COINTEGRATION BETWEEN HIGH BASE METALS PRICES AND BACKWARDATION: GETTING READY FOR THE METALS SUPER-CYCLE

Abstract

The objective of some agents in commodity markets is to manage future price structures to hedge their positions rather than to speculate on prices. In this paper, we demonstrate that markets tend to backwardate in rising price scenarios and that this cointegration tends to be linked with the most financialized metals: copper and aluminum. In this study, a triple analysis was performed: cointegration on the time series, panel data and structural breaks over the full time series. The connection between high prices and negative-futures price structure (backwardation) in tin, copper, aluminum and zinc is demonstrated for the full series and with structural breaks. Using panel data analysis, the base metal full matrix (price and futures price structure) is cointegrated. The results of this study are important for commodity traders, brokers and others to maximize their profits on their hedging positions.

Keywords

Normal backwardation; cointegration; base metals; hard commodities; futures price structure

1. Introduction

Since the beginning of the century, world metal markets have experienced a period of sustained strong demand. The first big metal shortage occurred between 2003 and 2008 (Humphreys, 2010; Ciner et al., 2020), followed by other periods of more balance. Metal markets have now become tense, primarily due to the revolution on metal markets between 2016 and 2020 but also with the appearance of electrical vehicles and their charging infrastructure as well as developing country electrification through minigrids (Boait et al., 2015), public policies (Best, 2017) and finally with the development of renewable energies (Vikström, 2020).

However, over this long period of strong demand, there have been two breaks in the growing trend of supply shortages: the global financial crisis (2008-2009), studied by Al-Yahyaee et al. (2019); and the recent COVID-19 pandemic (Umar et al., 2021; Borgards et al., 2021). The COVID-19 pandemic started as an epidemic in China, and markets did not react sharply, but once the virus had spread to different regions in Europe, and the pandemic was declared by the World Health Organization (WHO), lockdowns led the global economy to decline sharply. The effect on worldwide production and global trade has been studied in Zeshan (2020) and Guan et al. (2020); the difference between soft and hard commodities has also been explored by Sifat et al. (2021), and Zhang (2020) described how supply chains have readapted to the lack of products in different areas. The specific effect of the COVID-19 crisis on the development of contango in some markets has been analyzed by Corbet et al. (2020), focusing on the oil market. The timing of the COVID-19 pandemic has been studied in many papers; for example, Allam (2020) has done it in intervals of 50 days. One of the only possible temporal solutions to the economic situation is government economic stimulus, which has been studied by Narayan et al. (2021), even if the way each country reacted through economic stimulus has been different (Perasolo et al., 2020). As the worldwide COVID-19 vaccination progressed, the general demand for metals increased due to the economic stimulus in every country and the infrastructure improvements to use that money, and, conversely, from the breaks in the supply chains coming from trying to recover part of the lost production during the lockdown and the pandemic's worst time periods. The global market and the needs of metals by geography have had different rates of use during the pandemic, and trading activity has attempted to equate them, a process that has been difficult, as the world was working as a sole market for a long time. The threats appearing in the market with the lack of chips and components, primarily in the automotive industry, have markedly increased the world's metal demand, making supply chains struggle up to limits where some of the primary corporations, such as Tesla or Volkswagen, have been pushed to invest upstream in acquisitions to guarantee raw materials for their core business. These, among other reasons, have led to the presence of new agents with an eye on hard commodities markets.

Commodity market contracts are generally referenced to future points in time. Raw materials could be required currently or over a specific period to finance or for storage, which may not be affordable for the buyer. Thus, contractually, these steps are performed on futures markets. In metal markets, more liquid timing bases exist, meaning that actors in the market tend to buy, sell and allocate transactions around those dates. Based on Otto (2011), a 3-month basis is a liquid reference, and a 15-month basis is particularly liquid, too, which is why we chose a 3-month basis for this study. The London Metal Exchange (LME) also states that "the foundation of liquidity and price discovery is found in the 3-month rolling prompt date, while most of the open interest sits on 3rd Wednesday "monthly" contracts"[1]. The spot or cash price in addition to the 3-month basis are the two references that consolidate *metal future price structures*. This metal structure is thus defined as backwardation when spot prices are higher than 3 months, and therefore, the futures price structure is negative. Also, contango refers to the opposite, both are described below:

$$\text{metal futures price } structure = \text{metal } price3\ months - \text{metal } pricespot$$

$$\text{metal futures price } structure > 0 \rightarrow contango$$

$$\text{metal futures price } structure < 0 \rightarrow backwardation$$

In commodities markets, a backwardated situation is normally linked with a shortage of offers, a high demand, or a combination of both. This situation is called "normal backwardation", a situation in which participants are trading more due to real needs than to either speculation or financialization. This theory, introduced by Keynes (1930), has been evolving during recent decades, when financialization (Günter and Karner, 2020) and macroeconomic events are increasingly taking over. For example, Galán-Gutiérrez and Martín-García (2021) show how Brexit, a macroeconomic event, can influence the copper futures price structure.

In this article, we consider theories that link high prices and backwardation, and identify evidence of normal backwardation. Using cointegration methods, we consider the different metals priced in the LME, evaluating prices and future price structures. The analysis is based on time series cointegration with and without structural breaks and on a data panel structure. This high price-backwardation linkage can be a good tool for speculators, miners, funds and market players who do not speculate and try to leverage their hedged positions.

The primary contribution of this research is the finding of co-movements between the future price of base metals and spot prices, referenced through their futures price structure. Also, we report the usage of cointegration tests through time series and through data intervals, which are obtained through structural breaks, as well as strengthen these results via the study of data panel cointegration. In addition, we study whether there is a relation between the metal level of liquidity or financialization and backwardation.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on co-movements and base metal introduction. Data and methodology are reviewed in Section 3. A description of the results and an analytical review is presented in Section 4. Finally, conclusions and recommendations are discussed in Section 5.

[1] https://www.lme.com/Education-and-events/Online-resources/LME-insight/What-are-implied-markets

2. Review of the literature

2.1. Co-movements in the literature

There is a wide compendium of papers that relates the prices between the different commodities through co-movements, and many report important findings. Ma et al. (2021) found that linkages across energy commodities are stronger than those among agricultural or metal commodities. Mensi et al. (2020) studied precious metals and primary energy futures price returns, and concluded that the global financial crisis followed by the great oil price bust in 2014 intensified return co-movements. Cai et al. (2020) studied relationships between crude oil, precious metals, and agricultural commodities, and found a strong joint evolution during the crisis from 2007 to 2012. In addition, similarity in evolution occurs in the mid-term and the long term (Madaleno and Pinho, 2014, for oil markets and, again, Cai et al.,2020).

Focusing on metals, Al-Yahyaee et al. (2020) use the spillover index to find strong multiscale co-movements among nonferrous metals. Additionally, aluminum is the highest contributor to shocks in other metal markets, while lead and copper contribute the least. In the specific case of copper markets, Rutledge et al. (2013) found Granger causality among the world's three major metal futures markets: the Shanghai Futures Exchange (SHFE), the London Metal Exchange (LME), and the New York Commodity Exchange (COMEX).

Co-movements between metal prices, which are shocks in prices that occur due to changes in other metals, have recently become of interest to researchers, as reported by Ding and Zhang (2020), Cai et al. (2019), Adhikari and Putnam (2020) and Yu et al. (2021). The literature refers to shocks and co-movements even in food prices, which are focused on certain periods where governments fell, and humans suffered (Carter et al. 2011).

Other co-movements that involve hard commodities have been studied by Alquist et al. (2020), who analyzed the dependence structure between commodities and are typically categorized into 5 sectors: agriculture, energy, industrial metals, livestock, precious metals. Co-movements between metals (e.g., gold, silver, platinum and palladium) and macroeconomics were studied by Boako et al. (2020), specifically considering the evolution of African stocks and commodities. Golosnoy et al. (2018) identified two common factors that relate to nonferrous and precious metals using distinct autoregressive dynamics; these results agreed with those of Cai et al. (2019).

Other economic variables that can influence commodity markets have also been investigated, as shown in Table 1.

Study	Data	Method	Commodities	Other variables	Key findings
Batten et al. 2010	1986-2006	Conditional standard deviations	Gold, silver, platinum and palladium	Business cycle, monetary environment and financial market sentiment	Different responds on Gold volatility, Platinum and Palladium, and Silver
Chen 2010	1900-2007	Cross-sectional standard deviations	Al, Bo, Cr, Co, Cu, Au, steel, Fe ore, Pb, Mg, Mn, Mo, Ni, Pt, Si, Ag, S, Sn, Tg, Vn, Zn	Volatility	Macroeconomic factors dependence 34%, 66% depending on commodities-specific risk
Ge and Tang 2020	1993-2016	Panel regression	27 commodity futures traded in CRB	GDP	Prediction of GDP growths on next quarters by commodity price
Creti et al. 2013	2001-2011	DCC GARCH	Independent and aggregate Commodity price index	S&P 500 index	Correlations between comm. and stock markets are highly volatile
Guo 2018	1991-2015	DCC GARCH	Copper	Stock returns	Correlation between copper prices and China's activity
Lim et al. 2019	2008-2017	Regression and Unit Root tests	Freight prices	CBOE VIX, CSPOT, CSLOPE, CVOL, CORDER, CFLEETG, CCONTR, OECD, IPPRC, PRCIRON, PRCCOKE	Correlation between freight markets, VIX and other macroeconomic variables
Liu et al. 2020	1975-2015	FAVG, Predictive Regression and RWWD	17 commodities (including agricultural and metals)	Currencies AUD CAD NZD ZAR	Significant predictability of currencies exchange rate using a factor drawn from a 17 commodity prices panel
Fasanya and Awodimila 2020	1980-2017 (Head. Infl.) 2002-2017 (Core infl. SouthA.), 1995-2017 (Core infl Nigeria)	FQGLS estimator forecasting model	Energy and nonenergy commodities	Headline and Core Inflation	Commodity prices drive inflation in these two countries. Some of them, as energy, drives more Nigeria inflation than others.
Mandaci et al. 2020	1992-2019	TVP-VAR connectedness approach	WTI, NGF, HOF, GLD, SLV, PAL, PLT, COP	USB, DJD, DJE, DXY	Moderate interdependence among the volatilities of the assets
Bouri et al. 2021	2011-2020	TVP-VAR connectedness approach	S&P GSCI gold, crude oil, MSCI World	Effect of COVID-19 outbreak, USD index, PIMCO Investment Grade Corporate bond index	Clear evidence for strong spillover effects in financial markets
Ji et al. 2018	2011-2016	Granger causality and DCC model	Oil and gold	US and BRICS equities	Integration structure among markets volatility is limited

Notes: DCC GARCH: Dynamic conditional correlation GARCH model; FAVG: Factor average; RWWD: Random walk with drift; FQGLS: Feasible Quasi Generalized Least Square; TVP-VAR: Time-Varying Parameter Vector Autoregressions

Table 1. Linkage between microeconomic and macroeconomic variables and trends in commodities literature.

2.2. Primary base metals references.

On the supply-demand spectrum, the influence of economic cycles in metals has been investigated by Maranon and Kumral (2020). However, the entire metal environment is facing different challenges depending on the metal in the hard commodities (base metals) system selected. One of the exercises explored in this study is to check if there is a higher correlation between prices and structure of prices in metals that are more financialized than others. This exercise explores the data obtained on the LME's Commitment of Traders Report[2], with the number of lots traded of each commodity in the same period. There are several ways to study metal financialization: the number of lots traded (e.g., this study), the multiple of price per lot traded, or using only those lots that are out from the normal course of physical business. The first approach (Fig. 1) shows that aluminum and copper are the most financialized metals, followed by zinc and nickel, with tin and lead being the less financialized metals. In Fig. 2, a similar approach is used but nickel is the most financialized due to its high price reference. We will discuss in the Results and Conclusions sections how related these financialization levels and the high price-backwardation pair are.

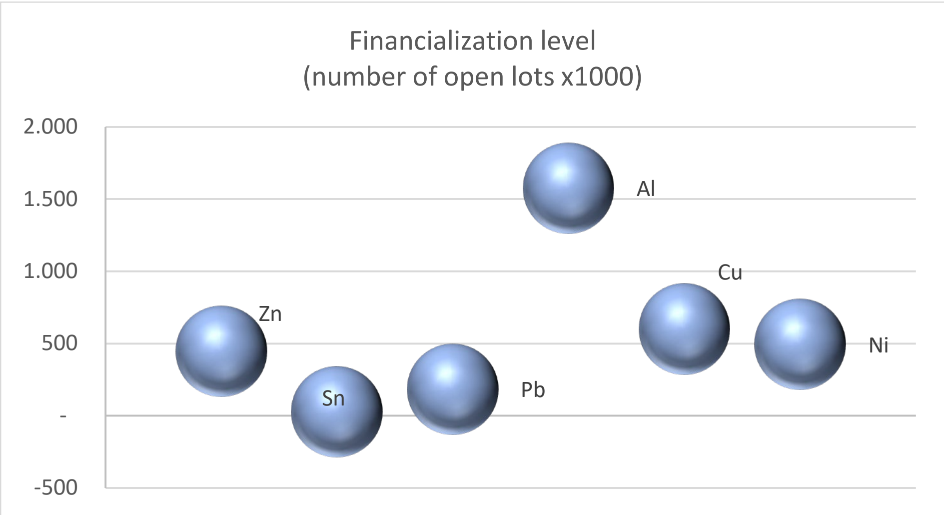


Fig. 1. Financial institution holdings in LME, lots based, formatted from authors' data.

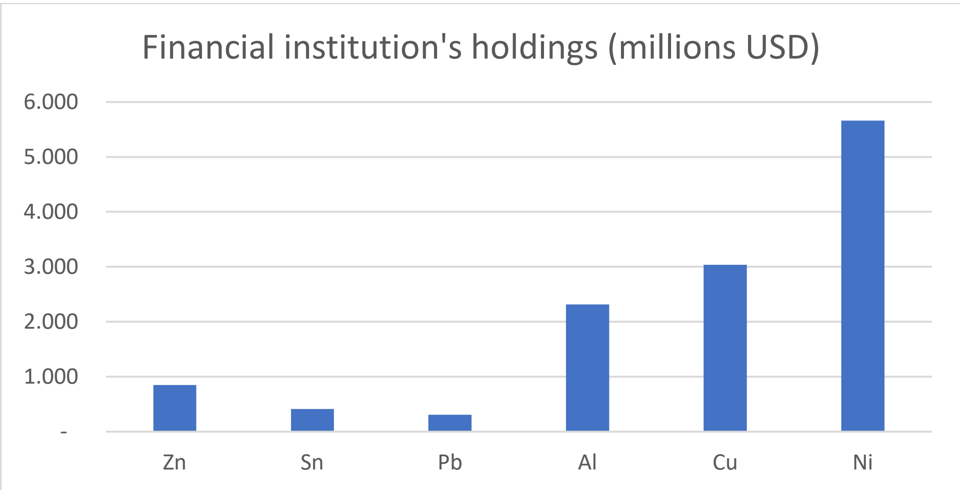


Fig. 2. Financial institutions' holdings in LME, lots per price base.

[2] https://www.lme. com/Market-Data/Reports-and-data/Commitments-of-traders#tabIndex=0.

Reviewing the specific situation of each base metal studied in this paper:

Copper: The International Copper Association (ICA)[3] continuously providing advice about the rising demand for copper, not only in 2019, sharing this view with other international associations such as AMM[4] (America Metals Market 2019 or Metals Market Magazine 2019). They cite the growth of the global middle class and the equivalence between GDP and copper consumption. Also, once immersed in the COVID-19 health crisis, they identify copper as one of the metals with the greatest potential for intensive consumption due to offsite units for social distance practices, thermal heating in buildings to reduce GHG (greenhouse gases) including sunlamps, electricity generation, renewable energy bumps, electricity supply networks, urban mining for sustainability and economic global stimulus schemes. They also cite an increase in copper use in electric vehicles globally (Jones et al., 2020).

Considering only classical mining and discovered resources, 2400 looks like the year when the world will run out of copper (Sverdrup et al., 2014), which is why recycling with the slogan of "Urban mining" is playing a key role in the short- and long-term outlooks of copper (Wallsten et al., 2013). Looking at these commodity warehouses' global stocks, we can also envision a tense situation that considers availability minus demand based on recently dropping copper prices at their highest level ever[5].

Aluminum is the most financialized metal, followed by copper, zinc and nickel. This conclusion implies that demand for aluminum is sometimes not linked to a real fundamental metal; however, the primary metal institutions also see aluminum as a key metal for future applications and its supercycle.

Li et al. (2021) described the increase in consumption of aluminum in recent years with the target to reduce the GHG emissions in certain regions, making this metal one with a higher ratio of increase (32 times higher than a decade ago) and in line to continue the same trend for the next 10 years.

The reports of the International Aluminum Association[6] state that in Aluminum Sector Greenhouse Gas Pathways to 2050, the role of recycling and the reduction of emissions in general makes aluminum one of the more interesting metals that is used in most industries, including automotive and transport; building and construction; and packaging and consumer goods.

Even if stocks on the LME appear sufficient for sourcing real demand in industry, the role of traders in moving the metal price forces a queue to extract these units from the LME's warehouses, a problem that has been described but still threatens every market player, as stated by Kim et al. (2021).

Nickel: Even if nickel consumption has reached 70% for stainless steel and 5% for batteries, according to the Nickel Institute[7], the recent increase in battery production due to

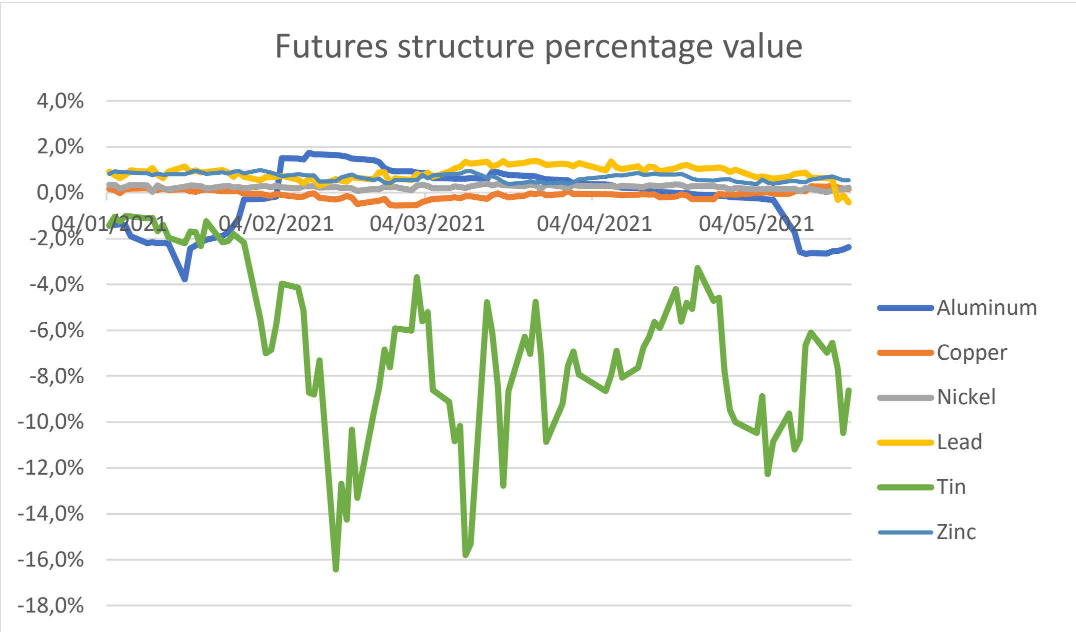
[3] https://copperalliance.org/about-ica/
[4] https://www.amm.com/
[5] https://www.mining.com/copper-price-hits-10000-again-as-chinese-investors-unleash-demand/#:~:text=Copper%20price%20hit%20a%20record,
high%20reached%20in%20February%202011.
[6] https://www.world-aluminium.org/statistics/primary-aluminium-production/
[7] https://nickelinstitute.org/about-nickel/#04-first-use-nickel

electric vehicles has increased this value (Olafsdottir and Sverdrup, 2021). A difference from other commodities is that zinc will likely always fulfil global need for the next century, according to the International Nickel Study Group (www.insg.org)[8]. This fact makes nickel a high price metal, primarily due to its costs of extraction, but not a real commodity role player in the exchanges. thus, nickel should not be a backwardated metal, but it is used as a case study in this paper.

Lead: Lead is currently one of the more discussed metals due to the recycling of batteries coming from electric vehicles (Baars et al., 2021). Lead's low price, compared with the other LME metal prices, also makes it one of the less used metals for speculators and traders to either force price changes or be involved in backwardation time frame scenarios. Per Figuerola-Ferretti and Gonzalo (2010), lead is one of the least liquid LME contracts, and therefore, an analysis of backwardation makes more sense than other LME contracts, such as aluminum, copper, nickel and zinc.

Zinc: In their 2020 annual report, the International Zinc Association[9] highlighted the growing role of zinc with lightening automotive structures' galvanized high-strength steel. Sverdrup et al. (2019) projected an increase in zinc world consumption up to the year 2100, also modeling a soft scarcity in this century for zinc, defining scarcity as "when demand is reduced due to a high price"; this information was also presented by Tokimatsu et al. (2017) using a mineral balance model. Regarding the future structure of this metal, zinc is facing normal backwardation sporadically, with the future price being a predictor of a price increase (Peterson, 2015), even at a lower significance value than other metals such as aluminum.

Tin is one of the more backwardated metals compared in total value with the other base metals, and its physical premiums and price have been reaching their highest values ever currently. When comparing the relative percentages between the futures price structure and price of each commodity, tin has more price structure volatility, as shown in Fig. 3.



[8] https://insg.org/index.php/about-nickel/production-usage/
[9] http://www.zinc.org

Fig. 3. Futures structure in percentage to the price. LME data.

The primary reason for this structure comes from a lack of availability in the market (e.g., entire global stocks in official LME warehouses of no more than 2,000 MTs, covering only approximately 0.5% of worldwide consumption, based on up to 400,000 MTs per year; Li et al., 2021) also also from the disappearing liquid positions in the respective exchanges, which primarily occur due to a concentrated production reported in the same study. When tin is not considered, we see that even if not achieving the same levels, aluminum is also in percentage (i.e., in reference to its value) eventually volatile in terms of its future price structure; this result was also previously described in the individualized analysis of metals.

3. Data and Methodology

3.1. Data

The data used for this study were LME cash values at the second ring close and the 3-months official prices (the most liquid, according to Otto, 2011) between 01/01/2016 and 31/12/2020 with the base metals in mining and economics, and traded under the non-ferrous indices on the London Metal Exchange: aluminum (AA), nickel (NI), lead (PB), tin (SN), zinc (ZI) and copper (CU).

The total data set contained 1,264 samples per metal, defining a 7,584 references matrix panel data, grouping by cash metal prices series (official price at the second ring close) and futures metals structure price series (defined as the difference of the 3-months basis price and the aforementioned cash priced):

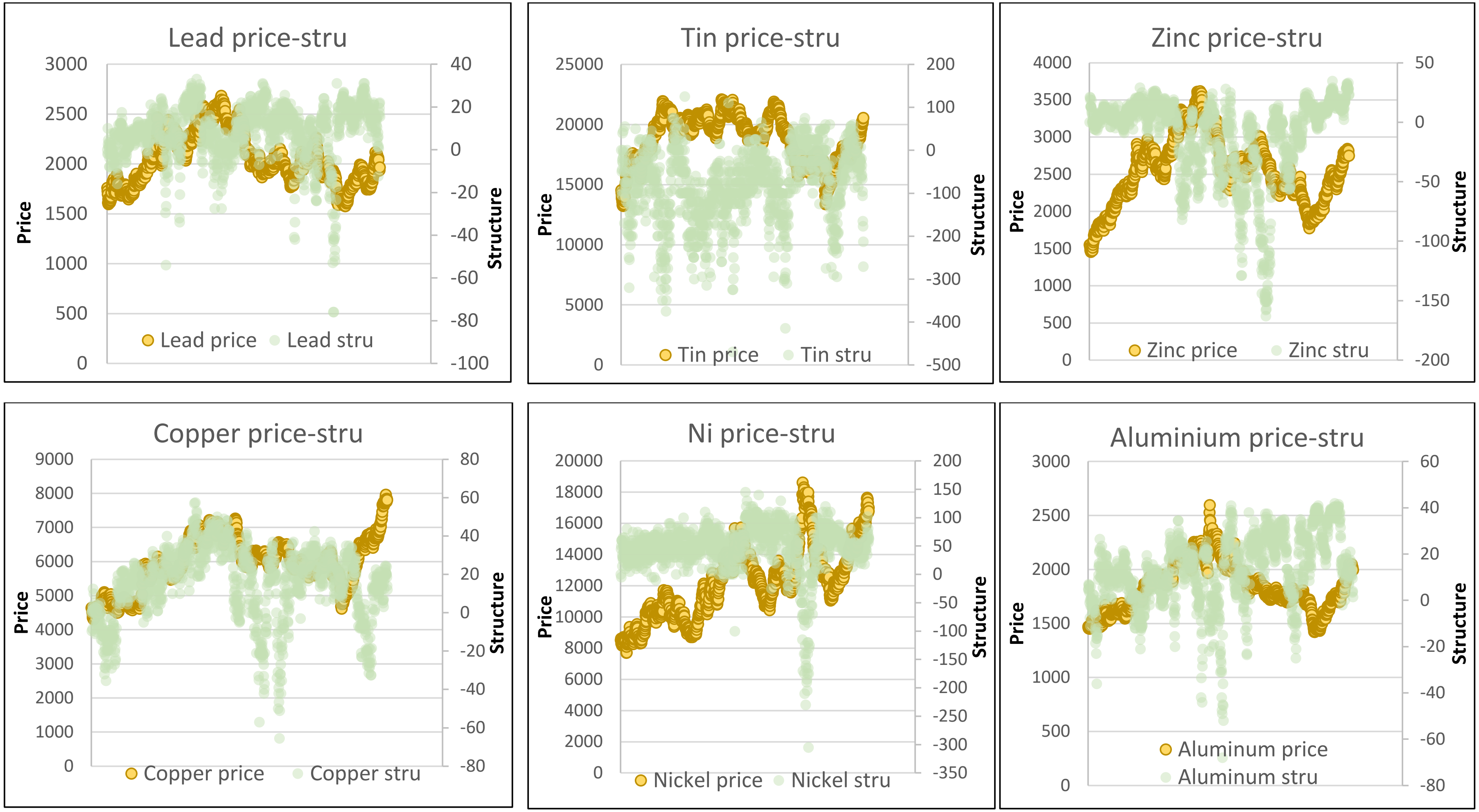


Fig. 4. Price data and futures price structure for every metal. LME data and authors' graphic.

3.2. Methodology

Cointegration and causality can be considered good tools to determine if two data series, such as price and the structure of future prices, are linked somehow. Thus, we analyzed the constructed data matrix in two ways:

- Using time data series causality
  - Across the entire data timeframe and metal by metal
  - Using intervals of study coming from structural breaks, metal by metal
- Using panel data structures causality

There are many previous studies of time series causality, including Engle and Granger (1987), who used the Johansen approximation (Johansen 2008): Eross et al. (2019), who applied the methodology to study bitcoins; Qadan (2019) and Rutledge et al. (2013), whose analyses of the same market environment explored in this study or other topical studies; and Hossain and Mitra (2017), Alam (2017), Hadi et al. (2019), Dong (2017), Chalmers et al. (2019) and Samsi et al. (2019) and more recently by Galán-Gutiérrez and Martín-García (2021). Unlike these time series approaches, there is also the chance to perform a global study using data panel analyses, increasing the number of data points and the interaction between the different time series, as in Banerjee and Carrion-i-Silvestre (2015) and Villca et al. (2020) and specifically in the world of commodities, Sharma (2020), Agnello et al. (2020) and finally Karabiyik et al. (2021) in the relationship between price metals and fundamentals. The usage of panel data series has different advantages compared to time series studies, such as those described in Hsiao (2007) and its different comments, Arellano (2007), Baltagi (2007), Mairesse (2007), Nerlove (2007), Park and Song (2007), Shin (2007), Sickles (2007) and Wansbeek et al. (2007). These advantages include more accurate inference of model parameters, greater capacity for constructing more realistic behavioral hypotheses, uncovering dynamic relationships, controlling the impact of omitted variables, generating more accurate predictions for individual outcomes, providing microfoundations for aggregate data analysis, and simplifying computation and statistical inference (Hsiao, 2014).

<u>With time series causality tests</u>, performing the Johansen approximation under Engle and Granger, we study the following series:

- Structure of copper futures prices, $(y_t)_{t=1}^{N}: (stru_t)_{t=01-01-2016}^{31-12-2020}$ (Equation 1a)
- Price of metals, $(z_t)_{t=1}^{N}: (PRICE_t)_{t=01-01-2016}^{31-12-2020}$ (Equation 1b)

Using the different metals (tin, lead, copper, aluminum, nickel and zinc), we have 12 time series, 6 price series and 6 structure series. This study will be done in 2-by-2 series packs for each metal.

These causality tests require stationary time series or nonstationary transformed series of the same order. Thus, several tests are performed to verify stationarity:

- Those where the stationarity of the series is the null Hypothesis H_0, such as KPSS (Kwiatkowski et al., 1992) and as the Leybourne tests and McCabe tests (Leybourne and McCabe, 1994). These tests have recently been used by Su et al. (2020) and by Cui et al. (2021), linking bitcoin and oil prices.

- Others where the null hypothesis assumes nonstationarity, such as the Dickey-Fuller test as well as the augmented Dickey Fuller test. This set of tests was initially introduced by Dickey and Fuller (1979) and extensively used over the years but more recently in Syed et al. (2021) or Li et al. (2021), the Phillips-Perron test (Phillips and Perron, 1988) and the

DF-generalized least squares tests (Elliot et al., 1996). The number of lags complies with the Bayesian information criterion (BIC), as suggested by Yao (1988), and the Akaike information criterion (AIC), Akaike (1974) and extended in Bai and Perron (2003). This set of tests is broadly referenced in real topics as oil and stock markets (Sarwar et al., 2020) or cryptocurrencies (Gil-Alana et al., 2020).

Based on Engle and Granger's causality cointegration, autoregressive vectors (VARs) were calculated. Johansen's approximation is used to look for the cointegration between the two series, as in Ivascu et al. (2021) and Mat et al. (2020). This method is valid when the tentative cointegrated series have a low stationarity value like I(1), even if it is also a tool with strength for other values (Hjalmarsson and Österholm, 2010). The trace test and λ_{max} one are the two variables used to execute the Johansen approximation.

- Engle and Granger's cointegration tests were used to estimate the two equations shown below from the two series of OLS transformed data:

$$stru_t = \alpha_0 + \alpha_1\, stru_{t-1} + \cdots + \alpha_1\, stru_{t-l} + \beta_1\, stru_{t-1} + \cdots + \beta_1\, PRICE_{t-l} + \varepsilon_t, \text{ (Equation 1c)}$$

$$PRICE_t = \alpha_0 + \alpha_1\, PRICE_{t-1} + \cdots + \alpha_1\, PRICE_{t-l} + \beta_1\, PRICE_{t-1} + \cdots + \beta_1\, stru_{t-l} + u_t \quad \text{(Equation 1d)}$$

where *l* is the number of delays used; α and β are the parameters to be studied; and ε_t and u_t are the errors or random disturbances, respectively, which are normally uncorrelated.

If βl = β1 = 0, there is no inter-series causation, while if βl ≠ β1 ≠ 0, the two are cointegrated, as defined by Granger.

The Johansen approximation yields α and β as the vectors:

$\alpha = |p,r|$ and $\beta = |m,r|$

where *r* is the number of cointegrating vectors, and *p* and *m* are the series vector components.

To understand if there are structural breaks and intervals of study to be investigated in detail, we use the references used by Gil-Alana (2002), Bai and Perron (2003), Gil-Alana (2008) and Caporale et al. (2020). Gil-Alana also used fractional unit root tests, which could be a base for a more accurate exercise in this study or in others of the same nature.

This theory is used when working with fractional integration as a generalization of the ARMA-ARIMA specifications, these I(d) models could use d integer or fractional values.

These studies use the test described by Chow (1960) for a classical linear model, and the null hypothesis of no structural break is constructed using a Wald statistic, whose properties are surveyed in Perron (2006).

Once a structural break is identified, we use descriptive analysis to find other possible structural breaks that will be checked in the way that the coefficients do not vary over the subsamples used. Structural breaks allow coefficients to change after a break date. If b is the break-date, the model is:

$$y_{it} = \begin{cases} \beta_i\, x_{it} + \gamma_i\, z_{it} + \varepsilon_{it} & if\ t \le b \\ (\beta_i + \partial)\, x_{it} + \gamma_i\, z_{it} + \varepsilon_{it} & if\ t > b \end{cases} \quad \text{(Equation 1f)}$$

The null and alternative hypotheses are H0= $\partial = 0$ and H1 = $\partial \neq 0$, respectively.

With the panel-data cointegration tests, we analyze cointegration individually inside each time series and the common trends of every of each metal together with a larger database (every metal instead of one by one), thus obtaining the same cointegration. In short, this test analyses the full series set (12 series).

Kao (1999), Pedroni (2001) and Westerlund and Edgerton (2008) used cointegration tests that relied on the common approach with a null hypothesis of no cointegration. Kao and Pedroni's tests demonstrate in their different theories that the studied variables are cointegrated throughout the range of data on the panel. Similarly, Westerlund's tests only show cointegration in certain metals.

These tests are based on the panel-data model for the dependent variable y_{it} :

$$y_{it} = \beta_i \, x_{it} + \gamma_i \, z_{it} + \varepsilon_{it} \text{ (Equation 1e)}$$

where i = 1,…,N denotes the individual panel, t = 1,….,T_i denotes time, x_{it} is the independent variable, $\beta_i$is the cointegration vector, and $\gamma_i$is the vector of coefficients on z_{it}.

The basis of these three package tests (Kao, Pedroni and Westerlund) is founded in the previously referred ADF, PP and KPSS tests using vectors and matrices instead of linear series under Equation 1e.

To summarize the methodology and steps performed in this paper, the primary target of this study is to investigate whether there should be some link between an increase in the price of a hard commodity (e.g., a base metal) and a negative futures price structure (backwardation).

We have investigated different metals, some of which are more financialized, and others are more dependent on their fundamental drivers.

In the first stage, we do have two different groups of studies:

- All of the data
- Data intervals as defined by structural breaks:

All data: Augmented Dickey Fuller and Phillips Perron tests have only shown a strong value to determine the same order between the price data and the futures price structure for some metals, even if other tests such as KPSS have shown the same for a wider range of them.

Data intervals: First, intervals are obtained via structural breaks with a given accuracy value and later through descriptive analysis, thus determining which values are more doable to be used as possible breaks and after. We also check if previous breaks can be used to reject the null hypothesis of no structural break.

In the second stage, we run the test throughout the panel data series for the entire data range, finding a global cointegration of all metals.

4. Results

In this section, we document the results of the double analysis described above: a two-in-two-variable analysis and the matrix defined by the full dataset with panel structure

4.1. Metal by metal results

Results show that aluminum, tin, zinc and copper are the only possible stationary series (under the KPSS tests, as ADF/PP only describes tin) and the only possible cointegrated metals. Time series stationarity tests, metal by metal and using the entire-time range are shown in Table 2:

p value	ADF	PP	KPSS	Stat.	Same order ADF/PP	Same order KPSS	Average price
Al price	< 0,0001***	< 0,0001***	< 0,0001***	Yes/No	No	Yes	$ 1.835
Al-stru.	0,646	0,801	< 0,0001***	No/No			
Ni price	0,042**	< 0,0001***	0,104	Yes/Yes	No	No	$12.167
Ni-stru.	0,316	0,884	< 0,0001***	No/No			
Pb price	< 0,0001***	< 0,0001***	0,082	Yes/Yes	No	No	$2.050
Pb-stru.	0,275	0,662	<0,0001***	No/No			
Sn Pric	0,001***	< 0,0001***	0***	Yes/No	Yes	Yes	$18.793
Sn-stru.	*0,073**	0,833	< 0,0001***	Yes/No			
Zn price	*0,097**	0,001***	0***	Yes/No	No	Yes	$2.544
Zn-stru.	0,341	0,822	< 0,0001***	No/No			
Cu price	0,014**	0***	0,006	Yes/No	No	Yes	$5.944
Cu-stru.	0,685	0,932	< 0,0001***	No/No			

Notes: *** 1% significance, ** 5% significance, * 10% significance

Table 2, stationary tests data

The application of the Johansen approximation of Engle and Granger's theory for metals whose series have the same level of stationarity shows that the time series (price and future price structure) are cointegrated (Table 3).

(Signif. value 5%) p value	VAR order	Lambda max test	Trace test	Adjustment coefficient alfa		Adjustment coefficient beta	
Al price	4	At least one Cointegration relation		1,300	0,266	0,000	0,001
Al-structure				-0,706	0,003	0,067	0,000
Sn price	4	At least one Cointegration relation		-1,305	3,289	0,000	0,000
Sn-structure				9,166	-0,197	-0,014	0,000
Zn price	3	At least one Cointegration relation		3,519	0,252	0,000	0,000
Zn-structure				-0,792	0,050	0,029	-0,002
Cu price	5	At least one Cointegration relation		3,436	-2,276	0,000	0,000
Cu-structure				-0,711	-0,049	0,057	0,001

Table 3, cointegration data

Lambda max and trace tests show that the four pairs of series are cointegrated with different VAR orders, with aluminum and tin of the same order (4), zinc with VAR order (3) and copper with order (5).

Finally, the results from the analysis of the entire data series show that on aluminum, tin, zinc and copper, the price data series are cointegrated with the futures price structure data series (p < 0,05). In connection with the hypothesis that financialization could be a driver for this connection of "normal backwardation" with high prices, we can initially say that this hypothesis is true with copper and aluminum (the two more financialized metals) but not with nickel. Conversely, we find that some less financialized metals, such as tin, exhibit this type of cointegration.

Once we have determined that the entire-time data series are cointegrated for some metals, we find structural breaks in the time series and perform stationarity and cointegration tests for the intervals obtained. Applying Chow tests for structural breaks in time-series data, we obtained the breaks shown in Table 4 ($p < 0.01$). To study their stationarity, we used the augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and finally the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

El.	**Break**	**Intervals per the first test**		**ADF**	**PP**	**KPSS**	**Johansen**
Al	**19/07/18**	04/01/2016	20/07/2018	**1st(0,013/0,001)**	1st(<0,0001/0,855)	1st(0,033/<0,0001)	N/A
	***	19/07/2018	30/12/2020	2nd(0,040/0,986)	2nd(0,006/0,568)	**2nd(0,009/<0,0001)**	
Ni	**15/07/19**	04/01/2016	16/07/2019	1st(0,001/0,407)	1st(<0,0001/0,837)	**1st(<0,0001/<0,0001)**	(1) AIC 5 p 1%
	***	15/07/2019	30/12/2020	**2nd(0,649/0,937)**	2nd(0/0,810)	**2nd(<0,001/<0,0001)**	(2) AIC 5 p >10%
Pb	**12/03/20**	04/01/2016	12/03/2020	1st(0,001/0,586)	1st(<0,0001/0,601)	1st(0,018/<0,0001)	N/A
	***	12/03/2020	30/12/2020	2nd(0,075/0,583)	**2nd(0,247/0,817)**	2nd(0,038/<0,0001)	
Sn	**18/06/20**	04/01/2016	19/06/2020	1st(0,002/0,080)	1st(<0,0001/0,820)	1st(0,102/<0,0001)	N/A
	***	18/06/2020	30/12/2020	**2nd(0,669/0,598)**	2nd(<0,0001/0,759)	**2nd(0,001/<0,0001)**	
Zn	**14/09/20**	04/01/2016	15/09/2020	1st(0,003/0,293)	1st(<0,0001/0,983)	**1st(0,001/<0,0001)**	(1) AIC 2 p 1%
	***	14/09/2020	30/12/2020	**2nd(0,130/0,904)**	2nd(0,009/0,522)	**2nd(<0,0001/<0,0001)**	(2) AIC 3 p 4%
Cu	**29/09/16**	04/01/2016	30/09/2016	**1st(0,296/0,310)**	1st(0,013/0,726)	1st(<0,0001/0,017)	N/A
	***	29/09/2016	30/12/2020	2nd(0,008/0,614)	2nd(0,001/0,932)	**2nd(0/0,002)**	

Notes: *** 1% significance, ** 5% significance, * 10% significance.

Bold on ADF/PP and KPSS indicate the same level of either stationarity/nonstationarity.

Table 4, Stationarity and cointegration for intervals defined through the structural break obtained

There is not the same stationarity I(x) with the ADF and PP tests for the time series of price structure and price of the different metals studied, even though the KPSS analysis shows that it can be present with nickel and zinc. We have considered that the two time series (price and price structure) in every interval have different stationarity levels; therefore, it is nonsensical to transform them using the Box–Cox method.

Using the Johansen approximation with nickel and zinc, we do not find that the two time series under the two intervals defined by the structural breaks are cointegrated in the same value. Only with zinc do we find a certain level of cointegration between the two time series in the two intervals in the first time series defined in the interval ($p < 0.01$) and in the second ($p < 0.04$). Therefore, in general, the analysis with two breaks does not show cointegration, which is why this analysis must be improved looking for more breaks for the full time series. These results thus could be considered in comparison to the linkage between financialization and the cointegration studied in this paper.

Searching for additional breaks that can better describe each metal price behavior, we performed a descriptive analysis of the time series per metal, finding additional breaks: three on aluminum, one in nickel, two in lead, four in tin, four in zinc and four in copper. These intervals make up for the shortcomings shown by the initial breaks. Through the Wald and likelihood-test ratio, different significance values were obtained (Table 5). The final intervals obtained are plotted in Annex I, Figures 5-10.

Metal	Other tentative breaks obtained Descriptive+Wald	Initial break obtained
Aluminum	07/01/18*** 22/07/18*** 28/11/19	22/07/18***
Nickel	10/10/19	16/07/19***
Lead	18/08/17 01/02/18**	13/03/20***
Tin	03/07/17** 19/11/18*** 15/06/20*** 13/10/20***	20/06/19***
Zinc	14/09/18*** 30/11/18*** 24/05/19*** 06/11/19***	15/09/17***
Copper	03/10/16*** 17/05/18** 11/05/20***	03/10/16***

Notes: *** 1% significance, ** 5% significance, * 10% significance.

Table 5. Structural breaks obtained

In the periods obtained through analysis, a stationary test and a cointegration test were performed with those series that had the same level of stationarity, except for nickel and lead, in which the structural break used previously was sufficient (i.e., no more highly significant breaks were found).

The new intervals obtained are shown in Table 6:

Metal	Intervals					
Al	04/01/2016 07/01/2018	08/01/2018 22/07/2018	23/07/2018 27/11/2019	28/11/2019 30/12/2020		
Sn	04/01/2016 19/11/2018	20/11/2018 20/06/2019	21/06/2019 15/06/2020	16/06/2020 13/10/2020	14/10/2020 30/12/2020	
Zn	04/01/2016 15/09/2017	16/09/2017 14/09/2018	15/09/2018 30/11/2018	01/12/2019 24/05/2019	25/05/2019 06/11/2019	07/11/2019 30/12/2020
Cu	04/01/2016 03/10/2016	04/10/2016 17/05/2018	18/05/2018 11/05/2020	12/05/2020 30/12/2020		

Table 6. Intervals per metal (Al, Sn, Zn, Cu)

Stationarity tests and cointegration tests in those with the same level of stationarity/nonstationarity are shown in Table 7.

	Stationarity			Causality
	ADF	PP	KPSS	Johansen
Al	**1st(0,002/0,003)**	1st(0,002/0,975)	**1st(0/<0,0001)**	**(1) var 5, 1%*** **
	2nd(0,698/0,358)	2nd(0,031/0,573)	**2nd(0/0,066)**	(2) var 1, No cointegrated
	3rd(0,356/0,142)	3rd(0,002/0,210)	**3rd(0,049/<0,0001)**	(3) var 1, No cointegrated
	4th(0,006/0,904)	**4th(0,264/0,884)**	**4th(0,003/<0,0001)**	**(4) var 1, 10%***
Sn	1st(0,013/0,115)	1st(<0,0001/0,856)	1st(0,056/<0,0001)	(1) N/A
	2nd(0,314/0,806)	2nd(0,021/0,630)	**2nd(<0,0001/0,001)**	**(2) var 3, 10%***
	3rd(0,671/0,122)	3rd(<0,0001/0,393)	**3rd(<0,0001/<0,0001)**	(3) var 5, No cointegrated
	4th(0,545/0,141)	4th(<0,0001/0,853)	**4th(<0,0001/<0,0001)**	**(4) var 4, 10%***
	5th (0,998/0,599)	**5th (0,987/0,978)**	**5th (<0,0001/<0,0001)**	(5) var 1, No cointegrated
Zn	1st(0,027/0,291)	1st(0,000/0,987)	**1st(0,002/<0,0001)**	**(1) var 3, 1%*** **
	2nd(0,337/0,753)	2nd(0,036/0,250)	**2nd(0,000/<0,0001)**	(2) var 1, No cointegrated
	3rd(0,036/0,175)	**3rd(0,935/0,900)**	3rd(<0,0001/0,028)	(3) var 1, No cointegrated
	4th(0,591/0,799)	**4th(0,701/0,682)**	**4th(<0,0001/<0,0001)**	**(4) var 4, 5%****
	5th (0,834/0,948)	5th (0,004/0,394)	**5th (<0,0001/<0,0001)**	(5) var 2, No cointegrated
	6th(0,014/0,693)	6th(0,003/0,779)	**6th(<0,0001/<0,0001)**	**(6) var 2, 5%****
Cu	**1st(0,290/0,304)**	1st(0,020/0,726)	1st(<0,0001/0,015)	(1) var 3, No cointegrated
	2nd(0,013/0,238)	**2nd(0,228/0,938)**	**2nd(<0,0001/<0,0001)**	**(2) var 5, 10%***
	3rd(0,065/0,111)	3rd(0,001/0,229)	**3rd(<0,0001/<0,0001)**	**(3) var 3, 10%***
	4th(0,620/0,646)	4th(0,036/0,999)	4th(0,002/0,1)	**(4) var 2, 5%****

Notes: *** 1% significance, ** 5% significance, * 10% significance. Bold levels on ADF/PP and Bold levels on ADF/PP and KPSS indicate the same level of either stationarity/nonstationarity.
Table 7. Stationarity tests and cointegration per metal and interval

There are several intervals (Table 7) where cointegration between the metal price and the future price structure exists for every metal studied. Copper and aluminum, the two more financialized metals, are again shown to confirm part of this theory.

Summarizing the first block of the results, we find the following:

- Across the entire data range, we identified cointegration between the price data series and the futures price structure with tin, aluminum, zinc and copper.
- The intervals obtained through the structural breaks analysis are shown:
    - Only zinc is cointegrated with some significance level for every two intervals obtained through the structural break of each data series.
    - Using a descriptive analysis and corroborating the structural breaks, two intervals were identified to exhibit cointegration between both series with aluminum and tin, and three intervals with zinc and copper.

4.2. Robustness test: Panel data results

On the second block of the analysis, in order to test the strength of the methodology and the cointegration of the data, rather than only to test the time series through the Johansen approximation, we have also run a data panel test. Rather than only test the time series using the Johansen approximation, we also run a data panel test that considers the matrix of every metal and the entire data range, thereby yielding a strongly balanced panel variable. Thus, the Kao, Pedroni and Westerlund tests were used for cointegration and yielded the following results.

Kao test for cointegration	
Ho: No cointegration	Ha: All panels are cointegrated
Number of periods = 1,262	Number of panels = 6
Cointegrating vector: Same	
Panel means: Included	Kernel: Bartlett
Time trend: Not included	Lags: 5.17 (Newey-West)
AR parameter: Same	Augmented lags: 1
	Statistic
Modified Dickey-Fuller t	-1.6e+02***
Dickey-Fuller t	-31.4654***
Augmented Dickey-Fuller t	-18.0906***
Unadjusted modified Dickey-Fuller t	-2.3e+02***
Unadjusted Dickey-Fuller t	-32.2141***

Notes: *** 1% significance, ** 5% significance, * 10% significance.

Table 8. Kao test for cointegration on the panel data for the entire database.

Pedroni test for cointegration	
Ho: No cointegration	Ha: All panels are cointegrated
Number of periods = 1,263	Number of panels = 6
Cointegrating vector: Panel specific	
Panel means: Included	Kernel: Bartlett
Time trend: Included	Lags: 7 (Newey-West)
AR parameter: Panel specific	Augmented lags: 1
	Statistic
Modified Phillips-Perron t	-63.8807***
Phillips-Perron t	-22.9082***
Augmented Dickey-Fuller t	-25.0929***

Notes: *** 1% significance, ** 5% significance, * 10% significance.

Table 9. Pedroni test for cointegration on the panel data for the entire database.

Westerlund test for cointegration	
Ho: No cointegration	Ha: Some panels are cointegrated
Number of periods = 1,263	Number of panels = 6
Cointegrating vector: Panel specific	
Panel means: Included	
Time trend: Included	
AR parameter: Panel specific	
	Statistic
Variance ratio	-2.4165***

Notes: *** 1% significance, ** 5% significance, * 10% significance.

Table 10. Westerlund test for cointegration on the panel data for the entire database.

Tables 8-10 show that that there is cointegration on the entire panel data ($p < 0.01$). From the Kao analysis, we find that the panel data are cointegrated ($p < 0.01$) based on the different versions of Dickey Fuller theories, the Pedroni tests with Phillips-Perron, Modified Phillips-Perron and finally with the Augmented Dickey-Fuller tests, thus confirming cointegration in every interval. Westerlund tests certify that cointegration exists in at least some intervals, as described in the methodology.

We also obtained the same results as those with the first block of data, finding cointegration for the different metals between their prices and their future price structure as a global data matrix. These results are also consistent with Yu et al.'s (2021) results for copper in specific time intervals.

Therefore, a relationship between the price and futures price structure of each metal is characterized as follows:

- Cointegration between aluminum, tin, zinc and copper using the full time series.
- Cointegration only with zinc at a low level using two intervals defined per structural breaks.
- Cointegration in two intervals with aluminum and tin, and in three intervals on copper and zinc using intervals defined by several structural breaks
- Cointegration between every metal series using panel data research.

5. Conclusions and policies

In this period of strong demand for raw materials that also includes the COVID-19 pandemic, and from which the recovery has been strong and consistent, there is a widespread belief in the industry that we are entering a new commodity supercycle, which could last for years or even decades. There are many factors that point to this conclusion. First, some factors that show common patterns between the early 2000s and the 2020s, such as China's economic performance and the investment cutback in metal companies during the 2012-2020 period due to a fall in prices, will likely lead to lower future supply and high prices. Second, new structural factors, such as the energetic transition and the development of electric vehicles, plus the electrification of the remaining parts of the world, are likely to lead to this supercycle. Third, financial issues currently exist, including commodities being used as haven securities for investors. Compared to other alternative assets (such as equities), commodities are cheap and have revaluation potential, particularly those more financialized, which is attractive to investors. Public stimulus is also an important factor. The end of the quantitative easing (QE) implemented after the 2007 crisis, which had such a negative impact on the price of commodities, and the entry of governments worldwide fiscal and monetary stimuli to boost the recovery of economic growth are also two factors that will favor these markets in the near future.

Thus, metals could be in a position to increase in price, thereby being in a position of "normal backwardation". In this context, this study searches for patterns and relationships to understand the joint behavior of price structure and level of price (high, low, increasing or decreasing) to assess market agents to optimize their positions. Causality tests using Engle and Granger's theory and Johansen´s approximation for the same stationarity series using ADF, PP and KPSS methodology were performed with the time series of metal prices.

Results show a clear linkage between increases in metal price and an increase in the short-term price compared with the long-term price (futures price structure). This effect is stronger for tin, copper, aluminum and zinc via independent data series analysis and on intervals defined by structural breaks. Robustness tests with data panel and a full data matrix confirm these results. Additionally, the linkage of financialization and this theory for the two most financialized metals (aluminum and copper) is demonstrated. This link has not been found for metals with low financialization.

Considering only the price and not the futures price structure, when the market is high and fundamentals propose an even tenser scenario, everyone thinks about buying the commodity today to be sold tomorrow. This strategy is commonly used by price speculators and, in general, high-risk investors. Instead, when the focus is set on price structure, agents who are in high-price tensioned markets and already have physically hedged positions could take advantage of backwardation, positioning short in the long term to achieve value from the carries (i.e., lending instead of borrowing) and staying long in the short term. This strategy would let them not speculate on price but on the price difference over time (price structure), which could be more stable than intraday or interday price changes.

This study provides a more reliable and econometric-based pattern to confirm that when prices are generally high, markets tend to backwardate (commodity spot prices are higher than future prices). The results of this study have important implications for players that hedge their exposure, using this theory to position profit taken and stop loss orders as hedging tools in scenarios where the metal price is high to ensure good results. For the variety of metals that price on the base metal LME structure, aluminum and copper (the most financialized metals) behave with the cointegration described in this paper, showing a linkage between financialization and normal backwardation in high price scenarios. The refuge of some investors on base metals depending on the global market situation is a fact; therefore, another justification to consider this theory to be a key factor to move the liquidation of positions between different stock values. Policy-makers can thus structure this cointegration as a reference to reduce volatility and instability that, in a specific period of time with high prices, could occur. Thus, countries' metal reserves can always be a strong tool to leverage the market.

Economic crisis and, more generally, unstable situations when markets were disturbed in some way should be investigated in future research, including subsamples studied with fractional integration trying not to lose any of the soft tentative cointegrations.

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Annex I:

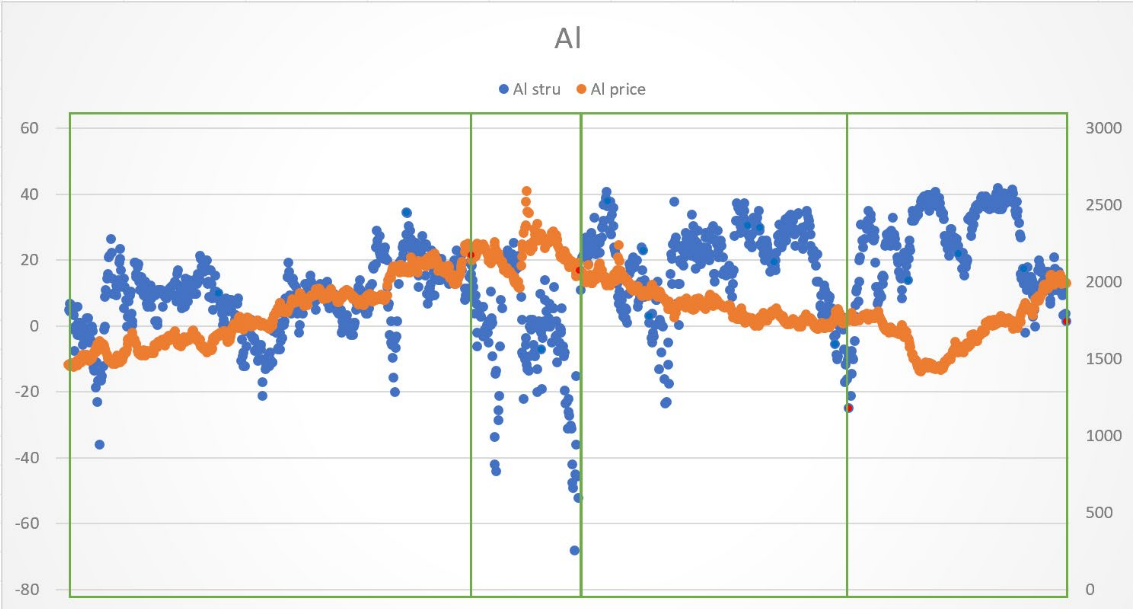

Fig. 5 Aluminum price and futures price structure divided into the intervals obtained.

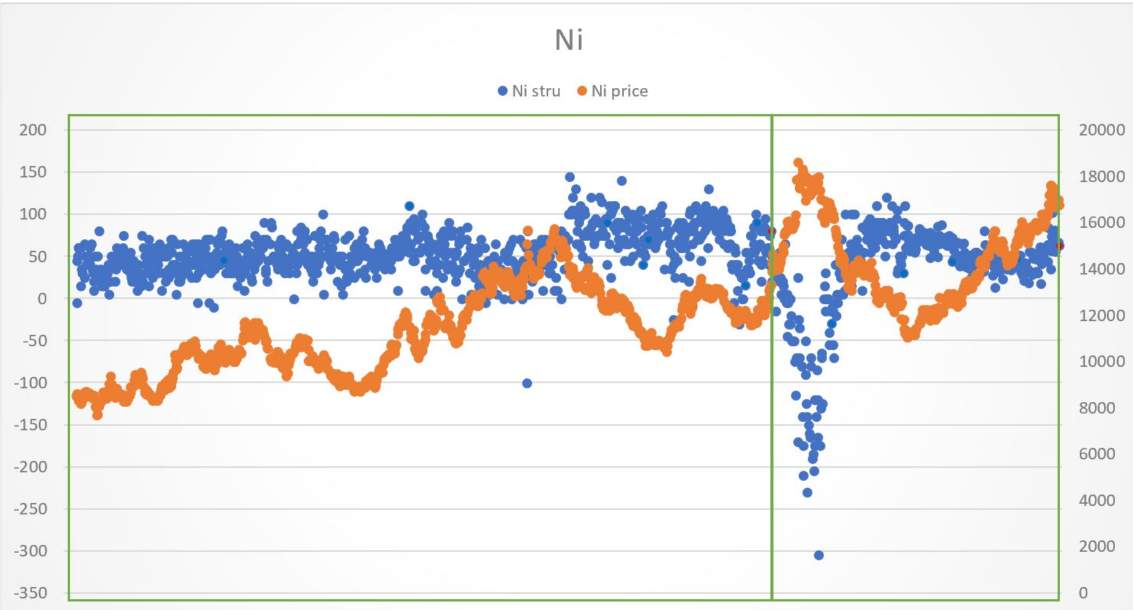

Fig. 6 Nickel price and futures price structure divided into the intervals obtained.

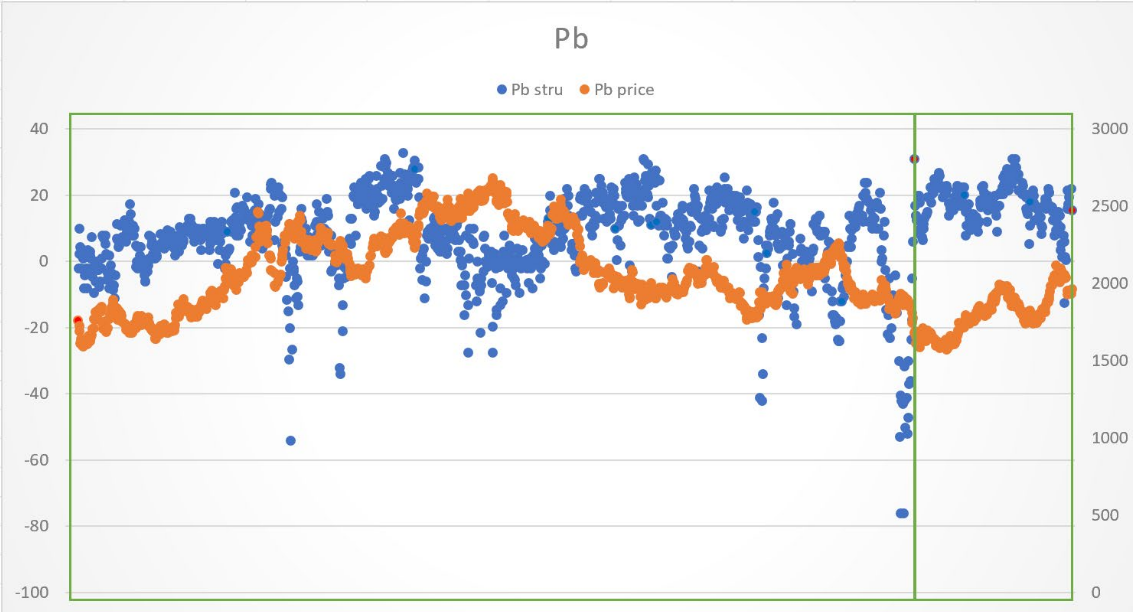

Fig. 7 Lead price and futures price structure divided into the intervals obtained.

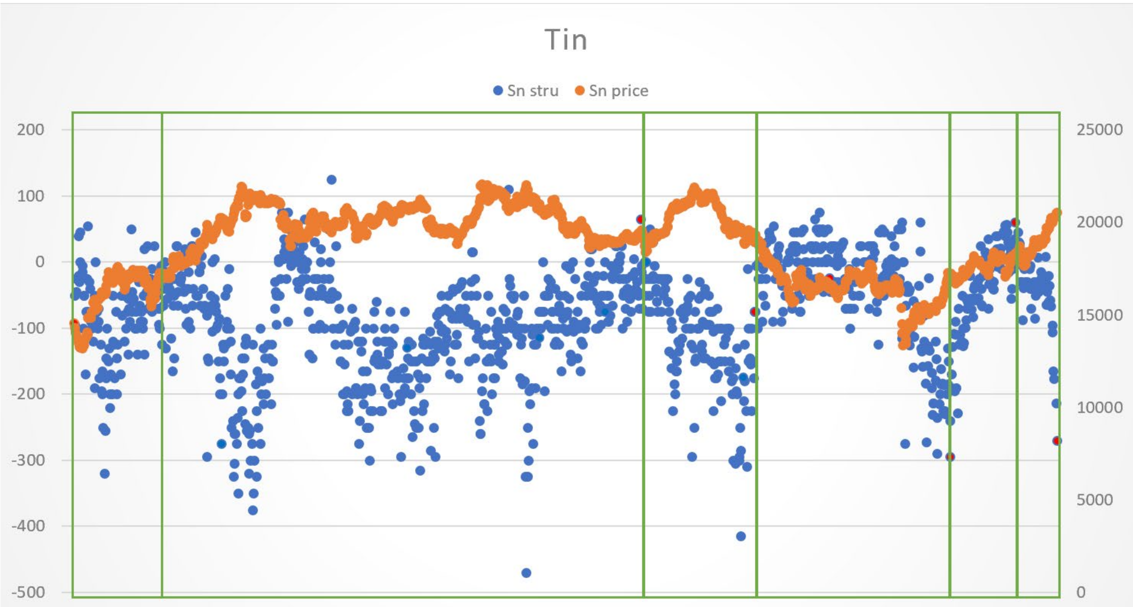

Fig. 8 Tin price and futures price structure divided into the intervals obtained.

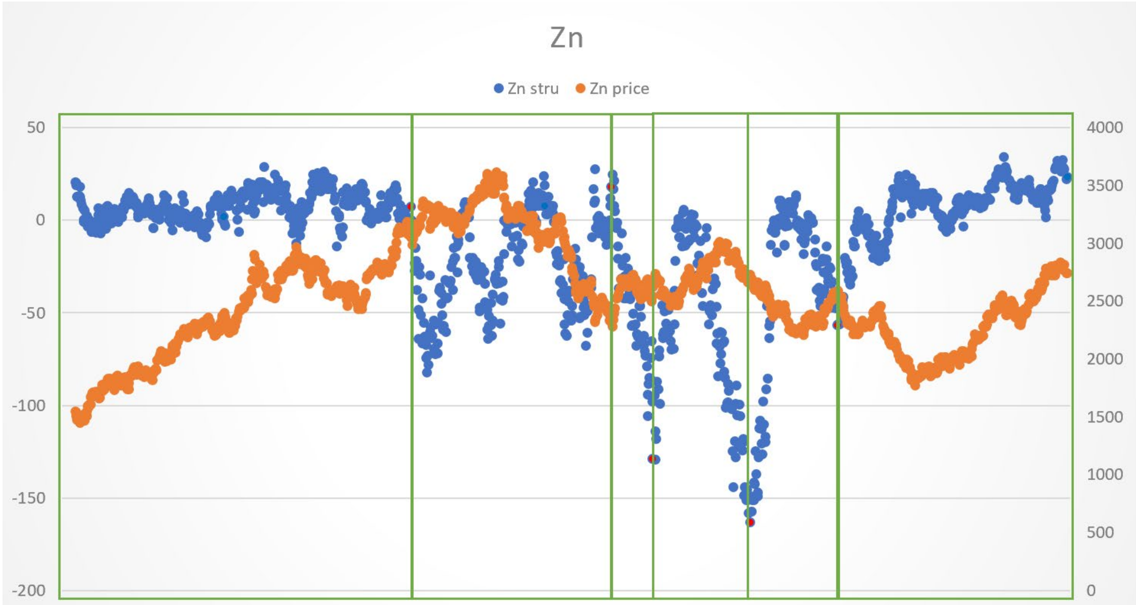

Fig. 9 Zn price and futures price structure divided into the intervals obtained.

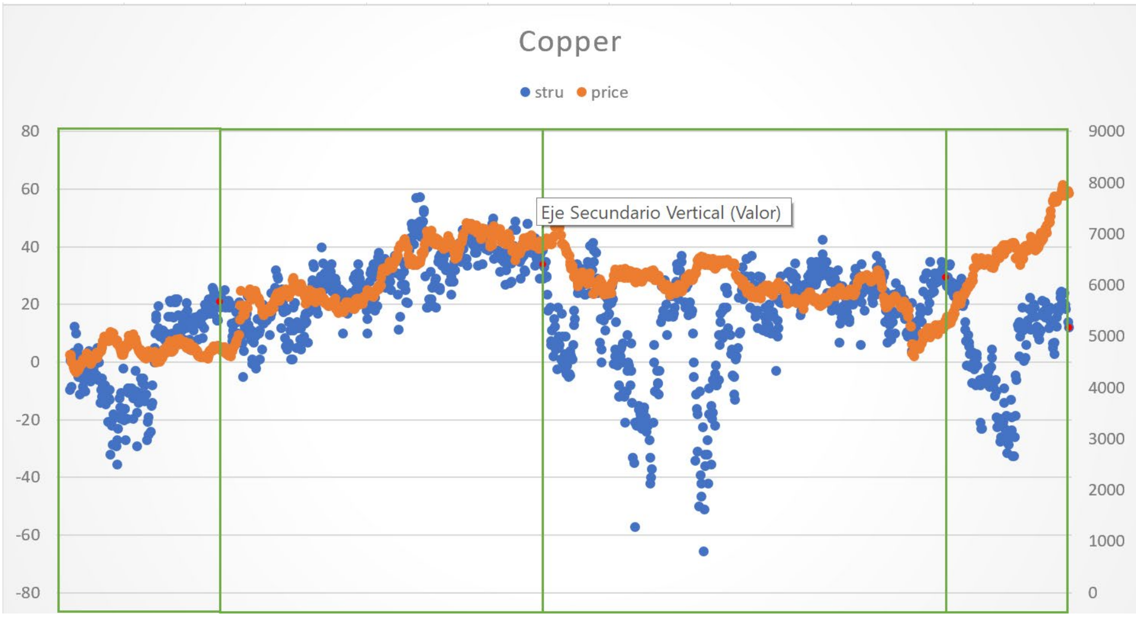

Fig. 10 Copper price and futures price structure divided into the intervals obtained.