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Volatility persistence in metal prices

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ABSTRACT

This article deals with the analysis of volatility persistence in a group of metal prices, namely gold, silver, copper, platinum, aluminium, palladium, lead, zinc and tin, using monthly data from January 1994 to February 2023. Applying fractional integration techniques, the findings show that all series are highly persistent, although the prices for Gold and Silver display a limited mean reversion. The volatility was approximated by the absolute and squared returns and the results show that in the case of the annual difference returns, the series are persistent and the evidence of mean reversion is only observed for Gold and Silver. In the case of monthly differences, the hypothesis of short memory ($d = 0$) behavior cannot be rejected in all cases. For the absolute returns, the values are all positive, denoting a long memory ranging from 0.14 for Gold to 0.18 for Silver. For the squared returns, the values are slightly smaller but positive, ranging from 0.11 (Gold) to 0.16 (Aluminum and Palladium). The supply-side economic policy should be intensified in the case of the most volatile metals.

1. Introduction

Metal price evolution seems to significantly impact economic activity (Labys et al., 1999). The monitoring of its ups and downs and the study of volatility persistence allows researchers and policymakers to understand business cycles more efficiently. Some metals such as gold maintain a negative correlation with the stock market (Tursoy and Faisal, 2018). However, other metals like iron, aluminum, and copper present with a positive association with the equity market which shows a positive relationship with economic activity (Tursoy et al., 2018).

The analysis of metal price volatility persistence is a key issue from an economic point of view because it is directly related to price stability uncertainty (Addison and Ghoshray, 2023). At the micro level, it may be challenging for producers to determine how much metal to remove and it can also be challenging for consumers to determine how much metal to utilize. If it is assumed that the prices will, on average, return to their historical mean over a period, both producers and consumers can plan for the prices to recover from abnormally high peaks or low troughs. Exporters and importers, for example, may not have difficulty predicting their respective revenues at the macro level, and exporters and importers might also not have problems determining the quantity of goods to import.

In this regard, many authors such as Gil-Alana et al. (2015), Uludag and Lkhamazhapov (2014), Ewing and Malik (2013), Arouri et al. (2012), and Watkins and McAleer (2008), among others, have investigated metal price volatility using different approaches in diverse time-periods. Based on these studies, we applied fractional integration techniques to analyze metal price volatility (gold, silver, copper, platinum, aluminum, palladium, lead, zinc, and tin) from January 1994 to February 2023. Our main contribution is the application of an innovative time series methodology to a very recent period that is highly associated with the current inflation pressures. In particular, the use of a long memory class of models denominated fractional integration that will permit us to determine if shocks in the volatility of a group of metals have permanent or transitory effects. According to Abakah et al. (2022), the utilization of this approach may be more suitable compared to conventional methods due to its enhanced capacity for flexibility in dynamic specification. This is particularly advantageous as it permits the inclusion of fractional degrees of differentiation.

Thus, a permanent impact on volatility could generate certain instability in cost inflation and economic growth, what would imply global downturns and recessions (but also upturns for metal exporters) (World Bank, 2021). Furthermore, policymakers should consider these consequences to apply counter-cyclical policies to shield the economy from metal price volatility. However, a transitory effect would allow markets to autoregulate themselves and recover the mean behavior in the long run.

Four sections complete the paper. First, we will go over the literature

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review. Second, we discuss the data and techniques utilized in the article. The third part covers the study's primary empirical findings. The results of our investigation are discussed in Section 4, and Section 5 provides the last reflections.

2. Metal price modeling in the literature review

Throughout history, commodity prices have been very unstable, with both rising and dropping trends (Brunetti and Gilbert, 1995; Pindyck, 2004; Gilbert, 2006; Fernández, 2008). In particular, the markets for metals are very reactive to changes in supply and demand as well as other aspects of the macroeconomy (Radetzki, 1989; Batten et al., 2010; Hammoudeh et al., 2010; Arezki and Matsumoto, 2017; Dinh et al., 2022).

Arouri et al. (2012) showed there to be a long-term dependence in the daily conditional return and volatility of gold, silver, platinum, and palladium. They used parametric and semiparametric techniques, incorporating the ARFIMA-FIGARCH model. Uludag and Lkhamazhapov (2014) observed anti-persistence in spot returns and no long memory in gold futures returns. They arrived at the decision that prolonged memory is a genuine quality of data and not the result of structural breaks. Using the GARCH model, Ewing and Malik (2013) found evidence of persistent volatility in gold both with and without structural breakdowns. In each of these studies, the presence of exogenous structural breakdowns was analyzed.

McMillan and Speight (2001) investigated the conditional volatility of daily non-ferrous LME prices from 1972 to 1995. Their study covers the period from 1972 to 1995. This paper argues that it is important and relevant to analyze the volatility of metal prices, as well as the existence of three distinct fundamental components underlying metal volatility as determined by a principal component analysis that were driving said volatility.

According to Watkins and McAleer (2008), the industry of industrial metals has shown a significant amount of interest in patterns of volatility in the metals market over the course of time. They estimated the volatility for daily returns on aluminum and copper futures prices by employing a rolling AR(1)-GARCH(1,1) model. This allowed them to make predictions about the future. When evaluated over a long horizon, the time-varying volatility processes represented by GARCH demonstrates that although the volatility in returns has not inevitably risen, the conditional volatility in the metals markets is time-varying. This holds true even if the return volatility has not grown significantly.

Using a modeling approach based on fractional integration, Gil-Alana et al. (2015) were able to identify structural discontinuities in the statistical features of the prices of five important precious metals. The metals were gold, silver, rhodium, palladium, and platinum. Except for palladium, they found structural breaks in almost every case and evidence of a rise in the level of persistence in most cases. This indicates that the distresses to these precious metals will continue for an extended period, necessitating significant efforts on the part of the government to bring the series back to equilibrium values.

Furthermore, Winkelried (2018) investigated the dynamic characteristics of relative commodity prices, namely the Prebisch-Singer hypothesis on their secular reduction. He did this through the utilization of a unique group of unit root tests based on the Fourier approximation of the data's underlying trend. The estimation took into account changes in the data that occurred at low frequencies, such as the structural breaks caused by theorized super cycles. He found substantially more evidence against non-stationarity in relative commodity prices in the existing body of literature, and little support for the hypothesis of Prebisch-Singer in this research.

In the context of this branch of metal price modeling, Jacks (2019) examined the data on the evolution of commodity prices from 1900 to 2015. He created and published a detailed typology of actual commodity prices which takes into account long-run patterns, medium-run cycles, and short-run boom and bust occurrences. He applied the test developed by Christiano and Fitzgerald (2003), supposing that the mechanism behind the production of the underlying data is of order one (namely, a random walk). This assumption may be tested in a very straightforward manner even though the simulations make it abundantly clear that the filter is unaltered by any misspecification of the mechanism that generates the data. The search for a unit root in the differenced commodity price index series revealed the following patterns: (1) commodity price cycles characterized by large and long-lasting deviations from underlying trends; and (2) boom/bust episodes, which were generally common.

Liu et al. (2021) analyzed the volatility spillovers between precious metal and industrial metal markets between the years 1993 and 2019. Their analysis was based on the DY and BK approaches. While volatility spillovers among industrial metals surpass that of precious metals, it is noteworthy that precious metals contribute to the overall volatility spillovers of industrial metals during periods of crisis. Additionally, the dynamics of volatility spillovers differ between the two clusters of metals across the short, medium, and long-term components with particular emphasis on the short and medium-term.

During the Asian Financial Crisis (1997), the Global Financial Crisis (2007–2008), and the Eurozone Crisis (2010–12), Sameen et al. (2022) explored the price stability features of precious metals. They employed the ICSS algorithm in conjunction with the GARCH model to explore the connection between precious metal prices and the performance of the stock market in the USA. According to the available information, gold is the most consistent precious metal. On the other hand, the silver, platinum, and palladium prices exhibited a positive association with market volatility in the United States in respect to the Dow Jones industrial average.

Addison and Ghoshray (2023) provide an empirical approach for tracking the fluctuations in the price of metals over the course of time. They claim that the insufficient elasticity of both demand and supply is what causes significant price volatility, making it impossible to forecast trends. They make use of the methods of integration in order to forecast future patterns in metal prices and take into consideration the non-stationary volatility that they note is a hallmark of metal pricing.

Based on the above literature, it seems clear that there are no many papers that show the existence of long memory in the volatility metals along with a lack of consensus about it. This is one of the main objectives in this paper noting that if long memory is present and is not taken into account, it would produce inconsistent estimates of the remaining parameters (like those related with deterministic terms) and poor performances in the forecasting exercises on the series of interest. This long memory property will be specified by using a fractionally integrated or I(d) model, which is a very convenient technique because with a single parameter, the order of integration, we can determine not only if long memory is present (if $d > 0$) or not ($d = 0$) but also if exogenous shocks in the series have transitory ($d < 1$) or permanent ($d \geq 1$) effects. Needless to say that this approach overpass classical methods like unit root tests that simple consider integer degrees of differentiation.

3. Data

We used the monthly data of the metal prices to analyze their volatility from January 1994 to February 2023, amounting to a total of 350 observations. The monthly data was calculated as an average of daily values, extracted from the metal 3-month future market. The metals we monitored were Gold, Silver, Copper, Platinum, Aluminium, Palladium, Lead, Zinc, and Tin. In the cases of Gold, Silver, Platinum, and Palladium, we measured USD per troy ounce, while for Copper, Aluminium, Lead, Zinc, and Tin, we used USD per metric ton. The data was obtained from Thomson Reuters Datastream. The time series were not seasonally adjusted and have been transformed from prices to returns in order to measure volatility, first in the annual and then monthly rates, and then in the absolute returns and finally, in the squared returns to eliminate negative figures.

Table 1 shows the main descriptive statistics for the prices. We observed an enormous range across min-max and a very high standard deviation in all cases, justifying the subsequent analysis of volatility to assess the persistence of shocks.

But before applying fractional integration to evaluate persistence in volatility, we offer a brief descriptive analysis in Appendix A: Gold shows more stability in all cases, probably in response to its value as a save heaven asset (see Tables A1, A2, A3 and A4, as well as Figures A1, A2, A3 and A4). However, Palladium, Lead and Zinc present a higher volatility based on Annual Rates Returns (Tables A1 and A2; also Figures A1 and A2). Furthermore, using Monthly Rates Returns, we observe more instability in the cases of Palladium, Silver, and Lead (Tables A3 and A4; and Figures A3 and A4).

4. Empirical results

We consider the following model,

$$y_t = \alpha + \beta t + xt, (1\text{-}B)^d\ xt = u_t, u_t = \rho u_{t-12} + \varepsilon_t, \tag{1}$$

where y_t refers to the observed data; and α and β are unknown coefficients, namely the intercept (constant) and linear time trend coefficient. B represents the backshift operator, such that $Bx_t = x_{t-1}$; x_t represents the errors from the regression, which are assumed to be fractionally integrated of order d or I(d), implying that the d-differences u_t are integrated of order 0 (I(0)) or short memory. Additionally, given the seasonal (monthly) nature of the data under examination, an AR(12) process is assumed for the I(0) disturbances u_t, where ρ is the seasonality indicator and ε_t is a white noise process with zero mean and constant variance. Note that if this seasonal component is unrequired the estimate of ρ will be close to zero. It may be argued that other autoregressive components might also be present in the data. However, we should note that the fractional polynomial in the second equality in (1) can be expanded as:

$$(1-B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2 - \ldots$$

and thus that equality can be expressed as

$$X_t = dX_{t-1} - \frac{d(d\text{-}1)}{2} X_{t-2} + \cdots + u_t.$$

In this context, if d is a fractional value, x_t will be a function of all its past history represented in terms of an infinite AR process. Nevertheless, we test for no autocorrelation using classical methods like Box and Pierce (1970), Ljung and Box (1978) along with the Lagrange Multiplier (LM) test of Breusch and Godfrey (Breusch, 1978; Godfrey, 1978), and the results indicate that no additional time dependence is found in the residuals.

The estimation is conducted via Whittle function (which is an approximation to the likelihood function) expressed in the frequency domain. For this purpose, we use a testing approach developed in Robinson (1994). It tests the null hypothesis H_o: $d = d_o$, where d_o is a given real value, and it has numerous advantages with respect to other methods. Thus, it remains valid even in nonstationary contexts ($d_o \geq 0.5$); it has a standard N(0,1) limit distribution and it is the most efficient method in the Pitman sense against local departures from the null. Its functional form can be found in any of the numerous applications that use this approach (see, e.g., Gil-Alana and Robinson, 1997).

Table 2 focuses on the observed prices. It shows the estimates for the differencing parameter d, as well as the accompanying 95% confidence range for three alternative set-ups corresponding to instances of (i) no deterministic terms, (ii) with an intercept, and (iii) with an intercept and a linear trend. The model for each series is highlighted in the tables. We can see that the time trend coefficient is only statistically significant in the case of Gold. For the rest of the series, an intercept suffices, save for Palladium, where the coefficient is similarly negligible.

The estimated coefficients for the selected models are reported across Table 3. We can see that mean reversion occurs in the cases of Gold (with d = 0.92) and Silver (0.87). For Aluminum, Copper, Lead, Palladium, Platinum and Zinc, the unit root null hypothesis cannot be rejected and this hypothesis is decisively rejected in the case of Tin (d = 1.24) in favor of alternatives with d > 1. We also observe in this table that for Gold, the time trend coefficient is significantly positive, while the seasonal coefficient is not very relevant in any of the series under examination.

The mean reversion in the cases of Gold and Silver may be correlated with the idea of save haven assets. In a period of crisis, their prices tend to rise and vice versa. Thus, to the extent that the business cycle changes, the persistence of the trend could relax as a consequence.

Next, we focus on the volatility structures. In Table 4, we consider the returns based on the annual difference: R(t) = [P(t)-P(t-12)]/P(t-12). The upper panel displays the estimates for the returns, the medium panel the absolute returns, and the lower panel the squared returns. Table 5 displays a similar structure but with the returns based on the monthly differences: R(t) = [P(t)-P(t-1)]/P(t-1). We perform the analysis on the same model as the one given by Equation (1) testing volatility throughout the differencing parameter d.

Starting with the annual difference returns, the first thing we observe in the upper panel of Table 4 is that the series is very persistent and evidence of mean reversion is only evident in the case of Gold and Silver with an order of integration of 0.86 and 0.87 respectively. The unit root null cannot be rejected for Lead and Platinum (d = 1.00) and Palladium (0.92), while for the remaining three (Aluminum, Cooper, Tin and Zinc), this hypothesis is rejected in favor of d > 1. That means an explosive behavior in volatility prices as well as big difficulties to achieve mean reversion in the long run, unless some specific measures are applied. In

Table 1
Descriptive analysis of metal prices.

	N	Minimum	Maximum	Mean	Stand. Dev.
Gold	350	254,00	1976,52	904,30	548,15
Silver	350	4,19	46,56	13,78	8,77
Copper	350	1341,25	10,343,00	4994,17	2655,10
Platinum	350	336,00	2174,00	930,89	428,86
Aluminium	350	1107,30	3501,00	1877,25	455,21
Palladium	350	114,50	2981,00	683,34	632,84
Lead	350	404,00	3596,00	1465,38	790,94
Zinc	350	763,00	4400,00	1884,56	858,38
Tin	350	3681,00	46,035,00	14,184,63	8791,91

Table 2
Estimates of d: Prices.

Series	No non-stochastic terms	An intercept	An intercept and a linear time trend
Aluminum	1.08 (1.00, 1.19)	**1.05 (0.96, 1.15)**	1.05 (0.96, 1.15)
Copper	1.09 (1.00, 1.19)	**1.07 (0.99, 1.18)**	1.07 (0.99, 1.18)
Gold	0.95 (0.89, 1.03)	0.92 (0.86, 0.99)	**0.92 (0.86, 0.99)**
Lead	0.94 (0.87, 1.03)	**0.94 (0.87, 1.04)**	0.94 (0.87, 1.04)
Palladium	**1.01 (0.93, 1.11)**	1.02 (0.94, 1.12)	1.02 (0.94, 1.12)
Platinum	1.01 (0.93, 1.11)	**1.02 (0.93, 1.12)**	1.02 (0.93, 1.12)
Silver	0.89 (0.83, 0.97)	**0.87 (0.82, 0.97)**	0.87 (0.82, 0.97)
Tin	1.25 (1.16, 1.37)	**1.24 (1.14, 1.35)**	1.24 (1.14, 1.35)
Zinc	1.01 (0.94, 1.10)	**1.00 (0.93, 1.08)**	1.00 (0.93, 1.08)

Note: The values in parenthesis are the confidence bands for the integration order, and the values in bold refers to the selected model for each series in relation with the non-stochastic terms.

Table 3
Estimated coefficients of the selected models in Table 2: Prices.

Series	d (95% band)	α (t-value)	β (t-value)	P
Aluminum	1.05 (0.96, 1.15)	1097.38 (9.07)	–	−0.029
Copper	1.07 (0.99, 1.18)	1751.43 (4.29)	–	−0.007
Gold	0.92 (0.86, 0.99)	383.18 (7.79)	4.368 (2.55)	0.036
Lead	0.94 (0.87, 1.04)	478.51 (3.24)	–	−0.115
Palladium	1.01 (0.93, 1.11)	–	–	−0.229
Platinum	1.02 (0.93, 1.12)	393.95 (5.21)	–	−0.037
Silver	0.87 (0.82, 0.97)	5.282 (3.16)	–	−0.004
Tin	1.24 (1.14, 1.35)	4746.72 (3.75)	–	0.013
Zinc	1.00 (0.93, 1.08)	1030.07 (4.41)	–	−0.056

Note: The values in parenthesis in column 2 indicates the 95% confidence bands of the non-rejection values of d. Those in columns 3 and 4 are the t-values associated to the estimated coefficients α and β respectively.
— indicates lack of significance.

Table 4
Estimated coefficients: Returns based on annual difference.

Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	1.09 (1.02, 1.19)	78.718 (8.79)	–	−0.436
Copper	1.13 (1.04, 1.24)	74.431 (6.23)	–	−0.387
Gold	0.86 (0.79, 0.95)	–	–	−0.465
Lead	1.00 (0.91, 1.10)	37.847 (2.57)	–	−0.447
Palladium	0.92 (0.85, 1.01)	–	–	−0.437
Platinum	1.00 (0.91, 1.12)	–	–	−0.537
Silver	0.87 (0.80, 0.97)	–	–	−0.412
Tin	1.15 (1.07, 1.25)	28.506 (2.56)	–	−0.447
Zinc	1.10 (1.02, 1.19)	13.099 (7.91)	–	−0.357
Absolute returns				
Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	0.88 (0.78, 1.00)	72.156 (8.70)	–	−0.004
Copper	1.01 (0.91, 1.14)	77.029 (6.26)	–	−0.039
Gold	0.75 (0.67, 0.83)	–	–	−0.275
Lead	0.91 (0.81, 1.03)	36.315 (2.67)	–	−0.107
Palladium	0.76 (0.67, 0.86)	–	–	0.076
Platinum	0.76 (0.67, 0.87)	–	–	0.076
Silver	0.75 (0.66, 0.86)	–	–	−0.049
Tin	0.98 (0.88, 1.10)	25.732 (2.42)	–	−0.126
Zinc	1.02 (0.93, 1.14)	12.864 (11.01)	–	−0.013
Squared returns				
Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	0.98 (0.86, 1.11)	5690.42 (10.93)	–	−0.009
Copper	1.08 (0.95, 1.23)	5344.58 (4.02)	–	−0.006
Gold	0.69 (0.60, 0.81)	–	–	−0.214
Lead	1.02 (0.89, 1.18)	–	–	−0.028
Palladium	0.65 (0.57, 0.75)	–	–	−0.113
Platinum	0.74 (0.63, 0.88)	–	–	0.045
Silver	0.66 (0.57, 0.76)	–	–	−0.029
Tin	0.94 (0.85, 1.05)	–	–	−0.183
Zinc	1.10 (0.99, 1.25)	–	–	−0.017

Note: The values in parenthesis in column 2 indicates the 95% confidence bands of the non-rejection values of d. Those in columns 3 and 4 are the t-values associated to the estimated coefficients α and β respectively.
— indicates lack of significance.

this regard, The World Bank (2023) states that in 2022 metals such as aluminium, copper, tin and zinc suffered severe supply disruptions caused by logistical problems, plant maintenance, power shortages, social unrest, adverse weather conditions, and high energy prices. For example, they highlight the drop production in South America (in particular in Chile) for copper, in Europe and China for aluminum and zinc, and in Indonesia for tin. This collapse affected not only in terms of an increase in prices, but also from an instability/volatility point of view.

Table 5
Estimated coefficients: Returns based on month differences.

Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	0.03 (−0.05, 0.12)	–	–	0.029
Copper	0.09 (0.02, 0.20)	–	–	0.010
Gold	−0.06 (−0.12, 0.00)	0.569 (3.46)	–	0.093
Lead	−0.01 (−0.07, 0.07)	0.761 (2.84)	–	−0.082
Palladium	0.01 (−0.06, 0.10)	1.256 (2.20)	–	−0.080
Platinum	0.01 (−0.07, 0.10)	–	–	−0.059
Silver	−0.07 (−0.14, 0.00)	0.801 (2.57)	–	0.016
Tin	0.14 (0.06, 0.24)	–	–	−0.010
Zinc	0.04 (−0.03, 0.12)	–	–	−0.031
Absolute returns				
Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	0.16 (0.10, 0.24)	4.789 (10.39)	–	−0.101
Copper	0.15 (0.09, 0.23)	5.350 (9.35)	–	0.021
Gold	0.14 (0.09, 0.21)	3.248 (9.76)	–	0.060
Lead	0.17 (0.12, 0.23)	6.104 (8.98)	–	0.053
Palladium	0.17 (0.10, 0.26)	7.270 (8.14)	–	−0.027
Platinum	0.15 (0.09, 0.22)	3.520 (4.24)	0.007 (1.99)	0.042
Silver	0.18 (0.12, 0.25)	6.219 (8.52)	–	−0.034
Tin	0.17 (0.12, 0.24)	3.589 (3.48)	0.009 (2.00)	0.051
Zinc	0.07 (0.03, 0.13)	3.967 (5.86)	0.089 (2.71)	0.117
Squared returns				
Series	No non-stochastic terms	An intercept (tv)	An intercept (tv)	Seasonal
Aluminum	0.16 (0.10, 0.23)	37.283 (5.68)	–	−0.040
Copper	0.13 (0.06, 0.21)	52.297 (4.61)	–	0.019
Gold	0.11 (0.05, 0.19)	19.945 (5.33)	–	0.015
Lead	0.16 (0.11, 0.22)	64.179 (4.42)	–	0.073
Palladium	0.14 (0.07, 0.22)	100.217 (4.57)	–	0.030
Platinum	0.22 (0.15, 0.31)	37.494 (2.84)	–	0.033
Silver	0.15 (0.10, 0.23)	70.516 (4.61)	–	−0.076
Tin	0.12 (0.06, 0.19)	21.271 (2.13)	0.178 (1.98)	0.018
Zinc	0.06 (0.02, 0.12)	33.015 (2.45)	0.116 (1.76)	0.164

� Note: The values in parenthesis in column 2 indicates the 95% confidence bands of the non-rejection values of d. Those in columns 3 and 4 are the t-values associated to the estimated coefficients α and β respectively. — indicates lack of significance.

Focusing on the absolute returns, the values are relatively high in most cases and although mean reversion takes place in four cases, the estimates of d are very high in the four series: Gold and Silver (with $d = 0.76$) and Palladium and Platinum (0.75). For the remaining four series, the values are 0.88 (Aluminum), 0.91 (Lead), 0.98 (Tin), 1.01 (Copper) and Zinc (1.02), and the unit root null is not rejected. Finally, for the squared returns (lower panel), the values are similar to the absolute returns: mean reversion is obtained for gold, silver, palladium and platinum and there is a lack of it for the remaining five, aluminium, copper, lead, tin and zinc.

Table 5 displays the results using the returns based on the monthly differences. The orders of integration are very close to zero in all cases. Only for Copper ($d = 0.09$) and Tin (0.14) are the estimates of d significantly positive and display a long memory pattern. For the remaining seven, the estimates range between −0.07 (Silver) and 0.04 (Zinc), and the hypothesis of short memory ($d = 0$) behavior cannot be rejected. For the absolute returns, the values are all positive implying thus long memory, ranging from 0.07 in the case of Zinc to 0.18 for Silver. For the squared returns, the values are slightly smaller though still all positive, ranging from 0.06 (Zinc) to 0.16 (Aluminum and Palladium).

As earlier mentioned, we test for no serial autocorrelation in the residuals of the estimated models and the results support this hypothesis in all cases. However, testing for Gaussianity, this hypothesis was rejected in practically all cases; nevertheless, it should be noticed that the methodology used in this work remains valid even in non-Gaussian contexts (see, Robinson, 1994).

In the final part of the manuscript we investigate if the results might be affected by the fact that the data are averaged values of the month. According to Working (1960), this may increase the level of persistence in the data. Thus, in Appendix B, we report the results based on the "end of the month "values rather than the averaged ones. Following this hypothesis, we should expect higher levels of persistence in the values reported across Tables 2–5. However, the results reported in Appendix B are completely in line with those reported in the manuscript. Thus, for the original prices, (Table B1) mean reversion is only observed in the cases of Gold (d = 0.92) and Silver (0.88) and though for Tin the estimate of d is higher with the averaging values (1.24 versus 1.18), the same hypothesis of d > 1 holds with the "end of the month" values. Focusing on the returns based on annual differences, in Table B2, though quantitatively there are small differences in the values of d, qualitatively they are very similar, with mean reversion in the cases of gold and silver returns, and for these two along with palladium and platinum in case of the absolute and squared returns. Moving to the returns based on monthly differences (Table B3) the same conclusions hold as in Table 5; thus, long memory is only observed in Copper (d = 0.09) and Tin (d = 0.11) (slightly smaller in the latter than with the averaging prices), and values of d significantly above 0 are found in the absolute and squared returns, not observing significant differences with respect to the averaging values. The explanation for this lack of higher persistence in the average values might be in the use of a long memory approach to describe the persistence in the data. Two decades later than the work by Working (1960), authors such as Robinson (1978) and Granger (1980) justified the existence of long memory with fractional integration by means of aggregation. Other authors have followed later the same approach: Souza (2005, 2007), Puplinskatie and Surgailis (2010), Hassler (2011), Haldrup and Vera Valdés (2017), Vera-Valdés (2021), etc.

5. Conclusions

Using the monthly data from January 1994 to February 2023, this paper examined the degree of volatility persistence in the prices of nine metals (aluminum, copper, gold, lead, palladium, platinum, silver, zinc, and tin). Using I(d) methods, the price-based results indicate that all series are highly persistent with the differencing parameter estimates very near to 1. In fact, only Gold and Silver exhibited a modest degree of mean reversion with orders of integration substantially below 1. This is likely due to the safe-haven quality of both assets.

For volatility, we approximated it using absolute and squared returns, and testing for the integration order in the series we observed in the case of annual difference returns. Shocks in the series were expected to be permanent and the evidence of mean reversion was simply found in Gold and Silver again. However, the hypothesis of short memory (d = 0) behavior cannot be ruled out using the returns based on the monthly differences since the orders of integration were always very near zero. For the squared returns, the numbers were slightly smaller but still all positive, ranging from 0.11 (Gold) to 0.16 (Aluminum and Palladium). For the absolute returns, the values were all higher than zero and suggested long memory, ranging from 0.14 for Gold to 0.18 for Silver.

In conclusion, we observed a different behavior between Gold and Silver and the rest of metals. The first two assets presented with a mean reversion in line with the business cycles. However, the other metals were not only affected by the economic outlook but also by the input market focused on production. Markets that have been directly influenced by bottleneck issues after Covid-19 are what may explain the high volatility and its persistence. Economic policy measures should be focused on boosting the supply side of metal markets to mitigate volatility prices, in particular, in the case of copper, platinum, aluminium, palladium, lead, zinc, and tin.

This article may be extended according to various aims. First, the possibility of structural breaks is an issue that should not be underestimated, especially considering that ignoring it may produce spurious evidence of long memory (Sibbertsen, 2001; Granger and Hyung, 2004; Lazarova, 2006; Arouri et al., 2012; etc.). An alternative approach may be the use of non-linear structures (Diebold and Inoue, 2001) like those proposed for the deterministic terms in Cuestas and Gil-Alana (2016) with Chebyshev polynomials in time, or in Gil-Alana and Yaya (2021) and Yaya et al. (2021) with Fourier functions and neural networks, avoiding then the abrupt changes produced by the breaks. Research and development efforts are currently underway in this area.

CRediT authorship contribution statement

Luis Alberiko Gil-Alana: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Writing – original draft. **Carlos Poza:** Conceptualization, Data curation, Project administration, Resources, Validation.

Declaration of competing interest

There is no conflict of interest with the publication of the present manuscript.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Descriptive analysis of Absolute Returns.
(Based on Annual Rates)

	Minimum	Maximum	Mean	Stand. Dev.
Gold	0,08	52,46	12,96	11,20
Silver	0,08	148,45	21,45	22,44
Copper	0,10	141,37	24,52	24,30
Platinum	0,00	81,48	18,06	15,45
Aluminium	0,27	76,56	17,59	14,74

(*continued on next page*)

Table A1 (*continued*)

	Minimum	Maximum	Mean	Stand. Dev.
Palladium	0,00	160,38	35,51	29,45
Lead	0,05	185,87	23,40	27,97
Tin	0,02	116,78	25,68	26,05
Zinc	0,17	175,52	24,49	28,54

Table A2
Descriptive analysis of Squared Returns
(Based on Annual Rates)

	Minimum	Maximum	Mean	Stand. Dev.
Gold	0,01	2751,96	293,17	464,78
Silver	0,01	22,038,15	962,54	2323,92
Copper	0,01	19,986,67	1190,84	2602,58
Platinum	0,00	6639,23	564,47	955,16
Aluminium	0,07	5860,76	526,26	906,46
Palladium	0,00	25,720,90	2126,11	3465,44
Lead	0,00	34,547,59	1328,38	3832,69
Tin	0,00	13,638,04	1336,40	2482,15
Zinc	0,03	30,808,52	1412,26	4096,77

Table A3
Descriptive analysis of Absolute Returns.
(Based on Monthly Rates)

	Minimum	Maximum	Mean	Stand. Dev.
Gold	0,02	20,87	3,39	3,02
Silver	0,00	34,80	6,41	5,69
Copper	0,00	33,80	5,44	4,88
Platinum	0,00	29,96	4,82	4,19
Aluminium	0,00	19,20	4,74	3,73
Palladium	0,00	43,21	7,46	6,88
Lead	0,03	33,29	6,19	5,35
Tin	0,00	31,58	5,20	4,88
Zinc	0,00	29,86	5,55	4,78

Table A4
Descriptive analysis of Squared Returns
(Based on Monthly Rates)

	Minimum	Maximum	Mean	Stand. Dev.
Gold	0,00	435,40	20,66	39,16
Silver	0,00	1210,84	73,50	131,46
Copper	0,00	1142,62	53,46	106,95
Platinum	0,00	897,51	40,82	79,91
Aluminium	0,00	368,53	36,43	53,23
Palladium	0,00	1867,09	103,01	206,61
Lead	0,00	1108,02	66,99	119,90
Tin	0,00	997,47	50,91	106,44
Zinc	0,00	891,39	53,67	98,13

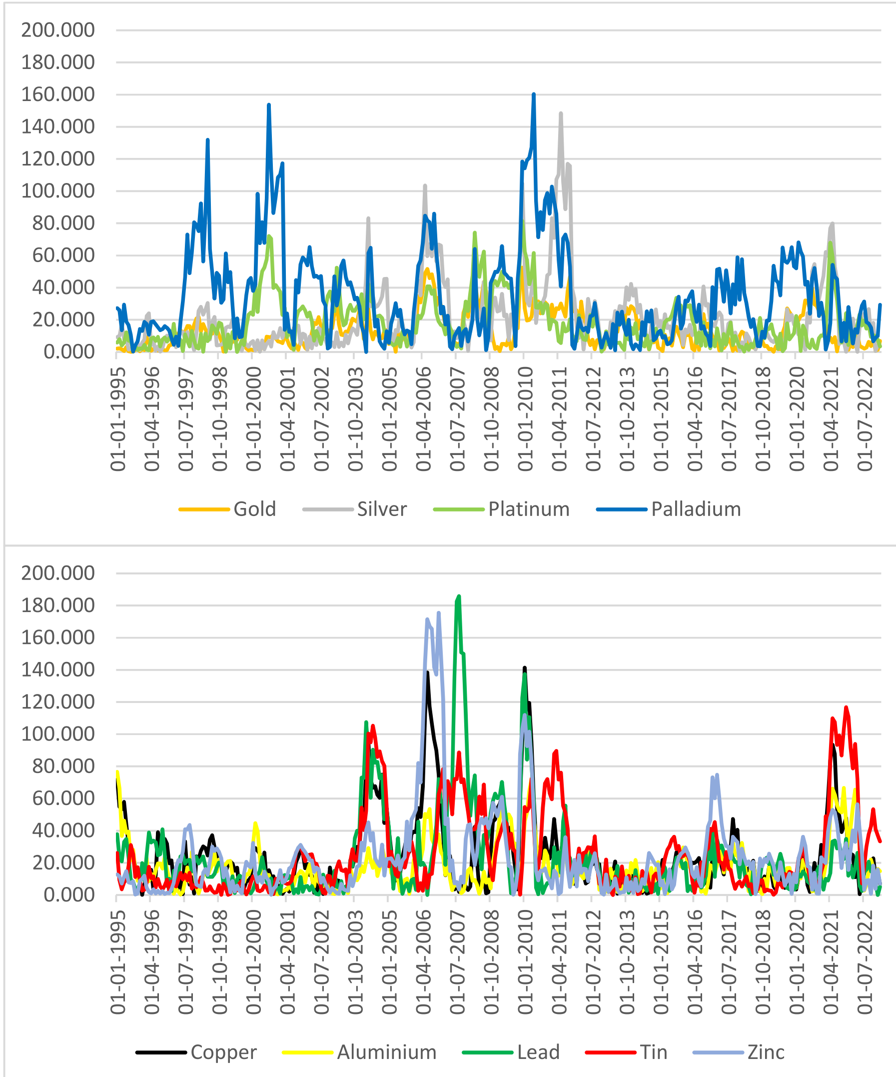


Fig. A1. Volatility in terms of Absolute Returns
(Based on Annual Rates).

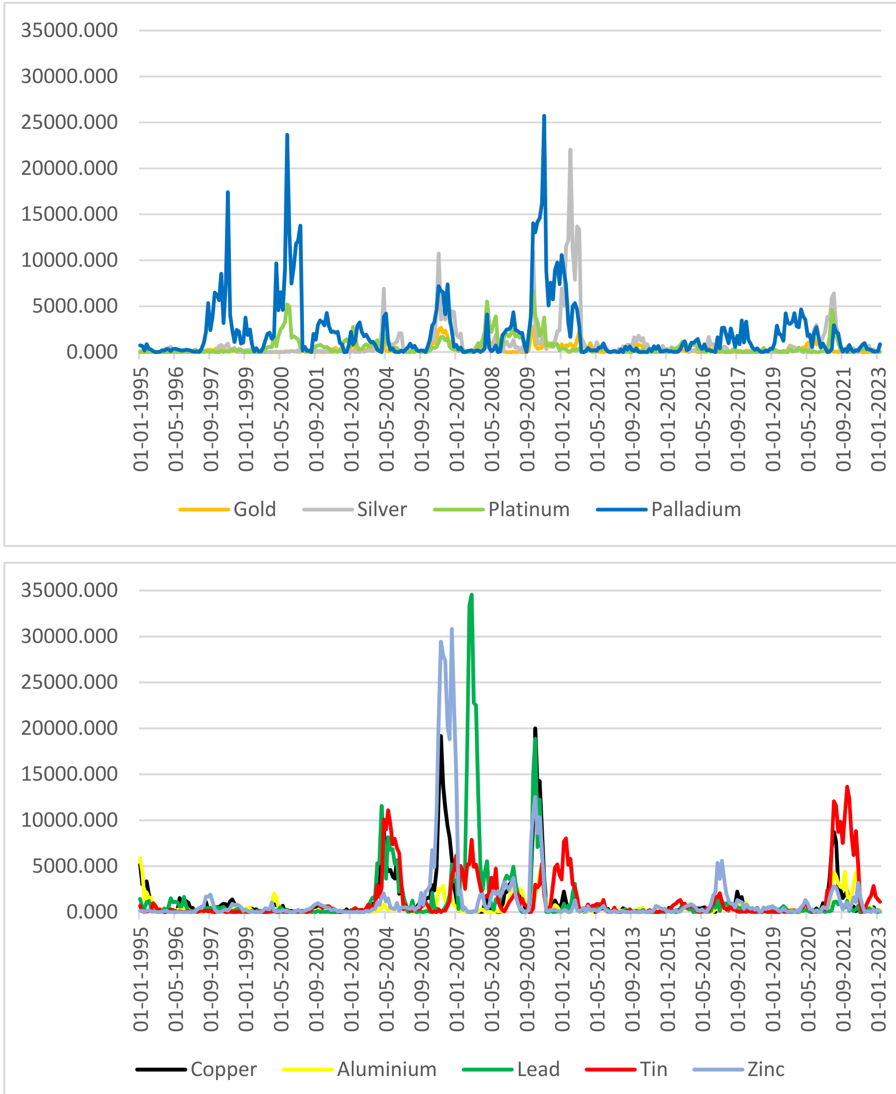
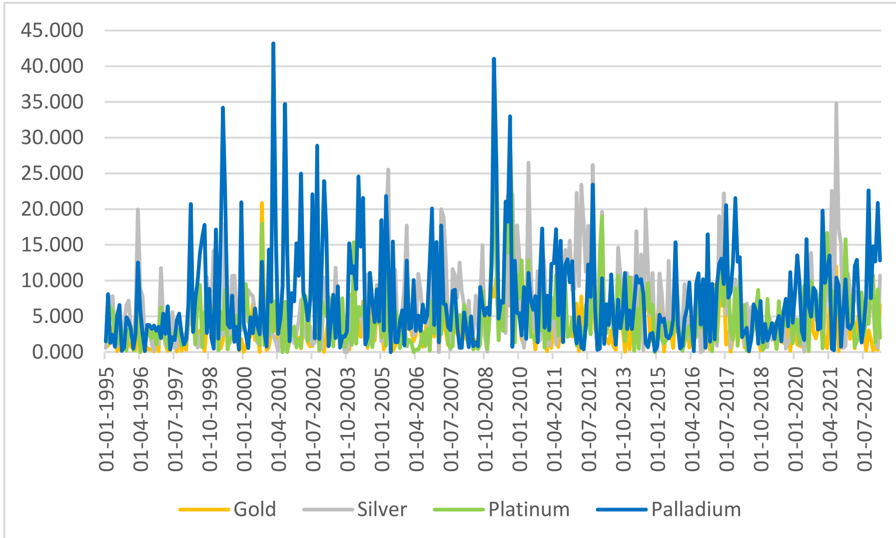


Fig. A2. Volatility in terms of Squared Returns
(Based on Annual Rates).



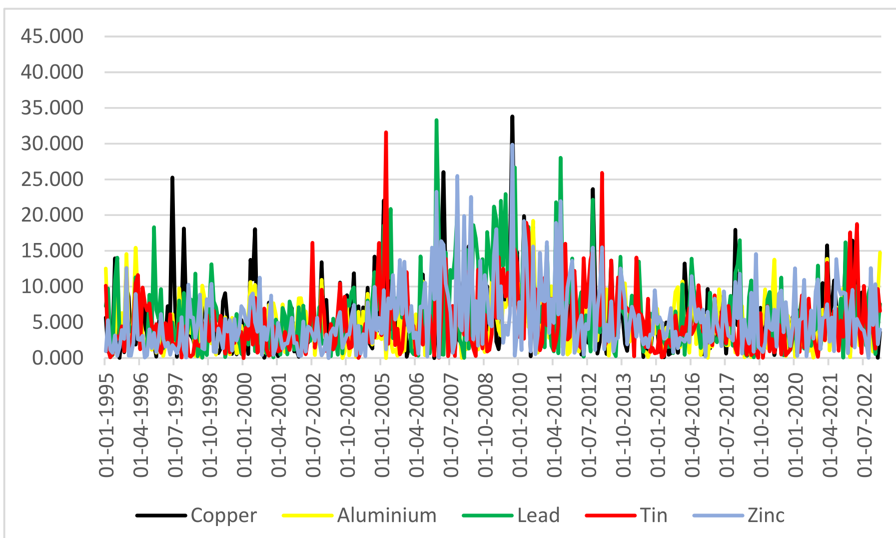
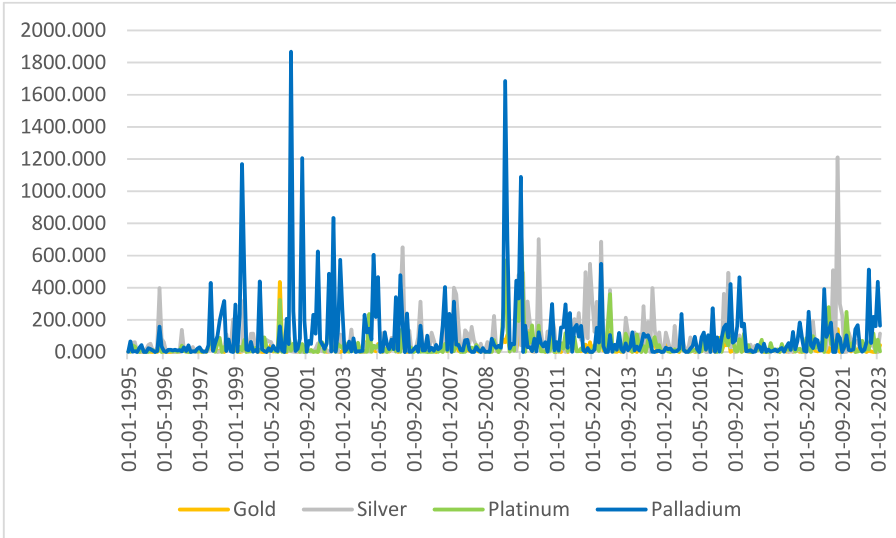


Fig. A3. Volatility in terms of Absolute Returns
(Based on Monthly Rates).



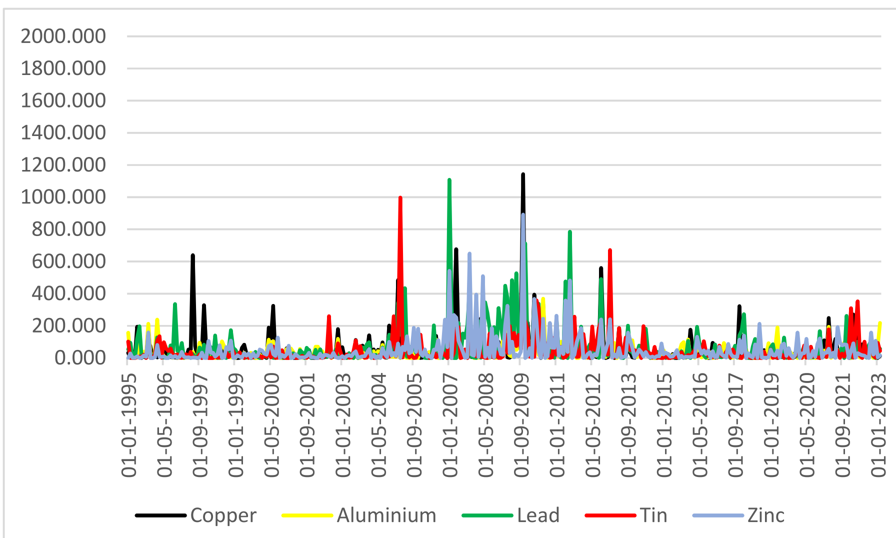


Fig. A4. Volatility in terms of Squared Returns
(Based on Monthly Rates).

Appendix B. Results based on "end of the month" data

Table B1
Estimates of d: End of the month Prices

Series	No non-stochastic terms	An intercept	An intercept and a linear time trend
Aluminum	1.04 (0.96, 1.13)	**1.04 (0.97, 1.14)**	1.04 (0.97, 1.14)
Copper	1.06 (0.98, 1.16)	**1.07 (0.99, 1.17)**	1.07 (0.99, 1.17)
Gold	0.94 (0.88, 1.02)	0.92 (0.86, 0.99)	**0.92 (0.85, 0.99)**
Lead	0.95 (0.88, 1.04)	**0.96 (0.88, 1.05)**	0.96 (0.89, 1.05)
Palladium	**1.03 (0.95, 1.13)**	1.04 (0.96, 1.12)	1.04 (0.96, 1.12)
Platinum	1.06 (0.97, 1.17)	**1.07 (0.98, 1.18)**	1.07 (0.98, 1.18)
Silver	0.88 (0.81, 0.96)	**0.88 (0.82, 0.96)**	0.88 (0.82, 0.96)
Tin	1.27 (1.08, 1.27)	**1.18 (1.09, 1.28)**	1.18 (1.09, 1.28)
Zinc	0.99 (0.92, 1.07)	**1.01 (0.94, 1.09)**	1.01 (0.94, 1.09)

Note: The values in parenthesis are the confidence bands for the integration order, and the values in bold refers to the selected model for each series in relation with the non-stochastic terms.

Table B2
Estimated coefficients: Returns based on annual difference

Series	No terms	An intercept	A linear time trend
i) Returns			
Aluminum	0.95 (0.90, 1.04)	**1.07 (0.99, 1.18)**	1.07 (0.99, 1.10)
Copper	1.06 (0.97, 1.07)	**1.09 (1.00, 1.20)**	1.09 (1.00, 1.20)
Gold	**0.87 (0.88, 0.96)**	0.87 (0.80, 0.96)	0.87 (0.80, 0.96)
Lead	1.00 (0.92, 1.10)	**1.01 (0.93, 1.10)**	1.01 (0.93, 1.10)
Palladium	**0.93 (0.86, 1.02)**	0.94 (0.87, 1.02)	0.94 (0.97, 1.02)
Platinum	**1.02 (0.92, 1.11)**	1.03 (0.93, 1.12)	1.03 (0.93, 1.12)
Silver	**0.88 (0.80, 0.97)**	0.88 (0.80, 0.97)	0.88 (0.80, 0.97)
Tin	1.15 (1.07, 1.24)	**1.15 (1.07, 1.24)**	1.15 (1.07, 1.24)
Zinc	1.07 (1.00, 1.16)	**1.08 (1.00, 1.17)**	1.08 (1.00, 1.17)
ii) Absolute Returns			
Series	No terms	An intercept	A linear time trend
Aluminum	0.77 (0.69, 0.88)	**0.90 (0.79, 1.02)**	0.90 (0.79, 1.02)
Copper	0.96 (0.86, 1.07)	**0.98 (0.88, 1.09)**	0.98 (0.88, 1.09)
Gold	**0.76 (0.67, 0.86)**	0.75 (0.67, 0.86)	0.75 (0.67, 0.86)
Lead	0.90 (0.81, 1.01)	**0.90 (0.81, 1.01)**	0.90 (0.81, 1.01)
Palladium	**0.75 (0.64, 0.85)**	0.75 (0.65, 0.85)	0.75 (0.65, 0.85)
Platinum	**0.79 (0.70, 0.90)**	0.79 (0.70, 0.90)	0.79 (0.70, 0.90)
Silver	**0.77 (0.67, 0.87)**	0.77 (0.67, 0.87)	0.77 (0.67, 0.87)
Tin	1.00 (0.91, 1.10)	**1.00 (0.91, 1.10)**	1.00 (0.91, 1.10)
Zinc	1.02 (0.92, 1.11)	**1.02 (0.93, 1.11)**	1.02 (0.93, 1.11)
iii) Squared Returns			
Series	No terms	An intercept	A linear time trend
Aluminum	0.73 (0.63, 0.85)	**0.97 (0.84, 1.11)**	0.97 (0.85, 1.11)
Copper	0.94 (0.82, 1.08)	**0.95 (0.82, 1.09)**	0.95 (0.82, 1.09)
Gold	**0.68 (0.56, 0.79)**	0.68 (0.56, 0.79)	0.68 (0.56, 0.79)
Lead	**1.05 (0.93, 1.19)**	1.05 (0.93, 1.19)	1.05 (0.93, 1.19)
Palladium	**0.66 (0.58, 0.75)**	0.66 (0.58, 0.75)	0.66 (0.58, 0.75)
Platinum	**0.85 (0.73, 0.97)**	0.85 (0.73, 0.97)	0.85 (0.73, 0.97)
Silver	**0.68 (0.59, 0.79)**	0.68 (0.59, 0.78)	0.68 (0.58, 0.78)
Tin	**1.03 (0.93, 1.10)**	1.03 (0.93, 1.10)	1.03 (0.93, 1.10)
Zinc	**1.03 (0.93, 1.12)**	1.03 (0.93, 1.12)	1.03 (0.93, 1.12)

Table B3
Estimated coefficients: Returns based on month difference

Series	No terms	An intercept	A linear time trend
i) Returns			
Aluminum	**−0.02 (-0.05, 0.11)**	−0.02 (0.05, 0.11)	−0.02 (0.02, 0.11)
Copper	**0.09 (0.02, 0.19)**	0.09 (0.02, 0.19)	0.10 (0.02, 0.18)
Gold	−0.05 (−0.10, 0.02)	**−0.05 (-0.11, 0.02)**	−0.05 (−0.10, 0.01)
Lead	0.01 (−0.06, 0.09)	**0.01 (-0.06, 0.09)**	0.01 (−0.06, 0.09)
Palladium	0.02 (−0.05, 0.10)	**0.02 (-0.05, 0.10)**	0.02 (−0.05, 0.10)
Platinum	**0.03 (-0.05, 0.13)**	0.03 (−0.05, 0.13)	0.03 (−0.06, 0.12)
Silver	−0.08 (−0.12, 0.02)	**−0.06 (-0.12, 0.02)**	−0.06 (−0.13, 0.02)
Tin	**0.11 (0.03, 0.20)**	0.11 (0.03, 0.20)	0.11 (0.03, 0.20)
Zinc	**0.04 (-0.03, 0.12)**	0.04 (−0.03, 0.12)	0.04 (−0.03, 0.12)
ii) Absolute Returns			
Series	No terms	An intercept	A linear time trend
Aluminum	0.14 (0.07, 0.23)	**0.14 (0.08, 0.23)**	0.14 (0.07, 0.23)
Copper	0.16 (0.09, 0.23)	**0.15 (0.09, 0.24)**	0.15 (0.09, 0.23)
Gold	0.12 (0.06, 0.18)	**0.13 (0.08, 0.20)**	0.13 (0.07, 0.20)
Lead	0.18 (0.13, 0.24)	**0.18 (0.13, 0.24)**	0.18 (0.13, 0.24)
Palladium	0.16 (0.08, 0.25)	0.16 (0.09, 0.24)	**0.16 (0.09, 0.24)**
Platinum	0.20 (0.12, 0.39)	**0.21 (0.14, 0.30)**	0.22 (0.13, 0.30)
Silver	0.18 (0.13, 0.27)	**0.19 (0.14, 0.27)**	0.19 (0.13, 0.27)
Tin	0.19 (0.13, 0.26)	0.20 (0.13, 0.27)	**0.19 (0.11, 0.27)**
Zinc	0.11 (0.06, 0.17)	0.12 (0.07, 0.18)	**0.12 (0.07, 0.18)**
iii) Squared Returns			
Series	No terms	An intercept	A linear time trend
Aluminum	0.16 (0.09, 0.25)	**0.16 (0.09, 0.25)**	0.16 (0.09, 0.25)
Copper	0.13 (0.06, 0.21)	**0.13 (0.06, 0.21)**	0.12 (0.06, 0.21)
Gold	0.12 (0.06, 0.20)	**0.13 (0.07, 0.21)**	0.13 (0.07, 0.21)
Lead	0.17 (0.12, 0.23)	**0.17 (0.12, 0.23)**	0.17 (0.12, 0.23)

(*continued on next page*)

Table B3 (*continued*)

iii) Squared Returns			
Series	No terms	An intercept	A linear time trend
Palladium	0.11 (0.04, 0.20)	**0.11 (0.04, 0.20)**	0.11 (0.04, 0.20)
Platinum	0.24 (0.16, 0.33)	**0.24 (0.16, 0.33)**	0.24 (0.16, 0.33)
Silver	0.17 (0.11, 0.24)	**0.18 (0.12, 0.23)**	0.17 (0.12, 0.24)
Tin	0.15 (0.10, 0.22)	0.16 (0.10, 0.23)	**0.15 (0.09, 0.22)**
Zinc	0.09 (0.04, 0.15)	0.10 (0.05, 0.16)	**0.09 (0.04, 0.15)**

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