model is described by the following stochastic process:

$$A_t = A_{t-1} + u_t \tag{3}$$

where u_t is the error term representing random variations in the process. The model parameters are estimated to use a Kalman filter and updated for each time period.

4.2. Generalized Forecast Error Variance Decomposition (GFEVD)

Using the impulse response functions obtained from the TVP-VAR model [23], the connectedness between variables is determined [24, 25]. The generalized variance decomposition of error (GFEVD) method is used to compute the measure of Connectedness [26]. The GFEVD matrix is expressed as follows:

$$\theta_{ij}^{(H)} = \sigma_{jj}^{-1} \sum_{h=1}^{H} \left(e_i' \psi_h e_j\right)^2 \tag{4}$$

where $\theta_{ij}^{(H)}$ is the variance contribution of variable j to variable i at time H, σ_{jj}^{-1} is the error variance, ψ_h is the impulse response function, and e_i and e_j are the corresponding unit vectors.

4.3. Connectedness Measurement and Indexing

In Gabauer and Gupt, the overall level of connectedness in the system is calculated using generalized variance decompositions derived from impulse response functions [21]. The general connectedness index is defined as follows:

$$C_{i\leftarrow j} = \frac{\sigma_j^{-1} \sum_{h=1}^{H} \left(\varphi_{ij,h}\right)^2}{\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{h=1}^{H} \left(\varphi_{ij,h}\right)^2} \times 100 \tag{5}$$

Where $C_{i\leftarrow j}$ denotes the total effect of variable j on variable i. $\varphi_{ij,h}$ denotes the components of the impulse response function, H denotes the time horizon of the estimation, and σ_j denotes the standard deviation of the error term. According to Gabauer and Gupta, the connectedness measures are divided into three main components: FROM, TO, and NET connectedness[21].

- **FROM Connectedness**: It expresses the information that a variable receives from other variables and is calculated as follows:

$$C_i^{FROM} = \sum_{j \neq i} C_{j \to i} \tag{6}$$

- **TO Connectedness:** It expresses the information that a variable gives to other variables:

$$C_i^{TO} = \sum_{j \neq i} C_{i \to j} \tag{7}$$

- **NET connectedness:** Indicates the net transmission of a variable in the system and is obtained by the following formula:

$$C_i^{NET} = C_i^{TO} - C_i^{FROM} \tag{8}$$

Analyzing these three components helps to identify whether variables within the system are influencing or being influenced. It plays a significant role in understanding the interactions between financial markets or macroeconomic indicators.

4.4. Reasons for Preference of Methods

The main reason for choosing the Granger causality test and the Gabauer and Gupta connectedness decomposition method in this study is to reveal both the directional causality and the dynamic interconnectedness structure among the analyzed variables. While the Granger causality test focuses on the short-run relationships among variables, the Gabauer and Gupta method analyzes the interconnectedness structure in the system from a broader perspective [21]. The TVP-VAR model provides a more flexible analysis with time-varying parameters and assesses the dynamic nature of interactions between variables.

These two methods provide a more comprehensive analysis, revealing both the direction of causality and the change in the level of connectedness in the system over time.

5. DATA

The data used in this study consist of daily frequency observations covering the period from January 2015 to December 2024. The main reason for choosing this period is to assess changes in the dynamic structures of the variables analyzed from a long-term perspective and to analyze structural breaks in financial markets more comprehensively. In particular, the period after 2015 is characterized by significant fluctuations in global financial markets, heightened geopolitical risks, and substantial changes in monetary policy. In this context, the selected period covers both crisis periods and economic recovery processes, thus providing a more robust basis for analysis. All data used in the study was sourced from the Investing.com website.

Table 1. Summary Statistics

	ALUMINUM	COPPER	COBALT	ZINK	NICKEL	WTI	BRENT	DUBAI
Mean	0.011	0.012	-0.009	0.01	0.001	0.011	0.01	0.011
Variance	1.387	1.364	2.036	2.155	6.564	7.14	5.623	4.248
Skewness	0.172	-0.167	-1.631	0.097	-6.47	-1.105	-1.017	-2.618
Ex.Kurtosis	3.547	2.627	31.611	2.231	356.583	50.079	17.874	76.83
JB	1553.357	857.696	123501.8	613.209	15570023.98	307293.6	39577.59	725225.1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-12.081	-6.411	-12.588	-12.708	-12.32	-4.896	-3.726	-2.299
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)
Q(20)	15.097	8.85	93.41	6.829	83.783	52.84	19.979	36.887
	(0.117)	(0.632)	(0.000)	(0.839)	(0.000)	(0.000)	(0.017)	(0.000)
$Q^2(20)$	310.68	103.333	165.845	85.119	173.358	334.68	377.754	72.945
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Skewness: D'Agostino (1970) test [27] ; Kurtosis: Anscombe and Glynn (1983) test [28] ; JB: Jarque and Bera (1980) normality test [29] ; ERS: Elliott et al. (1996) unit-root test [30], ; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics [31] . Values in parentheses represent p values.

The descriptive statistics in Table 1 show the main distributional characteristics of oil prices and metals used in renewable energy production. Average returns are low, with only cobalt having a negative average (-0.009), indicating that it depreciates in the long run. Regarding variance, the highest volatility is observed for nickel (6.564) and WTI oil (7.14). In terms of skewness, nickel (-6.47), WTI (-1.105), and Brent (-1.017) have negative skewness, indicating that they are more sensitive to extreme negative shocks. Regarding kurtosis values, all assets are more significant than 3, with nickel (356.583) and WTI (50.079) particularly having extremely high kurtosis values, indicating frequent outliers. The results of the Jarque-Bera test show that all assets reject the assumption of a normal distribution ($p < 0.05$) and that price movements exhibit a heavy-tailed dispersion. The results of the ERS stationarity test show that all variables are stationary, but Dubai Oil (-2.299, p=0.022) shows relatively weak stationarity.

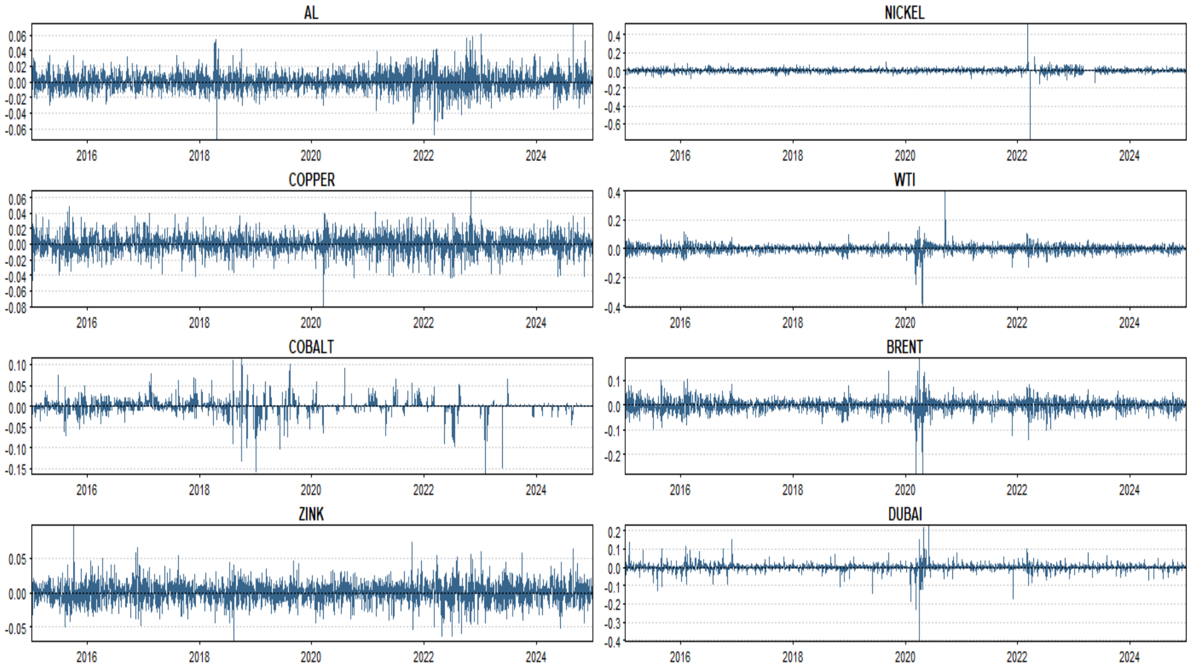

Fig 1. Returns on Variables

Figure 1 shows the log changes of the analyzed assets over time. In 2020, during the COVID-19 pandemic, there were large fluctuations in price changes, sharp falls in oil prices, and high volatility in metal prices. In 2022, the energy crisis led to sharp fluctuations in oil prices, and metal markets were also affected.

6. FINDINGS

This study examines the relationship between the prices of metals used in renewable energy production and oil prices. The results show that certain metals (copper, aluminum, nickel, and zinc) are closely linked to energy markets and play a leading role in price movements. However, the impact of oil prices on metal prices is found to be more limited. However, oil prices are found to be more sensitive to information flows from metal markets during crisis periods.

Table 2 Granger Causality Test Results

Null hypothesis:	Tested Causality	Result	p-value
AL does not Granger Cause BRENT	Granger Causality	H_0 rejected	0.0000*
AL does not Granger Cause WTI	Granger Causality	H_0 rejected	0.0000*
AL does not Granger Cause DUBAI	Granger Causality	H_0 rejected	0.0000*
BRENT does not Granger Cause AL	Granger Causality	H_0 not rejected	0.0529
WTI does not Granger Cause AL	Granger Causality	H_0 rejected	0.0319

DUBAI does not Granger Cause AL	Granger Causality	H_0 not rejected	0.2818
COPPER does not Granger Cause BRENT	Granger Causality	H_0 rejected	0.0414
COPPER does not Granger Cause WTI	Granger Causality	H_0 rejected	0.0003
COPPER does not Granger Cause DUBAI	Granger Causality	H_0 rejected	0.0020*
BRENT does not Granger Cause COPPER	Granger Causality	H_0 not rejected	0.9358
WTI does not Granger Cause COPPER	Granger Causality	H_0 not rejected	0.2248
DUBAI does not Granger Cause COPPER	Granger Causality	H_0 not rejected	0.2632
COBALT does not Granger Cause BRENT	Granger Causality	H_0 rejected	0.0222
COBALT does not Granger Cause DUBAI	Granger Causality	H_0 not rejected	0.7997
COBALT does not Granger Cause WTI	Granger Causality	H_0 not rejected	0.1548
BRENT does not Granger Cause COBALT	Granger Causality	H_0 not rejected	0.2998
DUBAI does not Granger Cause COBALT	Granger Causality	H_0 not rejected	0.8694
WTI does not Granger Cause COBALT	Granger Causality	H_0 rejected	0.0380
NICKEL does not Granger Cause BRENT	Granger Causality	H_0 rejected	0.0000*
NICKEL does not Granger Cause DUBAI	Granger Causality	H_0 rejected	0.0001*
NICKEL does not Granger Cause WTI	Granger Causality	H_0 rejected	0.0000*
BRENT does not Granger Cause NICKEL	Granger Causality	H_0 rejected	0.0000*
DUBAI does not Granger Cause NICKEL	Granger Causality	H_0 not rejected	0.2249
WTI does not Granger Cause NICKEL	Granger Causality	H_0 rejected	0.0000*
ZINK does not Granger Cause BRENT	Granger Causality	H_0 rejected	0.0030*
ZINK does not Granger Cause DUBAI	Granger Causality	H_0 not rejected	0.1596
ZINK does not Granger Cause WTI	Granger Causality	H_0 rejected	0.0008*
BRENT does not Granger Cause ZINK	Granger Causality	H_0 not rejected	0.7562
DUBAI does not Granger Cause ZINK	Granger Causality	H_0 not rejected	0.5155
WTI does not Granger Cause ZINK	Granger Causality	H_0 not rejected	0.3596

Note: For the Granger causality test, the lag length based on the Schwarz Criterion (SC) is 2.

The results of the Granger causality test indicate that the prices of aluminum (p = 0.000), copper (p = 0.0003), nickel (p = 0.000), and zinc (p = 0.0008) exert statistically significant causal influence on Brent, WTI, and Dubai crude oil prices. These findings underscore the existence of a strong lead-lag relationship, wherein base metals—particularly aluminum and copper—serve as leading indicators for oil price dynamics. Conversely, the reverse causality, from oil prices to metals, appears to be generally weaker. Notably, a bidirectional causality is observed between nickel and oil prices (p = 0.000), implying a mutually reinforcing dynamic whereby fluctuations in the nickel market both influence and respond to changes in crude oil prices.

Table 3. Internal Connectedness Decomposition

	AL	COPPER	COBALT	ZINK	NICKEL	WTI	BRENT	DUBAI	FROM
AL	52.33	16.4	2.35	12.29	9.17	0.00	0.00	0.00	40.22
COPPER	14.31	41.0	2.94	16.35	13.32	0.00	0.00	0.00	46.92
COBALT	2.70	6.12	69.11	7.18	5.16	0.00	0.00	0.00	21.16
ZINK	13.05	19.51	2.69	46.52	10.13	0.00	0.00	0.00	45.36
NICKEL	9.14	12.43	3.60	9.28	56.5	0.00	0.00	0.00	34.44
WTI	0.00	0.00	0.00	0.00	0.00	33.84	24.6	13.55	38.15
BRENT	0.00	0.00	0.00	0.00	0.00	20.56	35.16	14.27	34.83
DUBAI	0.00	0.00	0.00	0.00	0.00	19.28	25.4	29.31	44.68
TO	39.21	54.45	11.57	45.09	37.78	39.84	50.00	27.82	305.75
Inc.Own	91.54	95.44	80.68	91.62	94.28	73.68	85.16	57.13	cTCI/TCI
NET	-1.01	7.53	-9.59	-0.27	3.34	1.69	15.16	-16.85	43.68/38.22

Notes: Results are based on a TVP-VAR model with a lag length of order 2 (BIC) and a 10-step-ahead generalized forecast error variance decomposition. The following findings were derived using this structure.

FROM (Information Retrieval) values, Table 3 reveals that metals exhibit substantial intra-group information transmission. Copper receives the highest information share (46.92%), followed by zinc (45.36%), aluminum (40.22%), nickel (34.44%), and cobalt (21.16%). Aluminum is primarily influenced by copper (16.40%) and zinc (12.29%), while copper draws most information from zinc (16.35%) and aluminum (14.31%). Nickel is influenced mainly by copper (12.43%) and zinc (9.28%), and zinc receives the greatest input from copper (19.51%) and aluminum (13.05%). Cobalt receives the most information from an unspecified source at 7.18%. For crude oil markets, WTI absorbs 38.15% of total information, primarily from Brent (24.60%) and Dubai (13.55%). Brent receives 34.83%, with 20.56% from WTI and 14.27% from Dubai. Dubai exhibits the highest information reception at 44.68%, sourced from Brent (25.40%) and WTI (19.28%). These results highlight a strong interconnectedness among oil benchmarks, while indicating limited informational integration between oil and metal markets.

TO (Information Transmission) values in Table 3 indicate that copper (54.45%) is the dominant net transmitter, followed by Brent crude (50.00%), zinc (45.09%), WTI (39.84%), and aluminum (39.21%). Cobalt (11.57%) and Dubai crude (27.82%) exhibit the lowest transmission capacities, highlighting limited influence, particularly for Dubai in global energy pricing dynamics. The findings underscore that base metals, especially copper, zinc, and aluminum, serve as key information conduits relative to crude benchmarks. NET (Net Spillover) values further position Brent crude (15.16%) and copper (7.53%) as primary market drivers, while Dubai crude (-

16.85%), cobalt (-9.59%), and aluminum (-1.01%) are net recipients of market information. These results imply a structural asymmetry in information flow, with Brent and copper exerting outsized influence across the commodity system.

Table 4. External Connectedness Decomposition

	AL	COPPER	COBALT	ZINK	NICKEL	WTI	BRENT	DUBAI	FROM
AL	0.00	0.00	0.00	0.00	0.00	3.08	2.52	1.86	7.45
COPPER	0.00	0.00	0.00	0.00	0.00	2.68	5.68	3.72	12.08
COBALT	0.00	0.00	0.00	0.00	0.00	2.27	5.00	2.47	9.73
ZINK	0.00	0.00	0.00	0.00	0.00	1.85	4.24	2.02	8.11
NICKEL	0.00	0.00	0.00	0.00	0.00	2.17	3.41	3.48	9.06
WTI	6.47	7.62	2.33	5.15	6.44	0.00	0.00	0.00	28.01
BRENT	6.76	8.39	2.64	6.15	6.07	0.00	0.00	0.00	30.01
DUBAI	5.65	7.48	2.01	4.95	5.93	0.00	0.00	0.00	26.02
TO	18.87	23.49	6.98	16.25	18.44	12.06	20.84	13.55	130.48
Inc.Own	18.87	23.49	6.98	16.25	18.44	12.06	20.84	13.55	cTCI/TCI
NET	11.42	11.41	-2.75	8.13	9.38	-15.96	-9.17	-12.47	18.64/16.31

FROM (Information Retrieval) values in Table 4 indicates that Brent, WTI, and Dubai crude oil prices absorb 30.01%, 28.01%, and 26.02% of the total information, respectively. Copper emerges as the dominant contributor across all three markets, followed by aluminum, nickel, zinc, and cobalt.Specifically, Brent's information intake consists of 8.39% from copper, 6.76% from aluminum, 6.07% from nickel, 6.15% from zinc, and 2.64% from cobalt. Similarly, WTI draws 7.62% from copper, 6.47% from aluminum, 6.44% from nickel, 5.15% from zinc, and 2.33% from cobalt. Dubai's corresponding shares are 7.48%, 5.65%, 5.93%, 4.95%, and 2.01%. In terms of metals, copper absorbs the most external information (12.08%), followed by cobalt (9.73%), nickel (9.06%), zinc (8.11%), and aluminum (7.45%). These findings highlight copper's central role in information transmission and suggest that crude oil prices, particularly Brent and WTI, are significantly influenced by informational flows originating from base metal markets.

TO (information transmission) values in Copper is identified as the leading transmitter of information, disseminating 23.49% in total—7.62% to WTI, 8.39% to Brent, and 7.48% to Dubai. This is followed by aluminum (18.87%), nickel (18.44%), zinc (16.25%), and cobalt (6.98%). Among the crude oil benchmarks, Brent transmits 20.84%, Dubai 13.55%, and WTI 12.06%. These results underscore copper's central role as an information hub within the commodity network, with aluminum and nickel also functioning as key transmitters.

NET (Net Information Spread) values, copper is a net information disseminator with 11.42%, aluminum at 11.41%, nickel at 9.38%, and zinc at 8.13%. Cobalt is an information receiver with -2.75%. The largest net information receiver is WTI at -15.96%, followed by Dubai at -12.47% and Brent at -9.17%. These results suggest that copper, aluminum, and nickel are the strongest information disseminators in the market, while oil prices are mainly driven by external factors.

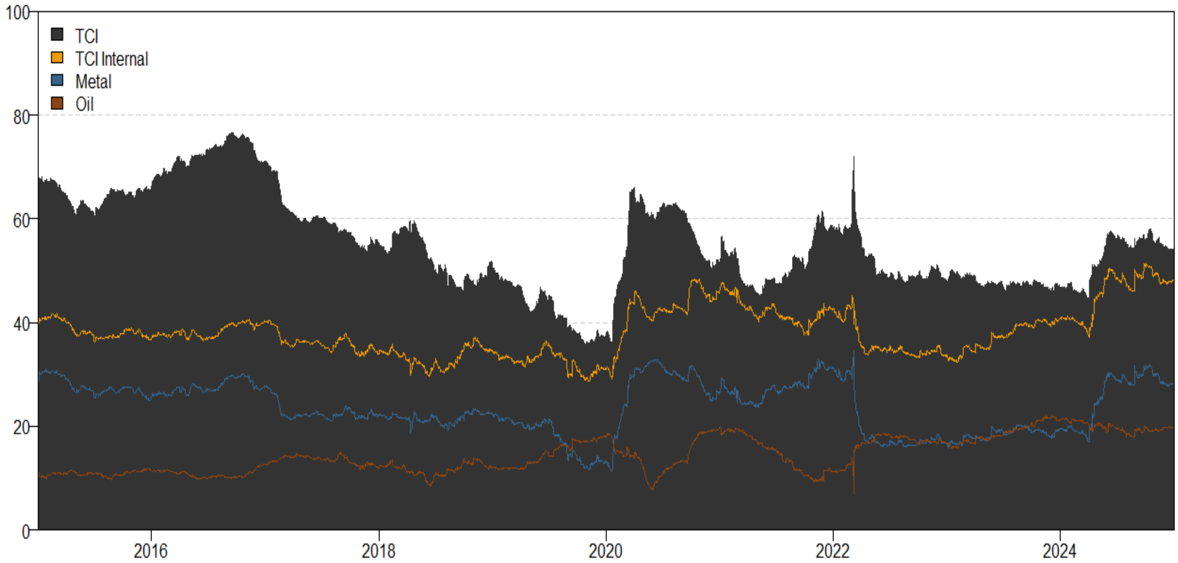

Fig 2. Dynamic total and Internal Connectedness

Figure 2 shows how aggregate and internal connectedness have changed over time. In 2020, internal connectedness increased sharply as the COVID-19 pandemic increased global economic uncertainty. During this period, the relationship between energy and metals markets strengthened, and changes in the risk perceptions of financial investors accelerated the diffusion of information across markets. During the 2022 energy crisis, aggregate connectedness increased again, and the relationship between Brent and WTI prices and metals such as copper and aluminum became more pronounced. These results suggest that energy and metals markets become more integrated during crises.

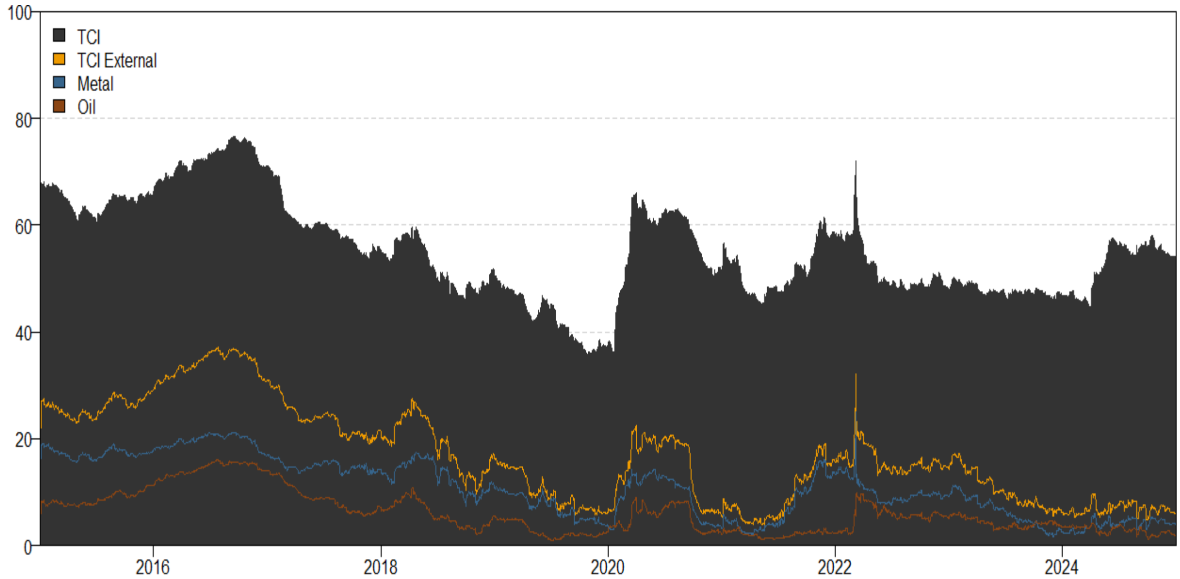

Fig 3. Dynamic total and external connectedness

Figure 3 shows the evolution of aggregate and external connectedness over time. In 2020, with the onset of the pandemic, the level of external connectedness increased rapidly, with metals, in particular, showing strong information spillovers to oil markets. In 2021, the level of external connectedness decreased as market uncertainty subsided, but in 2022, external connectedness increased again due to the impact of the energy crisis. In particular, there was a significant flow of information from metals such as copper and aluminum to oil markets during this period. These results suggest that shocks in energy markets are transmitted directly to metals markets and that information diffusion between markets varies over time.

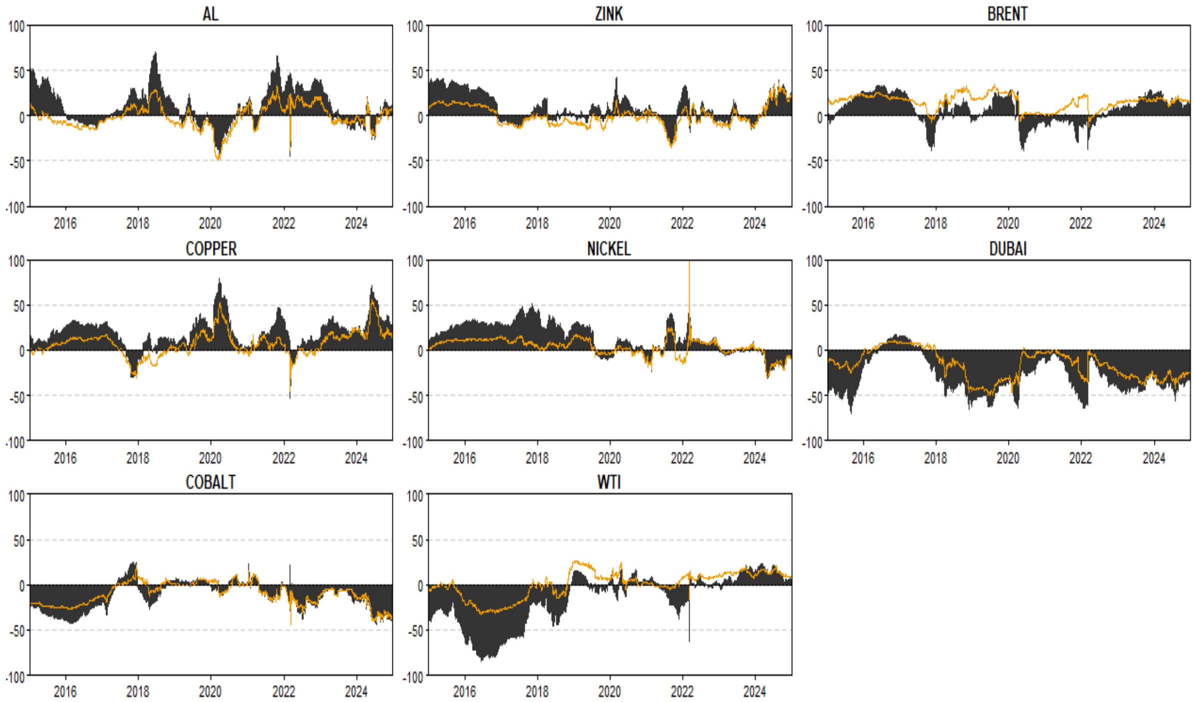

Fig 4. Net total and internal directional con nectedness

Figure 4 shows the evolution of net aggregate and internal connectedness over time. Black shaded areas illustrate the connectedness with internal connectedness whereas the orange lines represent the external Connectedness. In the graph, copper and Brent oil are net disseminators of information in most periods, while Dubai oil and cobalt are generally net receivers of information. In particular, during global crises, energy supply shocks, and significant price fluctuations, Brent and copper spread more information to the market, while Dubai oil and cobalt absorb more external influences. During the 2020 pandemic, there have been fluctuations in intrinsic connectedness, and the information dissemination capacity of some metals has varied. In the 2022 energy crisis, metals absorb more information as the influence of Brent and WTI oil prices increases. In more stable market conditions, the differences between net information disseminators and receivers have narrowed, and internal connectedness has become more balanced.

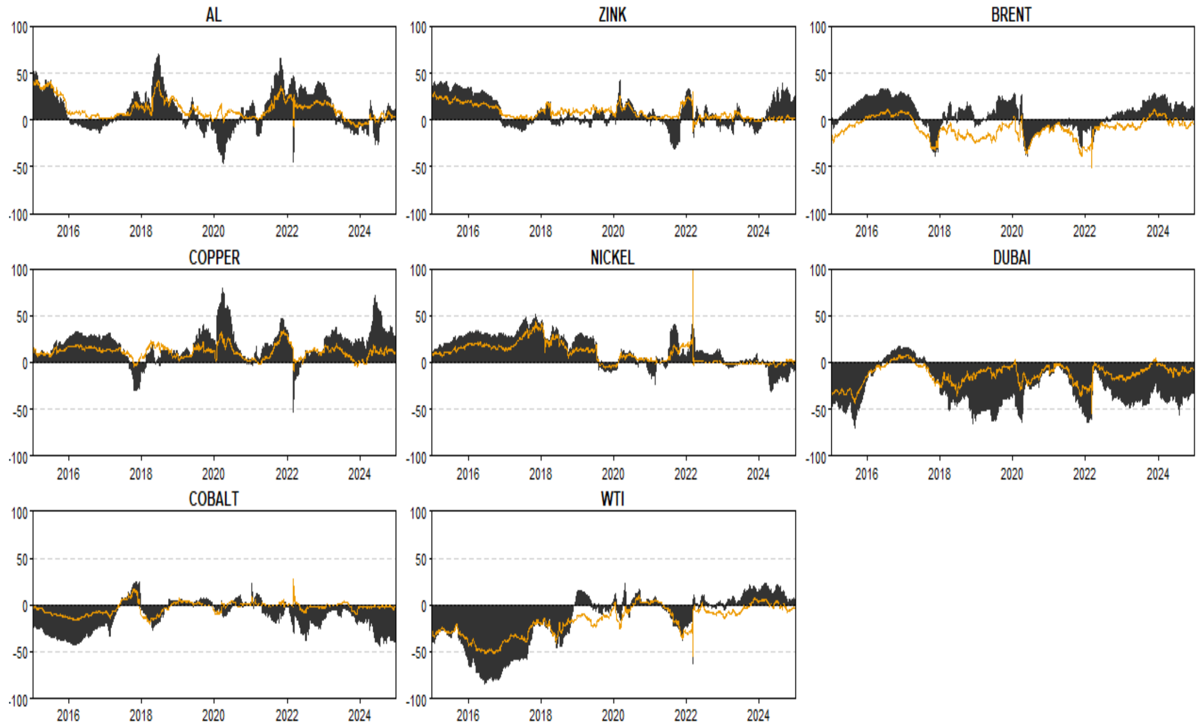

Fig 5. Net total and external directional connectedness

Figure 5 shows the evolution of net aggregate and external connectedness over time. Copper and aluminum are the most prominent emitters of exogenous information most of the time, while Brent, WTI, and Dubai oil prices are the most prominent receivers of external information. In 2020, during the pandemic-induced market turmoil, copper was the asset that most propagated external shocks, while Brent and WTI oil prices became external information receivers. In 2022, as oil market volatility increases, the external information-spreading capacity of Brent and WTI increases, but Dubai Oil remains an external information receiver. Over time, there are fluctuations in external connectedness, with some assets shifting from information disseminators to information receivers in specific periods. These shifts show how global economic dynamics and energy market developments shape the flow of exogenous information.

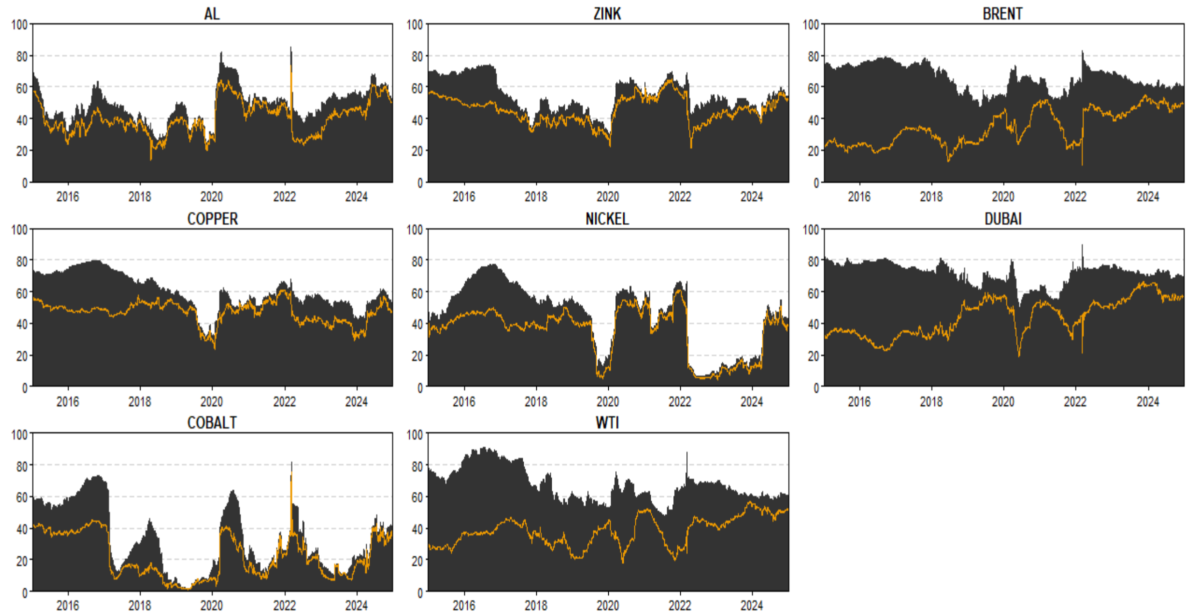

Fig 6. Internal directional connectedness FROM

Figure 6 shows the information received by the analyzed assets from other markets. The results show that Dubai oil is the most information-receiving asset, with information receptivity increasing, especially during crisis periods (e.g., the COVID-19 pandemic in 2020 and the energy crisis in 2022). Copper and zinc are found to be more sensitive to endogenous information spillovers. These results suggest that oil markets are more affected by global shocks, while metals markets can play a crucial role in this process.

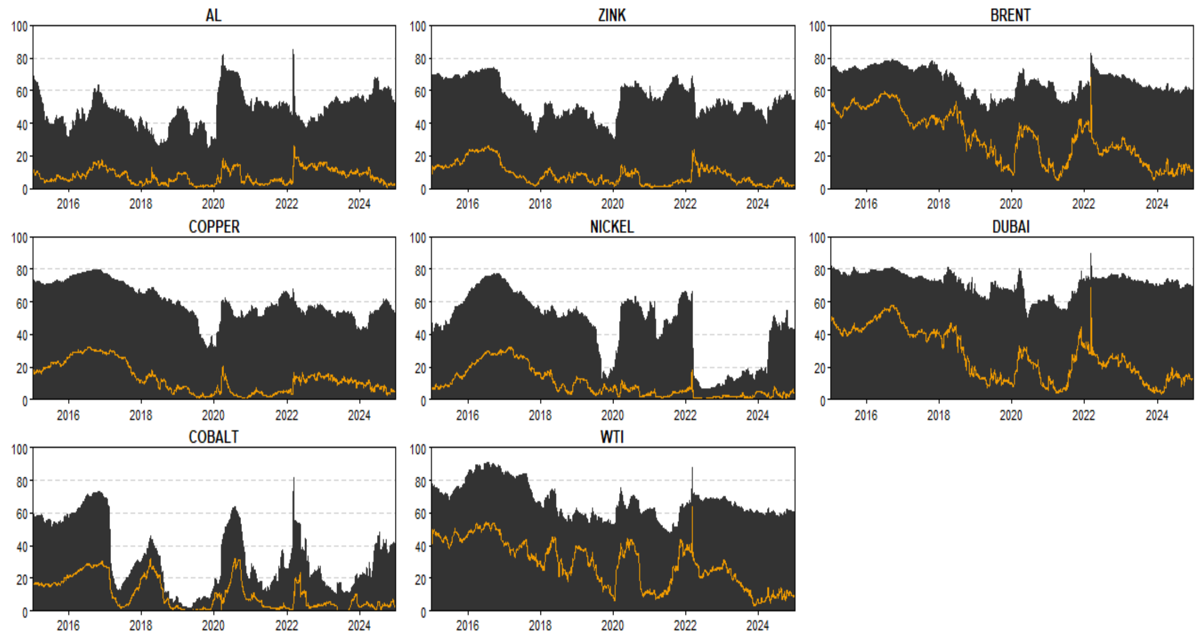

Fig 7. External directional connectedness FROM

Figure 7 shows how much information assets receive from external factors. The results show that Brent, WTI, and Dubai oil prices are the most informed assets in the face of global economic shocks and geopolitical risks. In particular, the sensitivity of oil prices to external shocks increases significantly during the 2020 pandemic and the 2022 energy crisis. Metals, on the other hand, have been shown to be affected by external factors at certain times but generally act more independently than energy markets.

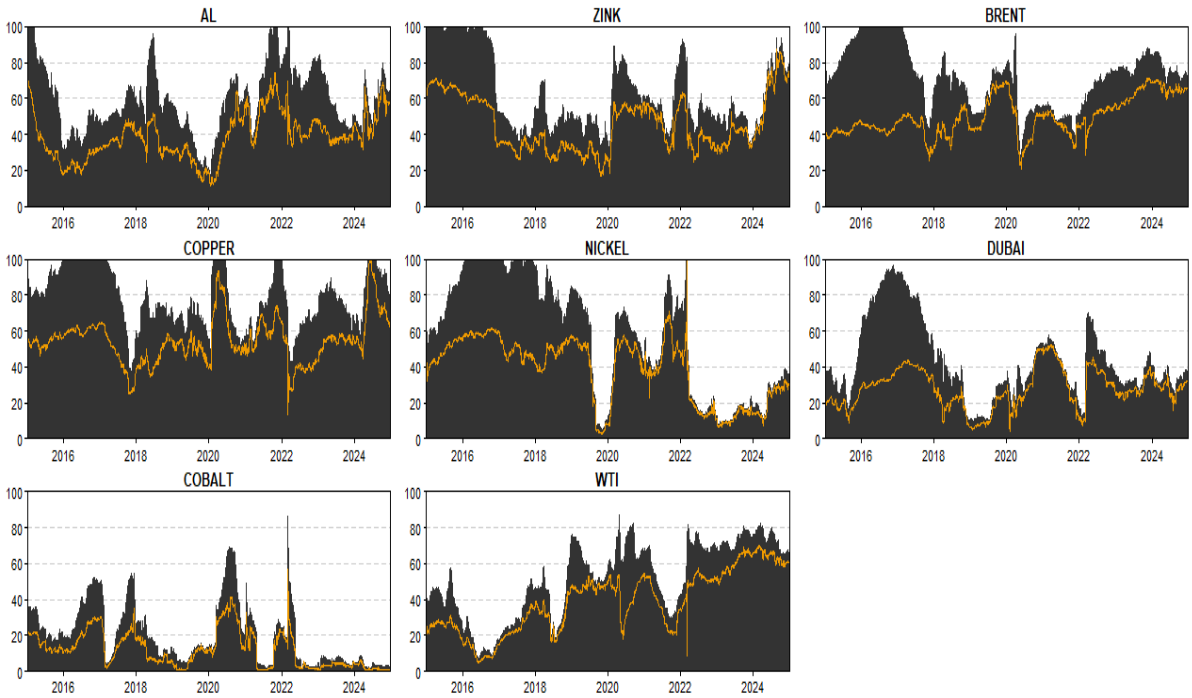

Fig 8. Internal directional connectedness TO

Figure 8 shows how much information the analyzed commodities spill over to other markets. The results show that Brent oil and copper have the strongest information spillovers. Especially during crisis periods (the COVID-19 pandemic in 2020 and the energy crisis in 2022), Brent seems to drive the energy markets, while copper drives the metals markets. Nickel has been found to increase its information spillover capacity in certain periods but is generally not as effective as Brent and Copper.

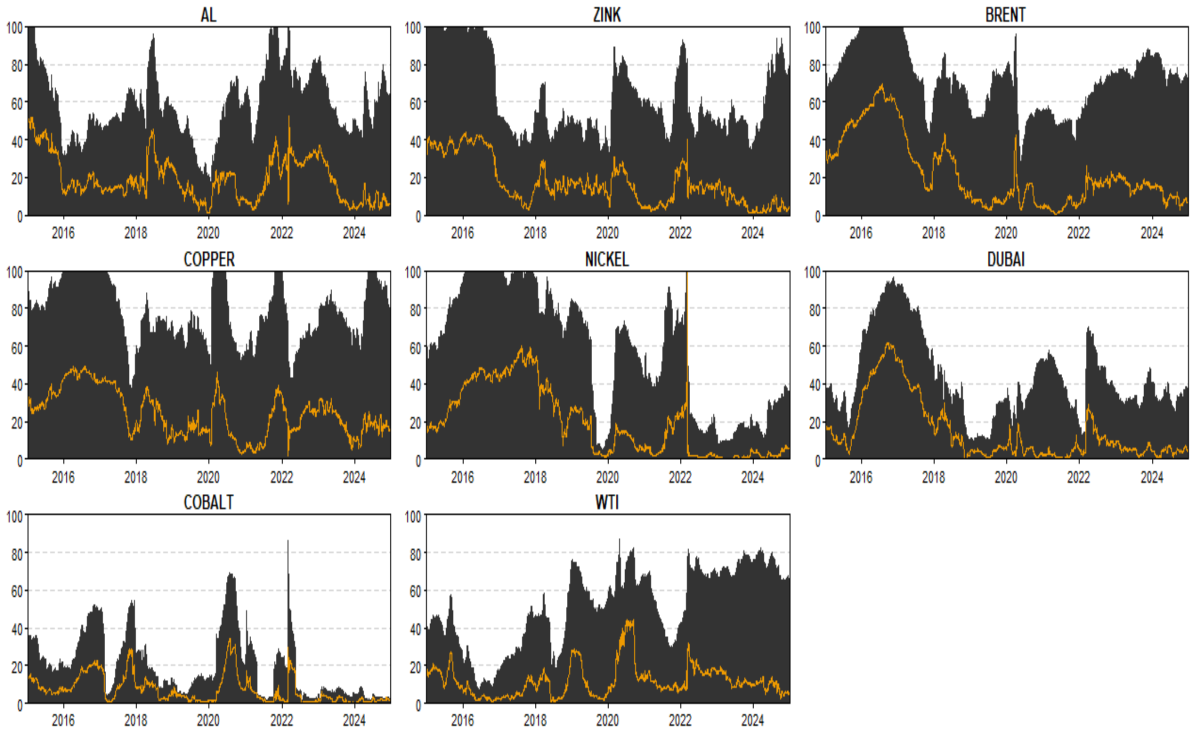

Fig 9. External directional connectedness TO

Figure 9 shows the extent to which information assets spill over to external factors. The results show that copper and aluminum are the strongest external information disseminators, driving markets, especially during economic fluctuations. In contrast, Brent and WTI oil prices are generally found to be external information receivers. In times of crisis, metals are more likely to channel external shocks, while energy markets absorb these effects.

7. DISCUSSION

This study comprehensively analyzes the relationship between the prices of metals used in renewable energy production and oil prices. The results show that certain metals significantly impact oil prices, but the inverse relationship is generally weaker. Compared to other studies in literature, our study's results have similarities and differences.

The results of our study show that the dynamic relationship between the prices of metals used in renewable energy production and oil prices is bidirectional and that metals drive oil prices under certain conditions. The fact that oil prices become more sensitive to information flows from metals markets, especially during crisis periods, can be explained by supply-demand shocks, financialization, and macroeconomic factors emphasized in literature.

Furthermore, the distinction between intrinsic and extrinsic connectivity offers a valuable lens for interpreting volatility spillovers between metals and energy markets. Intrinsic connectivity captures co-movements driven by industry-specific demand factors, technological interdependencies, and common investor behavior within the metals market. In contrast, extrinsic connectivity reflects broader macroeconomic influences and external shocks, including geopolitical risks or oil price fluctuations. This distinction helps to explain the differential roles of metals in information transmission dynamics, as also discussed in the systemic connectedness literature [11].

Baumeister & Hamilton [32], emphasize that the impact of demand-side shocks on oil prices has increased since the 2000s and that information from metal markets directly affects energy markets, especially during global economic crises and large financial fluctuations. The results of our study confirm that during periods such as the COVID-19 pandemic in 2020 and the energy crisis in 2022, Brent and WTI oil prices become more sensitive to information flows from metal prices.

Moreover, Büyükşahin & Robe [15] show that the financialization of commodity markets strengthens the connectedness between oil and metal prices. This financialization leads investors to view metal and energy markets together, especially in times of crisis, leading to synchronized price movements. Our study supports this view by showing that financialization increases the degree of connectedness and that metals have a higher information dissemination capacity than oil markets. However, not all metals exhibit high levels of information transmission. For instance, cobalt shows significantly lower information diffusion compared to metals such as copper and aluminum. This behavior can be attributed to cobalt’s distinct market structure as well as lower liquidity and less financialization in global markets. These factors reduce cobalt’s ability to act as an information transmitter and align with the literature emphasizing the role of market accessibility and systemic importance in determining spillover strength [33].

Goutte & Mhadhbi [16] also found that information spillovers between energy and metals markets increase during global crises and that metals such as copper drive oil prices during periods of uncertainty. Our study shows that copper and aluminum drive oil prices, especially during crisis periods. Brent and WTI prices have become more sensitive to information flows from metals markets.

Finally, the results of our study support the findings of Ajmi et al. [34] that copper is an indicator of global economic growth and is closely linked to the oil market. In particular, with the acceleration of the transition to renewable energy, copper's impact on oil prices has increased, making it a key commodity that drives energy markets in times of crisis.

In this context, the contribution of our study is to elaborate on the information flows between oil and metals markets during crisis periods and to clarify dynamics that are missing in the literature. The results support the emerging view that metals markets are passive price takers and powerful information disseminators that drive oil prices.

8. CONCLUSION

The results show that the interactions between energy and metals markets are dynamic. In particular, copper and aluminum play a crucial role in oil prices, while the impact of oil prices on metals markets is more limited. However, the bidirectional causality between nickel and oil prices suggests that oil prices can affect metal markets under certain conditions. The dynamic connectedness analysis shows that the interaction between energy and metals markets increases in times of crisis. These results emphasize that energy transition policies should be designed considering the strategic importance of critical metals.

Connectedness decomposition analysis shows that metals, especially copper and aluminum, are information disseminators in the market, while oil prices are positioned as exogenous information receivers. In particular, the dynamic connectedness analysis shows that the interaction between oil and metals markets increases during global crises and energy supply shocks. During the COVID-19 pandemic in 2020 and the energy crisis in 2022, oil prices are more sensitive to metal prices' impact. These results suggest that the growing demand for renewable energy could become a determining factor for the oil market.

9. RECOMMENDATIONS

The results of this study show the impact of the prices of metals that play a critical role in the transition to renewable energy on oil markets. Metals such as copper and aluminum are found to be information disseminators in the market, while oil prices are found to be exogenous information receivers. Moreover, oil prices are found to be more sensitive to information flows from metal prices during crisis periods. In this context, the following concrete and feasible policy recommendations are offered to reduce imbalances in energy markets, ensure the security of supply, and promote sustainable mining policies:

9.1. Establish and Manage Strategic Green Metal Reserves

Critical metals, like oil, must be placed in strategic reserves in the transition to renewable energy. Regulations such as the Critical Raw Materials Act, published by the US and the European Union in 2022, aim to mandate national and global reserves of strategic metals. China and the US have already started to build strategic reserves of critical minerals. An "International Green Metal Reserve Fund" should be established to stabilize supply and demand fluctuations in global markets. Supported by the International Energy Agency (IEA), the World Bank, and major industrialized countries (US, EU, China, and Japan), a reserve fund would protect renewable energy-dependent metals such as copper, nickel, and aluminum from speculative price movements. In an energy crisis, controlled sales from these reserves would reduce market volatility and give priority access to electric vehicle manufacturers and renewable energy companies.

9.2. Introduce a "Green Mining Obligation" for Carbon-Free Metal Mining

For the transition to renewable energy to be sustainable, the energy used in mining critical metals must also come from renewable sources." Green mining standards should be established in line with the OECD, the European Green Deal, and projects funded by the US under the Inflation Reduction Act (IRA). Mining companies should be required to pay an additional carbon tax for operations that do not use renewable energy, and low-interest loans should be made available to companies investing in carbon-free mining. The European Union plans to limit imports of critical metals from non-green mining companies by 2030, so similar policies should be implemented globally. For example, major mining companies such as Rio Tinto and BHP are making huge investments to transition to carbon-neutral mining.

9.3. Financing Renewable Energy through the Metals Value Chain

A portion of the taxes from the trade of metals such as copper and aluminum should go directly to renewable energy projects. For example, Chile and Indonesia are funding renewable energy infrastructure by increasing export taxes on copper and nickel. Similarly, models should be developed to channel 10% of public revenues from the copper trade directly to solar and wind energy projects. New subsidies should also be provided to encourage the use of critical metals for green hydrogen production.

9.4. Oil Companies Should Mandatory Invest in Metal Mining and Renewable Energy

Global oil companies should be encouraged, and to some extent required, to invest in the mining sector as part of the transition to renewable energy. Major oil companies like ExxonMobil and Shell have invested in lithium and nickel mining. A 'Mining and Clean Energy Fund' should be created for major oil companies, allowing them to channel a portion of their fossil fuel revenues into critical metal mining investments. Quotas should also be set for these companies to invest a certain percentage in wind and solar energy projects.

9.5. Long-term agreements with guaranteed metal supply for the electric vehicle industry

EV manufacturers should enter into long-term supply agreements of 10-20 years to secure the supply of critical metals. Tesla has led the way by signing a 10-year nickel supply agreement with BHP in 2021. Similarly, major automakers (Volkswagen, Toyota, and Ford) should strengthen their critical metals supply chains by working directly with mining companies. Governments should create low-interest financing mechanisms to support such long-term deals and stabilize the supply chain.

9.6. Mandatory Metal Recycling Quotas and Green Certificates

Mandatory recycling quotas should be imposed on industry to avoid the risk of future shortages of metals such as copper, aluminum, and nickel. The 30% recycled metal target the European Union sets under the Critical Raw Materials Directive should be implemented globally. Electric vehicle and renewable energy equipment manufacturers should be required to use at least 30% recycled metal in their new products. This could be increased over time to fully enable the industry to transition to a circular economy model by 2040. In addition, incentive mechanisms should be strengthened by awarding carbon credits to companies that use recycled metals.

9.7. Global Coordination in Critical Metal Supply Chains Should Be Enhanced

Major economic blocs such as the United States, the European Union, and China should establish a joint "Global Green Metals Agreement" to harmonize trade rules for renewable energy metals. This agreement should include common arrangements to ensure the security of the supply of critical metals, reduce speculative price fluctuations, and standardize trading arrangements. There should be greater coordination on critical metals supply across the G7 and G20 platforms.

This paper analyzes the interaction of metals critical to the renewable energy transition with oil markets. The results highlight the impact of specific metals on oil prices and show that this relationship intensifies during crisis periods. Future research should conduct longitudinal analyses of these dynamics using longer-term data. In addition, a comparative analysis of the interactions between metals and energy markets in different geographical regions could provide essential results in terms of global supply security. In addition, studies that more fully assess the role of financialization in commodity markets would contribute to a deeper understanding of price volatility. Finally, artificial intelligence and machine learning techniques can be used better to model the predictable relationship between oil and metal prices.

DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and legal-special permissions.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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