Resources Policy 82 (2023) 103433

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Mineral prices persistence and the development of a new energy vehicle industry in China: A fractional integration approach

Gloria Claudio-Quiroga [a,*], Luis A. Gil-Alana [b], Andoni Maiza-Larrarte [c]

[a] Universidad Francisco de Vitoria Faculty of Legal and Business Sciences, Universidad Francisco de Vitoria, Carretera Pozuelo a Majadahonda, Km 1.800, 28223, Pozuelo de Alarcón, Madrid, Spain
[b] University of Navarra and Universidad Francisco de Vitoria Faculty of Economics, University of Navarra, Edificio Amigos, E-31090, Pamplona, Spain
[c] Economics University of the Basque Country UPV/EHU, Spain

ARTICLE INFO

JEL classification:
C12
G12
O33

Keywords:
Mineral prices
Persistence
New energy vehicle industry
China
Fractional integration

ABSTRACT

In this paper we examine price persistence in a set of minerals critical for the production of new energy vehicles. We implement techniques based on fractional integration also allowing for non-linearities and structural breaks at unknown periods of time. The results show that the series are generally very persistent, with orders of integration equal to or higher than 1 in practically all cases. The only exceptions being cobalt, tin and zinc if breaks are permitted and only for a given subsample. These findings are extremely relevant to initiate a discussion about the challenges that the new energy vehicle industry faces in China. China's government has already enforced some relevant initiatives to stabilise prices, but we conclude that additional measures will be necessary considering the high degree of uncertainty of certain supply-demand factors.

1. Introduction

China's government is firmly decided on promoting a strong domestic electric vehicle manufacturing industry. In the early 80's, the People's Republic of China (PRC) decided that the automotive was a key industry for the country's growth and a few foreign manufacturers were selected to nurture the initial steps of the industry through joint ventures. Domestic automotive companies have developed strongly since then, and now the strategy to foster the transition from fuel vehicles to new energy vehicles[1] (NEV) aims to guarantee that the country will keep a strong automotive industry ready to cope with the new environmental challenges.

In 2009 the State Council issued the Auto Industry Adjustment and Revitalization Plan (State Council, 2009), with the objective of reaching production capacity of 500,000 BEVs and PHEVs by 2012. Shortly after, China's science and finance ministries jointly launched "Ten Cities, One Thousand Vehicles", with a vision for 10 cities to add 1000 new energy vehicles annually (Ministry of Finance of the People's Republic of China, 2009). More importantly, in 2012 the State Council issued the Energy Saving and New Energy Vehicle Industry Development Plan (2012–2020), with the objective of reaching cumulative sales of 5 million and an annual production capacity of 2 million BEVs and PHEVs by 2020 (State Council, 2012).

These initiatives have paid off and, in just a decade, China has become the world's largest electric vehicle market: in 2020 the PRC accounts an electric car stock of 4.5 million, nearly half of the global stock (IEA,[2] 2021a), and more than 90% of the world's electric buses and trucks (Jin et al., 2021). The New Energy Vehicle Industrial Development Plan for 2021 to 2035 is more ambitious. The plan sets a target of a 20% share for NEVs by 2025, and states that "the core technology of the Chinese NEV industry should leapfrog to the international advanced level in the next 15 years with energy consumption per 100 km dropping to 12 Kw/h." (State Council, 2020).

Nevertheless, China' NEV strategy is challenged by the scarcity and the price instability of some minerals which are essential to the production of battery and electric vehicles. Governments all around the world are adopting policies to foster an energy system powered by clean energy technologies that rely critically on minerals such as lithium, cobalt, copper, nickel and rare earth elements. The IEA foresees that mineral demand on the part of clean energy technologies will rise by at

---

* Corresponding author.
E-mail addresses: g.claudio.prof@ufv.es (G. Claudio-Quiroga), alana@unav.es (L.A. Gil-Alana), joseantonio.maiza@ehu.eus (A. Maiza-Larrarte).

[1] In the Chinese context, NEVs comprise battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCVs).

[2] The International Energy Agency (IEA).

https://doi.org/10.1016/j.resourpol.2023.103433
Received 20 March 2022; Received in revised form 24 February 2023; Accepted 24 February 2023

least four times by 2040, with particularly high growth for NEV-related minerals, because a typical electric car requires six times the mineral inputs of a conventional car (IEA, 2021b). In this sector, lithium would experience the fastest growth, with demand growing by over 40 times, followed by graphite, cobalt and nickel, all of them with an increase of around 20–25 times (IEA, 2021b). Meanwhile, on the supply side, geological reserves of cobalt, lithium and nickel have quickly reduced (Habib et al., 2020). Besides, geopolitical risk is very high due to extreme market concentration in some minerals: in 2022 Congo (Kinshasa) accounted for about 70% of world cobalt production and Australia for slightly less than half of lithium production (USGS, 2023). In consequence, other countries heavily depend on these concentrated sourcing countries, and for instance, 70% consumption of lithium in China is imported from Australia (Hao et al., 2017).

Being aware of these risks, China's government is committed to strengthening price controls on iron ore, copper, and other major commodities as part of its 14th five-year plan for 2021 to 2025 (National Development, 2021). The rapid development of national exchange markets was a relevant step forward to increasing the control over mineral prices. A forward contract of copper was first introduced in the Jin Peng Copper Exchange (JPCE) in 1991. One year later, the Shenzhen Non-ferrous Metal Exchange (SNME) was launched, and shortly after, the Shanghai Metal Exchange (SHME) was established (Shyy and Butcher, 1994). After some regulatory changes in 1999, the SHME became the largest non-ferrous metals futures exchange in China (Lien and Yang, 2008), and nowadays the SHME is the third largest exchange of its kind in the world.

The main objective of this paper is to assess to what extent the instability of mineral prices could challenge China's NEV strategy. To this purpose, we analyse the time series of the prices of cobalt and lithium, which are key components in lithium-ion batteries, along with five base metals, copper, lead, nickel, tin and zinc. We use long memory and, in particular, fractional integration techniques, which are very appropriate to determine if exogenous shocks in the series have permanent or transitory effects depending on the orders of integration of the series under study. Our results indicate that strong policy measures are needed to smooth the impact of potential shocks.

Focusing the analysis on China is particularly relevant for at least three reasons: first, in 2020 the PRC accounts for half of the global stock of electric-vehicle market; second, China is firmly determined to continue developing domestic NEVs industry according to highest international standards; and, third, the PRC has created a national reserve of critical minerals that altogether with other policies could enable the country to smooth the potential impacts of mineral prices instability.

The reminder of the paper is organized as follows: Section 2 focuses on the literature research. Section 3 describes the data and the methodology. Section 4 presents the empirical findings based on I(d) models. Next, in Section 5 we discuss the main results. Finally, in Section 6 we summarise the main findings and conclusions.

2. Review of the literature

Commodities markets and metal markets have always been quite unstable, and for that reason price instability and volatility have both been thoroughly analysed in the literature. In a pioneering study, the U. S. Non-fuel Minerals' Policy Review found metal prices to be four times more volatile than prices in the economy as a whole (U.S. Department of the Interior, 1979). Slade (1991) detected that the increase in metal-price instability in the 80s was explained by changes in the underlying market-structure and the organization variables. Brunetti and Gilbert (1995) determined that metals price volatility is stationary, evidencing that there was no change in the mean of the volatility process over the period 1972-95.

There are several other studies that examine the cyclicality in metal prices (Cashin et al., 2002; Davutyan and Roberts, 1994; Deaton and Laroque, 1992; Labys et al., 1998, etc.). Roberts (2009) identifies peaks and troughs in the inflation adjusted prices for metals from 1947 through 2007, finding many cases in which the duration of expansions, contractions, etc. are not purely random and have some degree of cyclicality. Rossen (2015) examined the dynamics of monthly price series of a variety of mineral commodities over 100 years, determining that price cycles are asymmetric; the average time spent in slump phases is longer than the average time spent in boom phases. Besides, Rossen (2015) nuanced that metal prices do not necessarily follow similar patterns.

Chen et al. (2014) demonstrated that highly persistent movements of commodity prices are mostly due to two common factors: the first common factor, the U.S. nominal exchange rate, explains the largest proportion of the variation in the panel of prices, which was found to be nonstationary; the second factor, de-factored idiosyncratic components are consistent with being stationarity, implying short-lived deviations from the equilibrium. Yaya et al. (2022) investigated the effect of time-variation of the precious metals' – oil price returns and shocks nexuses using the univariate GARCH-MIDAS-X regression, and the bivariate DCC-MIDAS model finding that precious metals exhibit hedging potentials against oil demand and supply shocks, with heterogeneity observed in the precious metal-oil shocks nexus.

Interestingly, Panas (2001) applied long memory and chaos analysis in the evaluation of the behaviour of metal prices of the LME market. The empirical results indicate chaos in tin and support the long memory hypothesis in the case of aluminium and copper. A short memory model explains the underlying processes of the nickel and lead returns series, while zinc returns reflect intermediate memory (an anti-persistent process). Watkins and McAleer (2006) applied econometric time series techniques to LME futures and spot price data and estimated long run pricing models for non-ferrous metals futures contracts. Gil-Alana and Tripathy (2014) determined that all the non-ferrous metal series exhibit a high degree of volatility persistence in Indian markets.

There are also relevant empirical papers analysing China's metal markets. Cheng et al. (2013) tested the long memory feature of price−volume correlations in China's metal futures market, applying an MF-DCCA approach, finding that the long memory feature with a certain period exists in price− volume correlation. Yue et al. (2015) examined the price linkage between Chinese and international non-ferrous metals commodity markets, and Zhu et al. (2017) determined that copper and aluminium futures market volatility in Shanghai Futures Exchange has strong heterogeneity and dynamic dependencies, which implies long memory in daily realized volatility.

This paper contributes to the existing literature in two main aspects: firstly, the methodology, which is based on fractional integration and allows for non-linear trends and structural breaks, and, secondly, we focus the analysis on a few minerals which are critical for the production of EVs, which allows us to use the empirical results of our econometric analysis to initiate a discussion about the potential impact of mineral price instability in the emergent Chinese NEV manufacturing industry.

3. Data and methodology

In our analysis, we have selected seven key components in the production of electric vehicles: cobalt and lithium, which are key components in lithium-ion batteries, and five base metals, copper, lead, nickel, tin and zinc.[3] We use weekly data from June 1, 2012 to October 13, 2021. Data were extracted from the EIKON Refinitiv database on October 14, 2021. EIKON Refinitiv collects data referred to the Shanghai Metal Exchange from the Shanghai Metal Market (SMM) data provider. More precisely, data correspond to the following series: Refined Copper (SMM-CU-REF), Refined Cobalt = 99.8% (SMM-REM-RCB), Lithium Metal = 99%, Industrial Grade, Battery (SMM-MIN-LTM), Secondary Refined Lead = PB99.97 (SMM-LD-REF), Refined Nickel = NI99.90 (SMM–NIC–RN1), Tin INGOT SN99.90 (SMM-TN-ING1) and Zinc Alloy (SMM-ZN-AL1). All the series are collected in RMBs and in metric tonnes.

The majority of the literature mentioned in Section 2 focuses on the London Metal Exchange. Instead, we use data from the Shanghai Metal Exchange (SHME), since our objective is to analyse the potential impact of mineral price volatility in the development of the electric vehicles industry in China. We think that this choice is relevant for the reason that there are differences in prices. These two markets are physically thousands of miles apart, i.e. the supply-demand balance and transportation costs connecting the two markets at the time, which can incentivise imports and exports of metal and arbitrage (Zehai and Huiyan-Zhang, 2013; Rutledge et al., 2013; Sang and Seong-Min, 2016). In this regard, it is convenient to recall that China is now the world leader in processing copper, nickel, cobalt, lithium and rare earth elements, with shares between 40% and 80% of the world total (International Energy Agency, 2021b). Another significant difference with respect to other empirical papers is that we use renminbi to limit the impact of the US dollar exchange rate fluctuation in our analysis. It is well known that shocks to the US dollar account for a substantial share of fluctuations in commodity prices (Akram, 2009; Chen et al., 2014).

Fig. 1 displays the time series plots (in logs). At first sight, none of the series show a consistent upwards/downwards trend. The charts exhibit several dips and peaks, though in all the series except lead the final value is significantly higher than the initial one. In fact, at the end of the period, the values of copper, lithium, nickel, tin and zinc are close to their maximum. Additionally, the basic descriptive statistics of price series (in Table 1) show that lead and copper are the ones with lower standard deviation levels, whereas the highest standard deviation values correspond to cobalt and lithium.

As far the methodology is concerned, we use fractional integration methods, to test for the order of integration of the series and allowing for fractional values. Note that this is a more general approach that the standard one that is based exclusively on integer degrees of differentiation, i.e., 0 for stationarity and 1 for nonstationarity. In fact, it is a well-known stylized fact that classical unit root methods have very low power for testing unit roots if the underlying series are fractionally integrated (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996; etc.). Moreover, several authors have argued that fractional integration might be an artificial artefact generated by the presence of structural breaks in the data that have not been taken into account (Granger and Hyung, 2004) and non-linearities is another issue that might be intimately related with this model. Thus, in the paper we also allow for structural breaks and non-linear deterministic trends, following the approaches developed in Gil-Alana (2008) and Cuestas and Gil-Alana (2016) respectively.

4. Empirical results

Tables 2 and 3 report the estimated values of the differencing parameter (d) in the model given by:

$$y_1 = \alpha + \beta t + x_t (1 - L)^d x_t = u_t, t = 1, 2 \qquad (1)$$

where y_t stands for the observed time series (in logs); α and β are the coefficients on the intercept (α) and the linear time trend (β); d is a real value that measures the degree of persistence in the data, and u_t is assumed to be integrated of order 0 or I(0). We obtain estimates of the parameter d from three different specifications: i) when α and β are set up to be 0, i.e. no deterministic terms are included in the regression model (1), ii) with β = 0, that is, allowing for an intercept, and iii) estimating α and β from the data and therefore allowing for both an intercept and a linear time trend; Further, the disturbance term u_t, is assumed to follow a white noise process (in Table 2) or, alternatively, to be autocorrelated (in Table 3) as in the non-parametric spectral approach proposed by Bloomfield (1973).[4] In both cases we select our preferred model on the basis of the significance of the regressors according to their t-statistics. We have marked in bold in the tables the selected deterministic models for each series. This has been chosen by means of the t-values in these deterministic terms.

We notice that the time trend coefficient is found to be statistically insignificant in all the series examined in both models for the error terms. Focusing on the differencing parameter d, no evidence of mean reversion is found in any single case. With white noise errors, the unit root null, i.e., evidence of d = 1, cannot be rejected for copper, lithium, nickel and zinc, while statistical evidence of d > 1 is found in the remaining three series: cobalt, lead and tin. Allowing for autocorrelated errors, the values of d are slightly smaller, and d above 1 is only found to be significant in the cases of cobalt and zinc, and the unit root null hypothesis cannot be rejected in the remaining series.

In Table 4 we consider a non-linear model for the time trend. The estimated model is:

$$y_t = \sum_{i=0}^{m} \theta_i p_{iT}(t) + x_t, \, (1 - L)^d x_t = u_t, t = 1, 2, \qquad (2)$$

where P_{iT} are the Chebyshev time orthogonal polynomials defined as:

$$p_{0,T}(t) = 1, p_{1,T}(t) = \sqrt{2} cos(i\pi(t - 0.5)/T), t = 1, 2, \dots, T; i = 1, 2$$

where the parameter m indicates the degree of non-linearity. Detailed descriptions of these polynomials can be found in Hamming (1973) and Smyth (1998) and Bierens (1997) and Tomasevic and Stanivuk (2009) showed that these orthogonal polynomials approximate highly non-linear trends with rather low degree polynomials. In this context, if $m = 0$ the model displays an intercept, and if $m > 1$ it becomes non-linear, and the higher m is the less linear the approximated deterministic component becomes. In Table 4 we estimate the model given by (2), and, to allow for some degree of generality, we set m = 3; therefore,

---

[3] Copper: the average electric vehicle contains over 80 kg of copper – in comparison to around 25 kg used in conventional cars – and the red metal is used for both the extensive wiring found in the power transfer system and electrics, and in the battery itself. Lead: 12v lead-acid batteries remain the solution in EVs to run systems including interior and exterior lights, air conditioning and windows. Nickel: demand has increased for use in lithium-ion batteries, and the need is likely to grow further still. Steel: modern forms of steel are lighter, thinner and stronger than traditional steels, helping to offset the weight of an EV battery. Tin: is an essential input for EVs and their batteries, as well as for renewable energy generation, energy storage and the electronics needed to control and distribute that energy. Zinc: Most vehicles contain zinc – in die-cast components as a thin protective coating on bodywork, components and weld sites. It is most often used to galvanise steel, protecting the metal underneath from corrosion – around 60% of all zinc consumed is used for galvanisation. (Source: https://www.lme.com/en/Metals/EV).

[4] This model approximates highly parameterized AR(MA) models with very few parameters and works very well in the context of fractional integration (see, Gil-Alana, 2004).

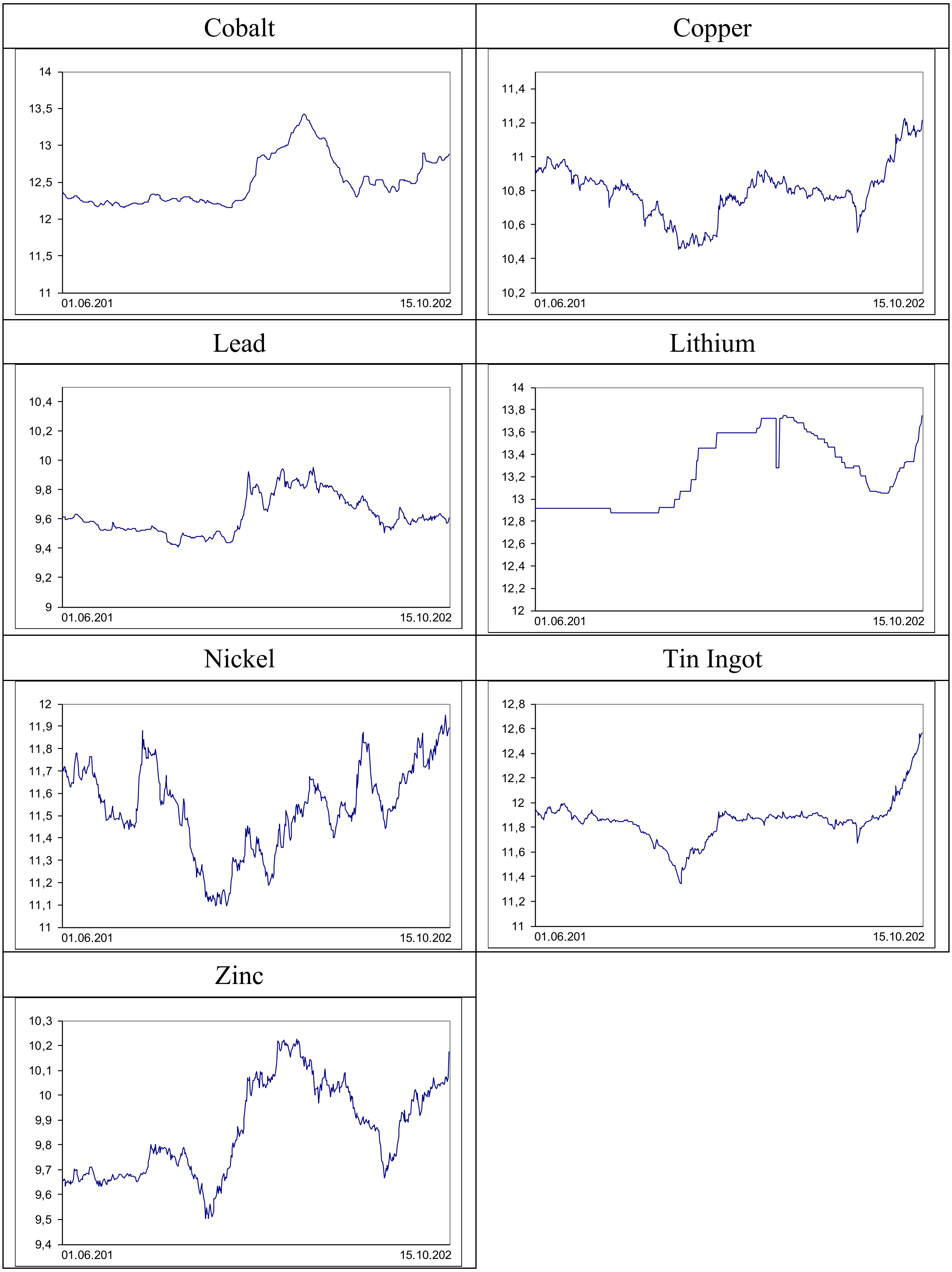

Fig. 1. Time series plots (in logs).

the data will contain non-linear structures if θ_2 and/or θ_3 are statistically significant.

The only evidence of non-linear trends is found in the case of lithium where the I(1) hypothesis cannot be rejected. For the remaining cases, there is no evidence of non-linearities and d is equal to or higher than 1 in all cases, finding thus no evidence of mean reversion. Using other approaches like the Fourier functions in time (Gil-Alana and Yaya, 2021) or even neural networks (Yaya et al., 2021) in the context of fractional integration produced no significant results.

We finally look at the possibility of structural breaks. We use the approach developed in Gil-Alana (2008), specifically designed for the case of fractional integration. This method is an extension to the

Table 1
Time Series Descriptives (in logs).

Series (in logs)	Max.	Min.	Mean	Mode	Std. Deviation
Cobalt	13.42099	12.15214	12.50869	12.24047	0.33362
Copper	11.22338	10.45536	10.79721	10.92233	0.15996
Lead	9.95228	9.41124	9.62471	9.52332	0.13323
Lithium	13.74830	12.87390	13.23574	12.91164	0.31085
Nickel	11.94892	11.09437	11.53365	11.45741	0.19643
Tin Ingot	12.56112	11.34154	11.85491	11.87409	0.17185
Zinc	10.22521	9.50301	9.85824	9.65503	0.18782

Table 2
Estimates of the differencing parameter. White noise error.

Series (in logs)	No terms	With an intercept	With an intercept and a linear trend
Cobalt	0.99 (0.94, 1.07)	**1.44 (1.36, 1.54)**	1.44 (1.36, 1.54)
Copper	0.99 (0.94, 1.07)	**1.02 (0.96, 1.08)**	1.02 (0.96, 1.08)
Lead	0.99 (0.93, 1.07)	**1.11 (1.05, 1.19)**	1.11 (1.05, 1.19)
Lithium	1.00 (0.94, 1.07)	**1.02 (0.96, 1.09)**	1.02 (0.96, 1.09)
Nickel	0.99 (0.93, 1.06)	**1.03 (0.97, 1.09)**	1.03 (0.97, 1.09)
Tin Ingot	0.99 (0.93, 1.06)	**1.06 (1.01, 1.12)**	1.06 (1.01, 1.12)
Zinc	1.00 (0.94, 1.07)	**0.99 (0.94, 1.05)**	0.99 (0.94, 1.05)

The values in bold refers to the selected specification for the error term.

Table 3
Estimates of the differencing parameter. Autocorrelated error.

Series (in logs)	No terms	With an intercept	With an intercept and a linear trend
Cobalt	0.98 (0.89, 1.11)	**1.25 (1.14, 1.37)**	1.25 (1.14, 1.37)
Copper	0.99 (0.90, 1.09)	**1.05 (0.95, 1.18)**	1.05 (0.95, 1.18)
Lead	0.98 (0.89, 1.09)	**1.11 (0.99, 1.26)**	1.11 (0.99, 1.26)
Lithium	0.99 (0.89, 1.00)	**0.99 (0.90, 1.12)**	0.99 (0.90, 1.12)
Nickel	0.98 (0.89, 1.11)	**1.10 (1.00, 1.23)**	1.10 (1.00, 1.23)
Tin Ingot	0.98 (0.90, 1.11)	**1.07 (1.00, 1.16)**	1.07 (1.01, 1.16)
Zinc	0.98 (0.89, 1.11)	**1.11 (1.01, 1.24)**	1.11 (1.01, 1.24)

The values in bold refers to the selected specification for the error term.

Table 4
Fractional integration in a non-liner deterministic trend model.

Series (in logs)	d	θ_0	θ_1	Θ_2	θ_3
Cobalt	1.44	**12.163**	0.177	−0.208	0.181
	(1.35, 1.54)	**(5.94)**	(0.13	(-0.48)	(0.75)
Copper	1.01	**10.768**	−0.031	0.105	0.035
	(0.94, 1.08)	**(39.39)**	(0.18)	(-1.29)	(0.65)
Lead	1.09	**9.627**	−0.053	−0.045	0.091
	(1.02, 1.18)	**(29.86)**	(-0.27)	(-0.50)	(1.58)
Lithium	0.99	**13.257**	−0.203	**−0.162**	**0.121**
	(0.93, 1.07)	**(36.15)**	(-0.92)	**(-1.65)**	**(1.82)**
Nickel	1.02	**11.539**	−0.039	0.143	0.021
	(0.96, 1.09)	**(28.77)**	(-0.16)	(1.20)	(0.27)
Tin Ingot	1.06	**11.825**	−0.032	0.083	0.035
	(1.01, 1.11)	**(37.92)**	(-0.17)	(0.93)	(0.61)
Zinc	0.99	**9.837**	−0.127	−0.057	0.058
	(0.93, 1.05)	**(42.92)**	(-0.92)	(-0.81)	(1.24)

Values in bold refer to significant coefficients at the 5% level.

Table 5
Number of breaks and break dates.

Series	N. of breaks	Break dates
Cobalt	3	01.07.2016, 20.04.2018 and 19.07.2019
Copper	3	27.11.2015, 27.10.2017 and 13.03.2020
Lead	3	24.06.2016, 22.06.2018 and 13.03.2020
Lithium	2	04.05.2018 and 11.12.2020
Nickel	1	20.05.2016
Tin Ingot	4	21.11.2014, 27.11.2015, 18.11.2016 and 13.03.2020
Zinc	4	11.07.2014, 11.12.2015, 18.08.2017 and 13.03.2020

fractional case of Bai and Perron (2003a) unit root approach. The results are displayed in Table 5. Four breaks are found in the cases of tin and zinc; three in the cases of cobalt, copper and lead; two for lithium and one for nickel.

The estimated coefficients for each subsample are presented across Tables 6 and 7, while Fig. 2 displays the estimated non-linear time trends. The structural breaks found in Table 5 are typically due to a change in policy or a sudden shock to the economy. Dealing with the degrees of integration at each subsample for each series, we observe that mean reversion is found in very few cases: in particular, in the third subsample for cobalt, and in the fourth subsamples for tin and zinc. In all the other cases, the estimated values of d are equal to or higher than 1, implying persistent (permanent) shocks and lack of mean reverting behaviour.

Obviously, the main factor motivating a global structural break in recent years was the COVID-19 pandemic in March 2020. Copper, lead, tin, zinc and several other commodities fell sharply in price when the United States and EU countries imposed curbs on travel, and about half of the world's population was asked to stay at home by their governments to prevent the spread of the virus. However, after the initial collapse, most commodities not only recovered their previous levels, but continued to rally throughout 2021, so that they were close to maximum levels in October 2021.

That major exceptional cause aside, many other reasons have motivated structural breaks in prices. Starting with cobalt, in July 2016 prices surged when positive forecasts surrounding the potential of the NEV sector exploded and after China released a new subsidy policy once it had cracked down on subsidy fraud relating to new energy vehicles. That trend continued until cobalt prices collapsed in April 2018. The NEV sector had not met the booming expectations and data about China's considerable stockpiling was known at a time when the Democratic Republic of the Congo's supply had increased. The excess of supply and the bearish feelings about market conditions continued until July 2019, when growth was forecast to outmatch supply in the following years.

Similar to cobalt, lithium prices shot up in the spring of 2016 as a consequence of the boom in electric vehicles. But prices came under pressure in May 2018 as miners speeded up production, consumers destocked supplies and China backed out of a subsidy for NEVs. The downward tendency was maintained until December 2020, when demand rebounded strongly due to record electric vehicle sales in China and Europe and lithium prices initiated a sharp rise towards the May 2018 maximums.

Nickel prices, like several other basic metal prices, began to rebound strongly in May 2016. The biggest trigger was the credit-fuelled construction boom that reinforced demand in China and the probability of an announcement from US President Donald Trump regarding a big push in infrastructure spending. With regard to lead, the analysis reveals a structural break in June 2016. In previous months, price had kept at low levels due to weak demand, particularly in China, and an excess of supply. In the summer of 2016, insights about the adoption of a new regulation in China to reduce environmental pollution from secondary

Table 6
Estimates of the differencing parameter for each subsample in each series.

Series (in logs)		No terms	With an intercept	With an intercept and a linear trend
Cobalt	1st	0.98 (0.89, 1.09)	**1.33 (1.21, 1.47)**	1.32 (1.21, 1.47)
	2nd	0.96 (0.83, 1.14)	1.38 (1.20, 1.63)	**1.38 (1.20, 1.65)**
	3rd	0.82 (0.71, 0.97)	**0.46 (0.30, 0.70)**	0.46 (0.30, 0.71)
	4th	0.97 (0.86, 1.13)	**1.45 (1.26, 1.70)**	1.44 (1.25, 1.68)
Copper	1st	0.97 (0.86, 1.12)	0.85 (0.73, 1.01)	**0.85 (0.72, 1.01)**
	2nd	0.96 (0.84, 1.14)	0.90 (0.78, 1.06)	**0.89 (0.76, 1.06)**
	3rd	0.98 (0.86, 1.12)	0.92 (0.69, 1.13)	**0.93 (0.76, 1.13)**
	4th	0.97 (0.82, 1.15)	0.97 (0.73, 1.22)	**0.99 (0.84, 1.20)**
Lead	1st	0.98 (0.90, 1.09)	**1.26 (1.15, 1.41)**	1.26 (1.14, 1.41)
	2nd	0.96 (0.85, 1.13)	**1.16 (1.03, 1.35)**	1.16 (1.02, 1.35)
	3rd	0.95 (0.82, 1.14)	0.96 (0.70, 1.17)	**0.98 (0.83, 1.16)**
	4th	0.96 (0.82, 1.16)	**0.96 (0.76, 1.21)**	0.96 (0.79, 1.20)
		0.98 (0.90, 1.09)		
Lithium	1st	1.01 (0.93, 1.10)	0.91 (0.83, 1.06)	**0.91 (0.82, 1.06)**
	2nd	0.97 (0.87, 1.12)	0.99 (0.90, 1.14)	**0.98 (0.85, 1.14)**
	3rd	0.92 (0.73, 1.20)	1.16 (0.96, 1.45)	**1.17 (1.00, 1.43)**
	1st	0.95 (0.82, 1.14)		
Nickel	1st	0.98 (0.89, 1.02)	**1.05 (0.97, 1.15)**	1.05 (0.97, 1.15)
	2nd	0.99 (0.91, 1.08)	**0.99 (0.91, 1.09)**	0.99 (0.91, 1.08)
Tin Ingot	1st	0.97 (0.86, 1.12)	**1.04 (0.92, 1.20)**	1.04 (0.92, 1.20)
	2nd	0.93 (0.75, 1.18)	1.25 (0.95, 1.71)	**1.25 (0.98, 1.71)**
	3rd	0.93 (0.75, 1.19)	0.81 (0.51, 1.17)	**0.90 (0.71, 1.15)**
	4th	0.98 (0.87, 1.10)	**0.79 (0.68, 0.96)**	0.80 (0.68, 0.96)
	5th	0.96 (0.82, 1.15)	0.88 (0.80, 1.00)	**0.87 (0.78, 1.01)**
Zinc	1st	0.97 (0.86, 1.13)	**1.04 (0.89, 1.22)**	1.04 (0.89, 1.22)
	2nd	0.95 (0.80, 1.16)	0.86 (0.76, 1.01)	**0.86 (0.74, 1.01)**
	3rd	0.97 (0.83, 1.16)	0.79 (0.68, 1.08)	**0.86 (0.73, 1.08)**
	4th	0.97 (0.86, 1.11)	0.84 (0.74, 0.98)	**0.84 (0.73, 0.98)**
	5th	0.96 (0.83, 1.17)	0.65 (0.56, 1.10)	**0.83 (0.67, 1.09)**

The values in bold refers to the selected specification for the error term.

Table 7
Estimated coefficients for each subsample.

Series (in logs)		d	Intercept	Time trend
Cobalt	1st	1.33 (1.21, 1.47)	12.372 (145.21)	–
	2nd	1.38 (1.20, 1.65)	12.129 (667.73)	0.0153 (1.74)
	3rd	0.46 (0.30, 0.70)	12.934 (20.27)	–
	4th	1.45 (1.26, 1.70)	12.284 (571.09)	–
Copper	1st	0.85 (0.72, 1.01)	10.928 (520.62)	−0.0023 (−3.03)
	2nd	0.89 (0.76, 1.06)	10.454 (415.57)	0.0044 (2.77)
	3rd	0.93 (0.76, 1.13)	10.905 (693.83)	−0.0018 (−1.76)
	4th	0.99 (0.84, 1.20)	10.546 (458.91)	0.0080 (3.30)
Lead	1st	1.26 (1.15, 1.41)	5.616 (1371.21)	–
	2nd	1.16 (1.03, 1.35)	5.442 (358.33)	–
	3rd	0.98 (0.83, 1.16)	9.955 (602.28)	−0.0043 (−2.67)
	4th	0.96 (0.76, 1.21)	5.508 (638.38)	–
		0.96 (0.76, 1.21)		
Lithium	1st	0.91 (0.82, 1.06)	12.907 (331.01)	0.0024 (1.79)
	2nd	0.98 (0.85, 1.14)	13.726 (953.83)	−0.0050 (−4.45)
	3rd	1.17 (1.00, 1.43)	13.035 (611.16)	0.0166 (2.90)
	1st			
Nickel	1st	1.05 (0.97, 1.15)	11.718 (404.85)	–
	2nd	0.99 (0.91, 1.09)	11.095 (348.02)	–
Tin Ingot	1st	1.04 (0.92, 1.20)	11.947 (942.85)	–
	2nd	1.25 (0.98, 1.71)	11.822 (915.82)	−0.0093 (−2.13)
	3rd	0.90 (0.71, 1.15)	11.335 (439.92)	0.0103 (4.03)
	4th	0.79 (0.68, 0.96)	11.896 (952.55)	–
	5th	0.87 (0.78, 1.01)	11-668 (490.55)	0.0104 (6.62)
Zinc	1st	1.04 (0.89, 1.22)	5.658 (969.90)	–
	2nd	0.86 (0.74, 1.01)	9.804 (562.19)	−0.0037 (−3.07)
	3rd	0.86 (0.73, 1.08)	9.498 (374.68)	0.0078 (5.03)
	4th	0.84 (0.73, 0.98)	10.219 (504.57)	−0.0035 (−4.03)
	5th	0.83 (0.67, 1.09)	9.666 (426.73)	0.0057 (4.37)

lead processes (finally passed in December 2016), and fears about its potential impact over the activity of some secondary smelters, took prices to substantially higher levels. The worries about shortages due to environmental inspections relaxed two years later, so that in June 2018 lead prices initiated a robust downwards tendency.

In the case of copper, the first structural break is observed in November 2015. After several years suffering a decline in Chinese consumption and a weak global demand, China's growth was expected to maintain at a sustainable level (6.5%), so that demand concerns were substituted with supply constraints. In fact, just the opposite occurred, at the end of October 2017, after two years of gains in copper prices, the impression that the market had become overextended gained impression at a moment when demand indicators were looming, and the supply side was keeping production levels high.

Tin prices kept quite stable until November 2014, when supplies from Myanmar flooded into the market causing an abrupt descent. In November 2015 prices hovered around a six-year low; the largest smelters promised output cuts and asked Beijing to stockpile more tin. Finally, the market reversed throughout 2016 thanks to the sharp fall in the output from the Myanmar tin mines that had disrupted the global market along with output falls in ore from producers such as Indonesia, Peru and China itself, which brought inventory levels to their lowest level since 2000. From November 2016 onwards the tin market stabilized until the arrival of the pandemic, when the collapse was followed by a strong upsurge.

Shanghai bonded zinc stocks registered very low levels in the second half of 2014 and zinc prices rose significantly in June–July 2014. Feelings were quite different in the second half of 2015, so that fears about rising stocks and waning demand in China sent prices to a five-year low in December 2015. On the other hand, in August 2017 zinc prices surged again to their highest in a decade. The metal used to galvanise steel benefited from expectations of strong global demand and Chinese infrastructure development, tight supplies and higher steel prices caused by capacity cuts. After the autumn of 2017 prices followed a consistent

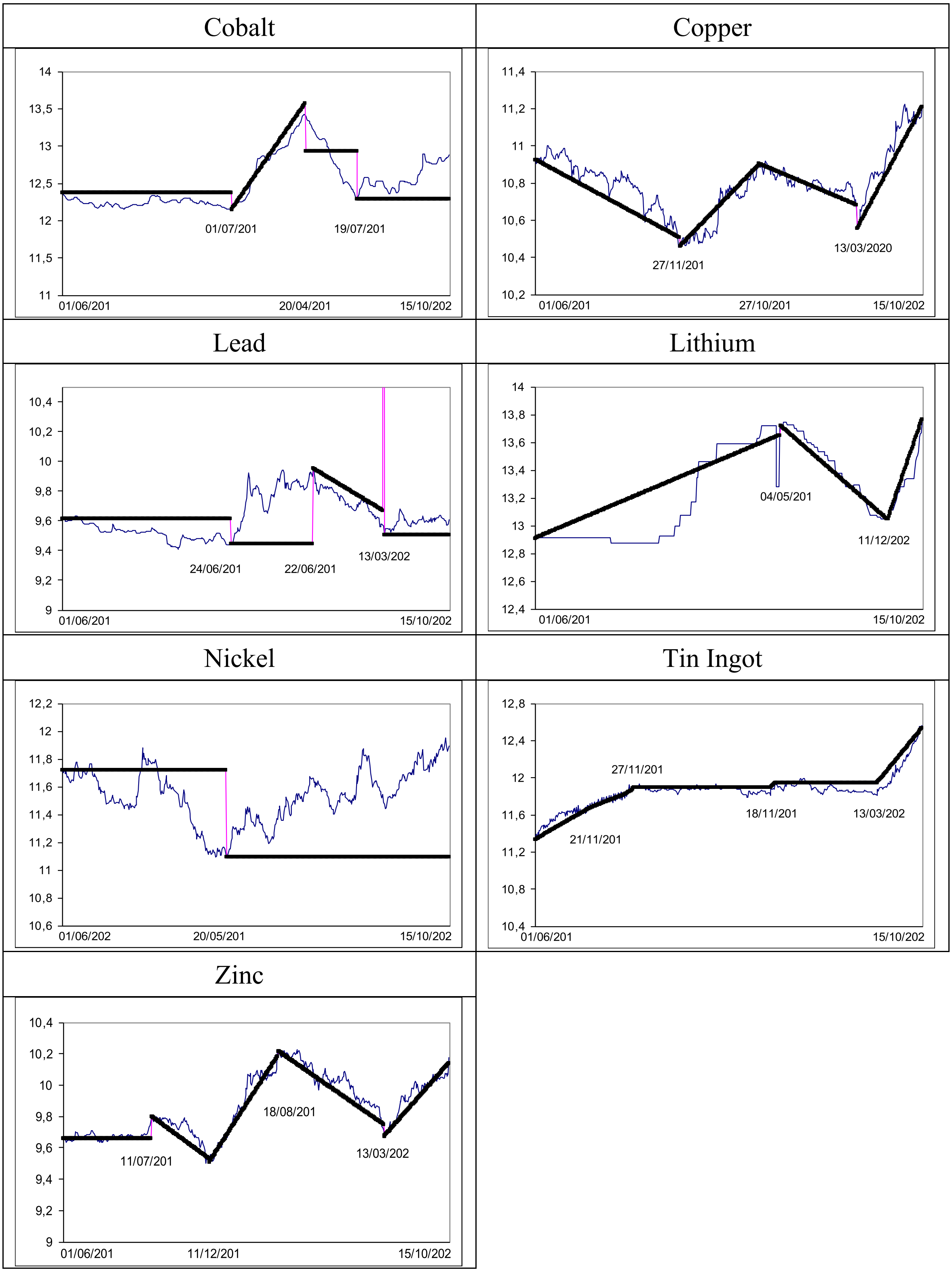

Fig. 2. Time series and estimated time trends.

descent until March 2020. It was only after that date that the approval of new fiscal stimulus packages and strong growth forecasts allowed zinc prices to surge vigorously until nearing August 2017 record levels.

5. Implications for China's public policy

Our results indicate that the series under examination are highly persistent, with orders of integration equal to or higher than 1 in the majority of the cases and thus showing lack of mean reversion, and supporting the hypothesis of permanency of shocks. According to these results, strong policy measures must be adopted in the presence of exogenous shocks to recover the long term projections of the data since the series will not recover by themselves in the long run. In this section, we discuss the effectiveness of some public measures to mitigate mineral prices shocks and foster the development of NEV industry.

Apart from extraordinary events (COVID-19), mineral prices shocks are caused by market-structure and organization issues, and sudden changes in supply and demand and in the expectations of economic agents. Regarding market structure, China's government has already implemented some relevant measures The development of highly liquid domestic exchange markets - particularly the SHME-guarantees that domestic mineral prices will not suffer additional pressure due to deficient market tools. Additionally, Chinese authorities are committed to further strengthening the regulation of the futures and spot markets to avoid activities that could manipulate the normal functioning of markets such as hoarding and speculation.

Main issues affecting the supply chain include the social and political stability of mineral-rich African and Latin American countries, the pace of exploitation of mines, regulation and technology associated with the extraction and processing of minerals, and the management of supply stocks to accommodate the volatility of demand. China enjoys relevant advantages with regard to the management of mineral supply: some Chinese public companies have acquired control over mines throughout Africa and Latin America (Gonzalez-Vicente, 2012; Koch-Weser, 2014; Farooki, 2018; Ericsson et al., 2020; etc.), and the PRC is the world leader in processing cobalt, lithium, nickel, copper and rare earth elements (IEA, 2021a, 31), which enables authorities to speed up or slow down production and export volumes according to domestic needs.[5]

China's National Development and Reform Commission has demonstrated that the government is determined to use national reserves to ensure stable supplies and prices and ease the pressure on enterprises' production and operations. On July 5, 2021 the State Food and Material Reserves Bureau of the NDRC sold state reserves of copper, aluminium, and zinc to reduce prices for the first time in over a decade (National Development, 2021). More importantly, in an era characterized by the global race for critical minerals (Kalantzakos, 2020), China's government has shown "*a strategic approach to mineral resources at both the domestic and international level*" (Andersson, 2020, 129). Resource security remains a key concern for Chinese policy makers,[6] and the state continues "*to play a dominant role in guiding resource investment and pricing*" (Economy and Levi, 2014, p. 20). Significantly, 5-year plans specify targets and quotas for production of selected minerals. However, since there are several essential supply issues beyond the control of China's government, such as the outbreak of conflicts in the main producer countries, strategic initiatives will need to be complemented with "ad-hoc" measures to smooth market reactions.

Unforeseen changes in the global demand for minerals may emerge due to much higher/lower levels of mineral consuming manufacturing activities, sometimes associated with the implementation of public programmes, environmental regulation and technological innovation. Overall, "projected mineral demand is subject to considerable uncertainty" (IEA, 2021b, 44). For example, according to IEA projections lithium demand in 2040 may be 13 times or 51 times higher than today's levels depending on climate policies and technology and technological change (IEA, 2021b, 53). Additionally, focusing on the NEV industry, China's authorities have to take into account the potential impact of not only domestic but also foreign new programmes subsidising NEV purchases and the speed of deployment of infrastructure (networks of recharging points, etc.). It is very complex to anticipate the impact of climate policies and technological disruptive innovation in the manufacturing process of such a young sector as the NEV, though *a priori* technology change might be expected to be oriented towards a less intensive use of scarce minerals, which would limit the consequences of price shocks.

In summary, it may be concluded that China's government has enforced some significant strategic public initiatives to soften the effect of exogenous shocks over minerals prices and facilitate an easier recovery of mean reversion. Additionally, Chinese authorities have demonstrated their full commitment to this objective by sending a clear message to market participants. This being said, taking into account the variety and number of highly uncertain factors that might cause a sudden change in prices, further measures will be needed to mitigate shocks. Li et al. (2019) found that the development of substitute materials and recovery technologies could address these minerals' demand in the long term, so that measures to accelerate the improvement of these technologies could become essential in order to reduce dependence on minerals.

6. Conclusions

In this paper we have analysed the potential impact of the volatility of mineral prices in the development of the electric vehicles industry in China. We have investigated the persistence of mineral prices and the development of the new energy vehicle industry in China. We have implemented techniques based on fractional integration also allowing for non-linearities and structural breaks at unknown periods of time. The results show that the series are generally very persistent. The only exceptions being cobalt, tin and zinc if breaks are permitted and only for a given subsample. In all the other cases, the estimated values of d are equal to or higher than 1, implying persistent shocks and lack of mean reverting behaviour. We also look at the possibility of structural breaks finding four breaks in the cases of tin and zinc; three in the case of cobalt, copper and lead; two for lithium and one for nickel. The main structural break was caused by the COVID-19 pandemic, whereas the rest are a response to sudden supply-demand imbalances.

China's strategy of promoting a strong domestic electric vehicle manufacturing industry should consider these results because the lack of mean reversion in the presence of exogenous shocks will condition the development of the sector. China's government has already adopted some relevant initiatives to mitigate the impact of these shocks. Nevertheless, considering the high degree of uncertainty of some elements affecting the supply-demand balance, additional policy measures will be needed to achieve mean reversion in the presence of exogenous shocks.

Future lines of research should also investigate the persistence in the volatility of the series under investigation, by looking for example, at the absolute returns and the squared returns of the series. According to some authors such as Ding et al. (1993), Lobato and Savin (1998), Granger and Hyung (2013), absolute and squared returns should also display the long memory property observed in the log prices. Work in this direction is now in progress.

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in *Resources Policy*.

---

[5] In July 2010, the government of the PRC announced that it was reducing export quotas for rare earth elements by 70% causing a dramatic surge in prices (Mancheri, 2015).

[6] Disruption in the mineral supply chain is a major cause of concern also in the United States (U.S. Department of Commerce, 2019; Nassar et al., 2020a,b), and in the European Union (European Commission, 2020).

Acknowledgements

Prof. Luis A. Gil-Alana gratefully acknowledges financial support from the MINEIC-AEI-FEDER PID2020-113691RB-I00 project from 'Ministerio de Economía, Industria y Competitividad' (MINEIC), 'Agencia Estatal de Investigación' (AEI) Spain and 'Fondo Europeo de Desarrollo Regional' (FEDER). He also acknowledges support from an internal Project of the Universidad Francisco de Vitoria, Madrid, Spain.

References

Akram, Q.F., 2009. Commodity prices, interest rates and the dollar. Energy Econ. 31 (6), 838–851. https://doi.org/10.1016/j.eneco.2009.05.016.

Andersson, P., 2020. Chinese assessments of "critical" and "strategic" raw materials: concepts, categories, policies, and implications. Extr. Ind. Soc. 7 (1), 127–137. https://doi.org/10.1016/j.exis.2020.01.008.

Bai, J., Perron, P., 2003a. Computation and Analysis of Multiple Structural Change Models. In: Journal of Applied Econometrics, vol. 18, pp. 1–22.

Bierens, H.J., 1997. Testing the unit root with drift hypothesis against nonlinear trend stationarity with an application to the US price level and interest rate. J. Econom. 81, 29–64. https://doi.org/10.1016/S0304-4076(97)00033-X.

Bloomfield, P., 1973. An exponential model in the spectrum of a scalar time series. Biometrika 60, 217–226.

Brunetti, C., Gilbert, C.L., 1995. Metals prices volatility 1972–95. Resour. Pol. 21 (4), 237–254. https://doi.org/10.1016/0301-4207(96)85057-4.

Cashin, P., Mc Dermott, C.J., Scott, A., 2002. Booms and slumps in world commodity prices. J. Dev. Econ. 69, 277–296. https://doi.org/10.1016/S0304-3878(02)00062-7.

Chen, S.-L., Jackson, J.D., Kim, H., Resiandini, P., 2014. What drives commodity prices? Am. J. Agric. Econ. 96 (5), 1455–1468. https://doi.org/10.1016/S0304-3878(02)00062-7.

Cheng, H., Huang, J.B., Guo, Y.Q., Zhu, X.H., 2013. Long memory of price–volume correlation in metal futures market based on fractal features. Trans. Nonferrous Metals Soc. China 23 (10), 3145–3152. https://doi.org/10.1016/S1003-6326(13)62845-9.

Cuestas, J.C., Gil-Alana, L.A., 2016. A nonlinear approach with long range dependence based on Chebyshev polynomials. Stud. Nonlinear Dynam. Econom. 23, 445–468.

Davutyan, N., Roberts, M.C., 1994. Cyclicality in metal prices. Resour. Pol. 20 (1), 49–57. https://doi.org/10.1016/0301-4207(94)90040-X.

Deaton, A., Laroque, G., 1992. On the behavior of commodity prices. Rev. Econ. Stud. 59, 23–40. https://doi.org/10.2307/2297923.

Diebold, F., Rudebusch, G.D., 1991. On the power of the Dickey and Fuller tests against fractional alternatives. Econ. Lett. 35, 155–160. https://doi.org/10.1016/0165-1765(94)90049-3.

Ding, Z., Granger, C.W.J., Engle, R.F., 1993. A long memory property of stock market returns and a new model. J. Empir. Finance 1 (1), 86–103.

Economy, E., Levi, M., 2014. By All Means Necessary: How China's Resource Quest Is Changing the World. Oxford University Press, New York.

Ericsson, M., Löf, O., Löf, A., 2020. Chinese control over African and global mining—past, present and future. Mineral Economics 33, 153–181. https://doi.org/10.1007/s13563-020-00233-4.

European Commission, 2020. Critical Raw Materials Resilience: Charting a Path towards Greater Security and Sustainability, 2020. COM, Brussels, p. 474, 3.9.2020.

Farooki, M., 2018. China's Mineral Sector and the Belt and Road Initiative. European Policy Brief. Strategic Dialogue on Sustainable Raw Materials for Europe. Policy Brief 02/2018.

Gil-Alana, L.A., 2004. The use of the Bloomfield (1973) model as an approximation to ARMA processes in the context of fractional integration. Math. Comput. Model. 39, 429–436.

Gil-Alana, L.A., 2008. Fractional integration and structural breaks at unknown periods of time. J. Time Anal. 29 (1), 163–185. https://doi.org/10.1111/j.1467-9892.2007.00550.x.

Gil-Alana, L.A., Tripathy, T., 2014. Modelling volatility persistence and asymmetry: a Study on selected Indian non-ferrous metals markets. Resour. Pol. 41, 31–39. https://doi.org/10.1016/j.resourpol.2014.02.004.

Gil-Alana, L.A., Yaya, O.S., 2021. Testing fractional unit roots with non-linear smooth break approximations using Fourier functions. J. Appl. Stat. 48 (13–15), 2542–2559.

Gonzalez-Vicente, R., 2012. Mapping Chinese mining investment in Latin America: politics or market? China Q. 209, 35–58. https://doi.org/10.1017/S0305741011001470.

Granger, C.W., Hyung, N., 2004. Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. J. Empir. Finance 11 (3), 399–421. https://doi.org/10.1016/j.jempfin.2003.03.001.

Granger, C.W.J., Hyung, N., 2013. Occasional breaks and long memory. Ann. Econ. Finance 2B, 721–746.

Habib, K., Hansdóttir, S.T., Habib, H., 2020. Critical metals for electromobility: global demand scenarios for passenger vehicles. Resour. Conserv. Recycl. 154, 2015–2050. https://doi.org/10.1016/j.resconrec.2019.104603.

Hamming, R.W., 1973. Numerical Methods for Scientists and Engineers. Dover.

Hao, H., et al., 2017. Material flow analysis of lithium in China. Resour. Pol. 51, 100–106. https://doi.org/10.1016/j.resourpol.2016.12.005.

Hassler, U., Wolters, J., 1994. On the power of unit root tests against fractional alternatives. Econ. Lett. 45, 1–5. https://doi.org/10.1016/0165-1765(94)90049-3.

International Energy Agency, 2021a. Electric Vehicles. Paris. November 2021. Retrieved 10th November 2021 from. https://www.iea.org/reports/electric-vehicles.

International Energy Agency, 2021b. The role of critical minerals in clean energy transitions. World Energy Outlook Special Report. Paris. May 2021. Retrieved 8th November 2021 from. https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions.

Jin, L., He, H., Cui, H., Lutsey, N., Wu, C., Chu, Y., et al., 2021. Driving a Green Future: A Retrospective Review of China's Electric Vehicle Development and Outlook for the Future. The International Council on Green Transportation and China EV100. January 2021.

Kalantzakos, S., 2020. The race for critical minerals in an era of geopolitical realignments. Int. Spectator 55 (3), 1–16. https://doi.org/10.1080/03932729.2020.1786926.

Koch-Weser, I., 2014. Chinese Mining Activity in Latin America: A Review of Recent Findings. In: Inter-American Dialogue. Report. September 2014.

Labys, W.C., Lesourd, J.B., Badillo, D., 1998. The existence of metal price cycles. Resour. Pol. 24 (3), 147–155. https://doi.org/10.1016/S0301-4207(98)00023-3.

Lee, D., Schmidt, P., 1996. On the power of the KPSS test of stationarity against fractionally integrated alternatives. J. Econom. 73, 285–302. https://doi.org/10.1016/0304-4076(95)01741-0.

Li, X., Ge, J., Chen, W., Peng, W., 2019. Scenarios of rare earth elements demand driven by automotive electrification in China: 2018–2030. Resour. Conserv. Recycl. (145), 322–331. https://doi.org/10.1016/j.resconrec.2019.02.003.

Lien, D., Yang, L., 2008. Hedging with Chinese metal futures. Global Finance J. 19 (2), 123–138. https://doi.org/10.1016/j.gfj.2008.01.004.

Lobato, I.N., Savin, N.E., 1998. Real and spurious long-memory properties of stock-market data. J. Bus. Econ. Stat. 16 (3), 261–268.

Mancheri, N.A., 2015. World trade in rare earths, Chinese export restrictions, and implications. Resour. Pol. 46, 262–271. https://doi.org/10.1016/j.resourpol.2015.10.009.

Ministry of Finance of the People's Republic of China, 2009. Notice on Implementing Energy-Saving and New Energy Vehicle Pilot Programs. Retrieved from. http://www.most.gov.cn/fggw/zfwj/zfwj2009/200902/t20090224_67588.htm.

Nassar, N.T., et al., 2020a. Evaluating the mineral commodity supply risk of the U.S. manufacturing sector. Sci. Adv. 6 (8), eaay8647 https://doi.org/10.1126/sciadv.aay8647.

Nassar, N.T., Alonso, E., Brainard, J.L., 2020b. Investigation of U.S. Foreign reliance on critical minerals—U.S. Geological survey technical input document in response to executive order No. 13953. Signed September 30, 2020. https://pubs.usgs.gov/of/2020/1127/ofr20201127.pdf.

National Development, Reform Commission, 2021. Measures to Ensure Commodity Prices Stable, 26th July 2021. Retrieved 28th October 2021 from. https://en.ndrc.gov.cn/news/mediarusources/202107/t20210726_1291555.html.

Panas, E., 2001. Long memory and chaotic models of prices on the London Metal Exchange. Resour. Pol. 27 (4), 235–246. https://doi.org/10.1016/S0301-4207(02)00008-9.

Roberts, M.C., 2009. Duration and characteristics of metal price cycles. Resour. Pol. 34 (3), 87–102. https://doi.org/10.1016/j.resourpol.2009.02.001.

Rossen, A., 2015. What are metal prices like? Co-movement, price cycles and long-run trends. Resour. Pol. 45 (C), 255–276. https://doi.org/10.1016/j.resourpol.2015.06.002.

Rutledge, R.W., Khondkar, K., Wang, R., 2013. International copper futures market price linkage and information transmission: empirical evidence from the primary world copper markets. J. Int. Bus. Res. 12 (1), 113–131.

Sang, K., Seong-Min, Y., 2016. Dynamic spillovers between Shanghai and London nonferrous metal futures markets. Finance Res. Lett. 19, 181–188. https://doi.org/10.1016/j.frl.2016.07.010.

Shyy, G., Butcher, B., 1994. Price equilibrium and transmission in a controlled economy: a case study of the metal exchange in China. J. Futures Mark. 14 (8), 1986–1998. https://doi.org/10.1002/fut.3990140803, 877.

Slade, M.E., 1991. Market structure, marketing method, and price instability. Q. J. Econ. 106, 1309–1340. https://doi.org/10.2307/2937966.

Smyth, G.K., 1998. Polynomial Approximation. John Wiley and Sons, Ltd, Chichester.

State Council, 2009. Auto Industry Adjustment and Revitalization Plan, 20th March 2009. Retrieved 28th October 2021 from. http://www.gov.cn/zwgk/2009-03/20/content_1264324.htm.

State Council, 2012. New Energy Vehicle Industrial Development Plan for 2021 to 2035, 28th June 2012. Retrieved 13th February 2023 from: http://www.gov.cn/gongbao/content/2012/content_2182749.htm.

State Council, 2020. New Development Plan for NEVs Unveiled, 2nd November 2020. Retrieved 13th February 2023 from: http://english.www.gov.cn/policies/latestreleases/202011/02/content_WS5f9ff225c6d0f7257693ece2.html.

Tomasevic, N.M., Stanivuk, T., 2009. Regression analysis and approximation by means of Chebyshev polynomial. Informatologia 42 (3), 166–172.

U.S. Department of Commerce, 2019. A Federal Strategy to Ensure Secure and Reliable Supplies of Critical Minerals. https://www.commerce.gov/sites/default/files/2020-01/Critical_Minerals_Strategy_Final.pdf.

U.S. Department of the Interior, 1979. U. S. Nonfuel Minerals Policy Review, Background Papers (Washington).

USGS, 2023. Mineral Commodity Summaries 2022. U.S. Department of the Interior. U.S. Geological Survey. Available at: https://pubs.usgs.gov/periodicals/mcs2023/mcs2023.pdf.

Watkins, C., McAleer, M., 2006. Pricing of non-ferrous metals futures on the London metal exchange. Appl. Financ. Econ. 16 (12), 853–880. https://doi.org/10.1080/09603100600756514.

Yaya, O., Ogbonna, A.E., Gil-Alana, L.A., Furuoka, F., 2021. A new unit root analysis for testing hysteresis in unemployment. Oxf. Bull. Econ. Stat. 83 (4), 960–981.

Yaya, O., et al., 2022. Time-variation between metal commodities and oil, and the impact of oil shocks: GARCH-MIDAS and DCC-MIDAS analyses. Resour. Pol. 79 https://doi.org/10.1016/j.resourpol.2022.103036.

Yue, Y., Liu, D., Xu, S., 2015. Price linkage between Chinese and international nonferrous metals commodity markets based on VAR-DCC-GARCH models. Trans. Nonferrous Metals Soc. China 25 (3), 1020–1026. https://doi.org/10.1016/S1003-6326(15)63693-7.

Zehai, L., Huiyan-Zhang, L., 2013. An empirical study of international linkages of the Shanghai copper futures market. Chin. Econ. 46 (3), 61–74. https://doi.org/10.2753/CES1097-1475460304.

Zhu, X., Zhang, H., Zhong, M., 2017. Volatility forecasting in Chinese nonferrous metals futures market. Trans. Nonferrous Metals Soc. China 27 (5), 1206–1214. https://doi.org/10.1016/S1003-6326(17)60141-9.