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Discerning trends in international metal prices in the presence of nonstationary volatility

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\textbf{A B S T R A C T}

In this paper, we develop an empirical framework that allows us to trace out a time path of metal prices. This framework shows that unpredictable shifts in demand, extraction costs and discovery of reserves, make estimation of the slope of this underlying trend an empirical question. Further, the low elasticity of demand and supply cause large volatility in the prices, which makes estimation of the trend difficult. We estimate the trend in metal prices employing econometric procedures that are robust to the underlying order of integration of the data and allow for nonstationary volatility, which we note is a characteristic feature of metal prices. We further analyse whether metal prices are characterised by stochastic trends by conducting unit root tests that allow for nonstationary volatility. Applying these procedures on metal prices for over a century, we draw conclusions that relate to policy.

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\textbf{1. Introduction}

In this paper, we analyse the long run trend in metal prices and persistence to shocks in metal prices over a century worth of data. We aim to answer two key questions. First, do we find evidence that metal prices are increasing or decreasing in the long-run? Secondly, are shocks to metal prices short-lived? A problem that has been overlooked so far, is that metal prices are known to be volatile and this can cause a problem in the estimation of trends and persistence to shocks. Accordingly, we employ robust methods and we find that for most metal prices, the effect of any exogenous shock is short-lived in nature. With regards to the trend estimation, we find no significant trend in most metal prices. These findings are important as metals are a crucial input for industrial production and are therefore important for both producing and consuming countries. For example, in the case of many metal exporting countries, the revenue from metal exports is often their main source of income, and a declining trend in metal prices can cause a widening deficit in the balance of trade, that could cause currency instability and harm economic growth. Likewise, for many metal importing countries the imports are crucial for industrialisation and infrastructure development. In this context, increasing metal prices can cause import bills to increase over time and hamper economic growth. Therefore, knowledge of the underlying long run dynamics of metal prices help governments and industries, especially in metal dependent countries, to tackle the problem of macroeconomic risk management.

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The pioneering work of Hotelling (1931) has seen natural resource stock, including metals, as a form of capital, where the rate of return from holding onto an exhaustible resource as an asset grows at a rate equal to the interest rate. From the 1950s to the 1970s, this capital theoretic framework was applied to a range of natural resources (e.g., Dasgupta and Heal, 1974; Solow, 1974; Devarajan and Fisher, 1981). As climate change issues started attracting attention, the concept of natural capital expanded to include other non-market environmental public goods (Nordhaus, 1974). By the turn of the 20th century, natural capital broadened further to include ecosystems because they support economic activity and enhance human welfare (Fenichel and Abbott, 2014; Barbier, 2019). It is important to understand the broadening of the concept of natural capital to embrace new environmental challenges, because it documents how economic views on natural resource scarcity have evolved from the 1950s to the present (Barbier, 2021), thereby the need to analyse data over a long period.

Metal prices in unregulated competitive markets are determined at each point in time by the intersection of short run supply and demand curves (Tilton, 2006). Production of metals would continue as long as there is capacity and the price of metals exceeds variable costs. If there were an increase in the demand for metals, which can happen due to increased economic growth in metal importing countries, or simply by positive expectations of future business conditions, then additional factors of production would be needed to meet the increased production thereby pushing up prices so that they exceed the variable costs. When production starts to reach its full capacity, the supply curve tends to become steeper, and at full capacity is almost vertical. At these points of time, if there is an increase in demand, the price increase will be quite high. Alternatively, there can be shifts in supply, where a leftward shift in the short run supply curve can arise due to strikes, and a rightward shift in the supply curve can result due to natural resource discoveries. These shifts in demand and supply in the short run cause prices to fluctuate. Cashin and McDermott (2002) comment on the short run variability of commodity prices describing the important features of prices exhibiting rapid and often large movements and this variability is largely caused by the low price elasticity of demand for metals. The price elasticity of supply can be a contributing factor to large variability in prices when the capacity is almost fully utilised. Such variability of metal prices are a problem for countries that are heavily dependent on the export income from such metals.

For depletable extractive natural resources such as metals, we would expect prices to fluctuate over time in response to unexpected changes in demand, the costs of extraction and the discovery of reserves. As elucidated by Pindyck (1999), one can expect that an increase in demand for natural resources would lead to an increase in the price of the natural resource. Similarly, an increase in extraction costs would lead to an increase in prices. In contrast, an increase in new discoveries and technological progress, would lead to an increase in the level of reserves, depressing the price of the natural resource. However, these changes in reserves and demand and extraction costs can vary unpredictably over time; these unpredictable changes have an impact on the trend of natural resource prices. The question is whether such trends are increasing or decreasing over time. Besides, extractive resource prices are known to be highly volatile (Cuddington and Jerrett, 2008) given the low price elasticity of demand and supply, making the estimation of the underlying trend notoriously difficult. Metal prices are subject to large shifts in demand following the business cycles and the supply cannot adjust accordingly due to capacity constraints (Dooley and Lenihan, 2005).

The dynamic price adjustment around a trend, if present, is of interest as well. For example, if price declines from its equilibrium level, one would expect that the production of metals should contract. However, if the fall in price is deemed to be temporary, then there is no incentive to cut back on production as it would be costly to expand production again when the price returns to its equilibrium level. In other words, it would be economical to suffer a ‘temporary loss’, when prices do not cover variable costs (Radeski and Wårell, 2016). However, if shocks to prices are not transitory in nature, then that would imply the price contains a stochastic trend which would have an impact on production decisions. In this light, it would be important for policy makers and investors to know if price shocks are indeed temporary.

In what follows, we provide an empirical framework to trace out the plausible dynamic time path of metal prices using demand and supply curves, and make conjectures on how the underlying trend may evolve over time depending on the discovery of new reserves or deposits of metals. We also establish how the low elasticity of demand for metals contributes to the high volatility in metal prices over time. This framework motivates the empirical methods we use to make a robust estimate of the trend taking into account the underlying volatility. Further, we determine whether shocks to metal prices are transitory or not, allowing for volatility as well as a possible break in trend. To our knowledge, these methods have not been applied to examine metal prices, and would therefore be of interest, as they would inform policy makers in countries that are dependent on metals. We find limited evidence of significant trends in metal prices lending support to the popular quip by Deaton (1999); ‘what commodity prices lack in trend, make up for in variability’. We also find that the evidence is in favour of shocks not having a permanent effect on metals prices. This paper is organised as follows: Section 2 provides a literature review; Section 3 briefly lays out the empirical framework using demand and supply curves to explain how metal prices may evolve over time, and how the low elasticity of demand for metals contributes to the price volatility; Section 4 describes the robust econometric methods that allow us to test for trends and persistence in the presence of nonstationary volatility; Section 5 describes the data and empirical results; and finally Section 6 concludes.

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1 Since this represents the returns on all other capital in an economy, natural resource stocks are treated as a form of capital.

2 Barbier (2021) provides a discussion to understand the absolute (Malthusian) and relative (Ricardian) scarcity. A further discussion can be found in Hall and Hall (1984).
2. Background and literature review

The subject of long run trends in commodity prices, which includes metal prices, has been a subject of intense discussion and debate since the mid-twentieth century. The long held classical view was that the trend of real commodity prices (defined as the ratio of primary to manufactured goods) should be positive, as the supply of primary commodities would be constrained by the fixed amount of land while the supply of manufactures are augmented by technical progress. This view was overturned by two independent but concurrent studies by Prebisch (1950) and Singer (1950). They concluded that real commodity prices should decline in the long run, popularly known as the ‘Prebisch-Singer Hypothesis’. Later, using the well-known Lewis Model (see Lewis, 1954), Deaton and Laroque (2003) argue that prices of real primary commodities produced in developing countries, where there is an abundant supply of labour, would exhibit no significant trend.

Metals are a natural resource and therefore scarce in supply, given that there is a finite amount of resources under the Earth’s crust. According to the Malthusian theory, as the demand for metals grow, which can happen with population growth over time, the price should increase. A popular theory due to Hotelling (1931), argues that the unexploited metal prices will increase over time with the rate of interest. However, in recent years, the Hotelling theory has come under scrutiny and recent research (see e.g., Anderson et al., 2014, Stuermer and Schwerhoff, 2015) and tends to suggest that the observed patterns of oil production and prices are not compatible with Hotelling (1931). One of the main reasons for the lack of a positive trend in natural resources is that as reserves are depleted, new reserves are found. Kilian (2009) argues that demand and supply shocks are not alike. Demand shocks have long run effects; for example, an increase in demand leads to an increase in prices, which in turn makes investment in research and development for extraction of resources and discovery of new deposits more profitable, eventually leading to an increase in supply. In contrast, supply shocks have short-run effects (Kilian, 2009). These supply shocks can for example be strikes, cartel action, and natural disasters, which lead to temporary supply disruptions.

The question of whether long run trends exist in metal prices is an empirical one. As a result, a large volume of studies have examined the trend in commodity prices, which include metal prices. Barnett and Morse (1963) conclude that the trend is neither increasing nor decreasing by examining a graph of mineral prices over a long period, 1870–1957. Some of the later studies that employed regression analysis assumed no persistence in the error terms of the regression while estimating the underlying trend. For example, Smith (1979) makes use of recursive residuals, instead of ordinary least squares (OLS), to estimate the trend as well as a further test using log-likelihood ratio to account for an abrupt change in the trend. The results from his study show that there is no significant trend and concluded that the data is characterised by volatility that overshadows any possible trend. In contrast, Grilli and Yang (1988) find a negative trend in real commodity prices. They construct an index, now popularly known as the Grilli-Yang Index, which has been widely used in empirical studies, and estimate a regression using OLS on this index using a maximum likelihood test to correct for serial correlation. In contrast, Slade (1982) found evidence of an upturn in prices in the 1970s, preceded by a substantial decline. In a subsequent study, Slade (1991) notes that since the 1970s, the prices have displayed substantial volatility that can diminish evidence of a significant trend. Thirlwall and Bergevin (1985) find approximately an equal duration of upward and downward trends. They estimate the trends using OLS and incorporate dummy variables to measure the upswings and downswings in commodity price data. Halvorsen and Smith (1991) note that when estimating trends of non-renewable resource prices, a problem arises about the non-availability of data. Their point is that shadow prices are required to test for the theory of exhaustible resources. Prices would only increase with the rate of interest if extraction costs are zero, but the problem is exacerbated if the extraction costs are decreasing with time. Their analysis however, is based on tentative results due to the high level of aggregation in the data, and the theoretical model is based on complete certainty and perfect arbitrage. Slade and Thille (1997) suggest that a declining trend in prices is consistent with variants of Hotelling’s rule (e.g., discovery of large stocks can increase the size of stock and can cause prices to fall), but argue that in the long run prices should rise.

However, the above studies have shortcomings and they largely surfaced after the seminal study by Perron (1988), where he highlighted the problem of ignoring the persistence of the error term when estimating the trend. He concluded that the correct specification of the trend function could be affected by the presence of a unit root. If for example, the data series contains a unit root, then severe size distortions could occur when using OLS to test for the presence of a trend. Conversely, if the data does not contain a unit root, but is modelled as a unit root process, then the tests for the presence of a trend will be inefficient and will lack power relative to the trend stationary process (Perron and Yabu, 2009a), Cuddington (1992) modelled prices as difference stationary if the shocks to the error terms are permanent. Otherwise, if no unit root is present, the price series are modelled as trend stationary. Berck and Roberts (1996) argue that natural resource prices including metals should be difference stationary. They base their argument that metal prices are the sum of marginal cost of extraction and resource rent. Resource rent, they argue, should be difference stationary as it can be an asset. Both Cuddington (1992) and Berck and Roberts (1996) find limited evidence of positive trends; on the contrary, their results conclude that metal prices in general, do not exhibit a significant trend.

The trend estimation is further complicated if structural breaks are present in the price series. For example, if a structural break is ignored, one can incorrectly conclude the series to be a unit root process, when actually the series is trend stationary with a structural break (Perron 1989). Alternatively, in a difference stationary series, neglecting a trend break can lead one to incorrectly suggest the presence of stationarity (Leybourne et al., 1998). Accordingly, subsequent studies explicitly include structural breaks when testing for unit roots. The presence of structural breaks lead to breaking trend estimation, instead of estimating secular trends, leading to a vast plethora of studies (e.g., León and Soto, 1997; Kellard and Wohar, 2006; Ghoshray, 2011; Arezki et al., 2014). Further studies that use robust tests of structural breaks include Harvey et al. (2010) who provide...
limited evidence of trends in metal prices; Ghoshray et al. (2014) find no trend in metal prices; and Sun and Shi (2015)3 conclude no trend for various metal prices. These studies face a limitation that the number of breaks are restricted to two over a century long data set, which makes the analysis rather restrictive. For the sample size we have in this study, choosing too many breaks would not be an appropriate strategy as the unit root process can be seen as a limiting case of a stationary process with multiple breaks (see Ghoshray et al., 2014). This would be hard to justify from an economic perspective, by concluding that only two are breaks are permissible in a century where several significant events may have caused as many breaks. Alternative approaches include using low frequency band-pass filters, where Cuddington and Nülle (2014) make a case for analysing variable trends rather than constant long run trends in real mineral prices. However, they acknowledge the analysis can be best described as an exercise in descriptive statistics and lacks statistical inference. In a similar study, using band-pass filters for a century long data span, Rossen (2015) finds that multiple changes in turning points are common in a variety of metal prices and an overall declining trend can be found for most metal prices. Using a similar data set that comprises of annual metal prices spanning a century, Chen (2010) examines the long term behaviour of metal prices. Strong evidence is found that metal prices are highly volatile and the underlying secular trend in metal prices is widely variable, dominated by the large variance caused by the uncertainties associated with these prices. Based on these past studies we argue that the unconditional volatility in commodity prices, rather than the imposition of a maximum of two/three structural breaks, are more likely to affect the trend estimation.4 Accordingly, we analyse the trend and persistence of metal prices taking the nonstationary volatility into account.

The volatility in metal prices affects consumers as it affects the cost of production. If the duration of a price swing causing the price to move away from its long run equilibrium level were to be short-lived, (e.g., two years or less), then smoothing of production costs may be possible to a certain extent; on the contrary other strategies would be required to smooth production costs if the deviation of metal prices from its long term level were to be long-lived (Roberts, 2009). Understanding the general nature and characteristics of the swings in metal prices helps determine the appropriate policies to cope with these problems. Estimations of the trend in commodity prices can be influenced by the sample size or time horizon. Typically, long run trends in prices can be affected by events in the distant past or very recently. Given that metal prices are highly volatile, large spikes in metal prices at the end of the sample period can affect the underlying estimate of the trend. We pose the research question: do discernible trends exist in metal prices in the presence of nonstationary volatility? Demand driven episodes (e.g., mass industrialisation, urbanisation) can generate upward swings in metal prices. Usually such episodes are followed by supply responses (such as exploration and R&D) causing prices to return to trend. This leads to the next research question: are shocks to metal prices permanent? Before we use robust procedures to provide answers to these two research questions, we provide a brief motivation for the empirical analysis, outlining some conjectures that can be applied to demand and supply curves, which in turn can trace out a time trend of metal prices where the sign of the slope can be subject to different possibilities.

3. Empirical motivation

Let us consider the demand for metals (denoted \(d(t)\)) to be a downward sloping constant elastic demand curve at a given time period \(t\), and income \(y\) is fixed in the short run, but can change in the long run. The price at a given time period is denoted by \(p(t)\). The demand curve can be stated as:

\[
d(t) = y/[p(t)]^\alpha \quad \alpha < 1
\]

where \(\alpha\) denotes the elasticity of demand and the demand curve is shown to be inelastic. The price elasticity of demand is expected to be low as the cost of metals is usually a small proportion of the final good. Following Tilton (2006), the supply of metals (denoted \(s(t)\)) in the short run (that is, at a given time period \(t\)) is an upward sloping exponential function, asymptotic at the fixed amount of reserves \(R_0\) in the short run. The supply curve can be described as:

\[
s(t) = R_0(1 - e^{bt})
\]

Assuming markets clear, we set \(s(t) = d(t)\) and obtain:

\[
p^\alpha(1 - e^{bt}) = y/R_0
\]

The supply curve can adjust to the right due to technological progress by investing in research and development, or making new discoveries, and can happen when there is sufficient time to increase capacity. For example, when existing capacity is fully utilised, then there will be an incentive to invest in capacity expansion. These capacity expansions will shift the short run supply curve to the right. The intersections of demand and shifting short run supply curves will trace out the long run supply curve. The long run supply curve will tend to be relatively flat as more metals can be extracted with higher costs (Radetski and Wärell, 2016). In the short run, supply can be adversely affected by strikes as long as it is widespread, to dent global supply. In the long run, the reserves \(R_0\) can be increased with technological progress and also in response to an increase in demand, that is \(y\).

3 Sun and Shi (2015) allow for more than two breaks as they employ weekly data over approximately three decades thereby incorporating sufficient data points. The number of breaks is restricted to the sample size (see Kejriwal and Perron, 2010).

4 On a further note, while the structural break tests (Kejriwal and Perron, 2010) are robust to the order of integration in the data, they are not robust to nonstationary volatility. To our knowledge, no such robust tests for structural breaks exist and therefore we do not pursue this issue as it is beyond the scope of the paper.
Therefore in the medium to long-term one can expect incomes to change, leading to an increase in demand; and to meet this increased demand, new reserves will be found, thereby increasing \( R_0 \). Therefore, income and reserves will both be functions of time. This allows us to write:

\[
p(t)^* = y(t)/R_0(t)
\]  

(4)

If the long run cost is relatively flat, then the price will remain unchanged in the face of increasing demand for metals. However, it has been argued that the supply curve can shift downwards as cost can be reduced with technological progress, which means the marginal cost of extraction falls, leading to a declining trend in prices. Alternatively, the marginal cost could increase as economic depletion occurs, so that the prices could gradually increase with time, leading to an upward trend (Radetski and Wårell, 2016). To obtain the dynamic time path of the price of the metal, we differentiate (4) with respect to time \( t \) and obtain the following:

\[
a p^* - (dp/dt)(1 - e^{-\phi}) + p^* (dp/dt)\{(1/R_0^2) [R_0(dy/dt) - y(dR_0/dt)]\}
\]  

(5)

This can be simplified to:

\[
(dp/dt)[\alpha(p^*/p)(1 - (1/e^p)) + \lambda p^*(1/e^p)]
\]  

(6)

The term \( \alpha(p^*/p)(1 - (1/e^p)) + \lambda p^*(1/e^p) \) on the left hand side of Eq. (6) is positive, therefore the sign of the term \( [(1/y)/(dy/dt) = (1/R_0)(dR_0/dt)] \) on the right hand side of Eq. (6) will determine the change in price over time, that is \( dp/dt \). For example, if the rate of growth of demand \( (1/y)/(dy/dt) \) exceeds the rate of growth of reserves \( (1/R_0)(dR_0/dt) \), then we would expect \( [(1/y)/(dy/dt) - (1/R_0)(dR_0/dt)] > 0 \) and so prices will increase with time, as this results in \( dp/dt > 0 \). However, if the rate of growth of reserves, that is \( (1/R_0)(dR_0/dt) \) exceeds the rate of growth of demand, that is \( (1/y)/(dy/dt) \), then we would expect \( [(1/y)/(dy/dt) - (1/R_0)(dR_0/dt)] < 0 \) and so prices will decrease over time, as we obtain \( dp/dt < 0 \). The low elasticity of demand, that is \( \alpha < 1 \), makes the change in price more variable, contributing to the variability of metal prices over time. Two issues become imminent from the above discussion. First, over time, depending on the rate of growth of demand being less (greater) than the rate of growth of reserves, this would render the underlying trend to be significantly negative (positive). Indeed if the rate of growth of demand is equal to the rate of growth of reserves, this would lead to no significant trend in metal prices. The upshot is that the existence or not of an underlying long-term trend in metal prices is an empirical one. The large variability of metal prices can overshadow any trend as shown by the low elasticity of demand given by \( \alpha \). In what follows, we make a contribution by employing empirical methods to conduct a robust estimate of the trend taking into account the underlying volatility. Further, we determine whether shocks to metal prices are transitory or not allowing for volatility as well as a possible break in trend. These methods have not, to our knowledge, been applied to examine metal prices and would therefore be of interest as they would inform policy makers in countries that are dependent on metals.

4. Econometric methods

In the first instance, we estimate the trend in prices by setting up the following regression:

\[
p_t = \mu_0 + \beta_0 t + u_t, \quad t = 1, 2, ..., T
\]  

(7)

\[
u_t = \rho u_{t-1} + \sum_{i=1}^{k} \varphi_i \Delta u_{t-i} + \epsilon_t, \quad t = 2, 3, ..., T, \quad u_1 = \epsilon_1
\]

where \( p_t \) denotes the natural logarithm of real metal prices, and the error term, i.e. \( u_t \), can be either \( I(0) \), that is, \(|\rho| < 1 \), or \( I(1) \) that is, \( \rho = 1 \). The number of lags \( k \), is chosen according to the modified Akaike Information Criterion (MAIC) and \( k \) is allowed to be in the range \([0, [12(T/100)]^{0.25}]\) where \( T \) is the sample size. The trend estimate is given by the parameter \( \beta_0 \). We apply an econometric method due to Perron and Yabu (2009a), hereafter referred to as PY, that allows one to be agnostic to the nature of persistence of errors in the trend function.

To briefly describe the PY procedure to estimate the trend; first, the following auto-regression on the error term in (7) is estimated:

\[
\hat{u}_t = \alpha \hat{u}_{t-1} + \sum_{i=1}^{k} \varphi_i \Delta \hat{u}_{t-i} + \epsilon_t
\]  

(8)

We obtain from regression (8) the corresponding estimate \( \hat{\alpha} \), and to in order to improve the finite sample properties of the test we use a bias-corrected version denoted \( \hat{\alpha}_M \) following recommendation by Roy and Fuller (2001)\(^5\). PY construct the super-efficient estimate \( \hat{\alpha}_{MS} \) as follows:

---

\(^5\) See Perron and Yabu (2009b) for details.
\[ \tilde{\alpha}_{MS} = \begin{cases} \tilde{\alpha}_M & \text{if } |\tilde{\alpha}_M - 1| > T^{-0.5} \\ 1 & \text{if } |\tilde{\alpha}_M - 1| \leq T^{-0.5} \end{cases} \]  

(9)

The super-efficient estimate allows us to implement procedures that yield nearly identical limit properties with I(0) and I(1) variables. The super-efficient estimate \( \tilde{\alpha}_{MS} \) is then used to estimate the following quasi-differenced regression:

\[ (1 - \tilde{\alpha}_{MS} L)y_t = (1 - \tilde{\alpha}_{MS} L)\Psi_0^0 + (1 - \tilde{\alpha}_{MS} L)u_t; t = 2, 3, \ldots, T \]

\[ y_t = x_t'\Psi_0^0 + u_t \]  

(10)

where \( \Psi_0^0 = (\mu_0, \beta_0)' \). Denoting the estimate \( \hat{\beta}_0 \) from this regression, we construct a 100(1 - \( \alpha \))% confidence interval for \( \beta_0 \) valid for both I(1) and I(0) errors, and is given as follows:

\[ \hat{\beta}_0 \pm c_{a/2}2(\bar{h}_v)\{X^T\widehat{CC}X_2^{-1}\}^{1/2} \]

(11)

where \( c_{a/2} \) is such that \( P(x > c_{a/2}) = \alpha/2 \) and \( \bar{h}_v \) is an estimate of 2\( \pi \) times the spectral density function of \( v_t = (1 - \alpha I)u_t \) at frequency zero (see Perron and Yabu, 2009b for details). We define \( X^T\widehat{CC}X_2^{-1} \) where \( x_1^{FC} = [1 - \tilde{\alpha}_{MS}, t - \tilde{\alpha}_{MS}(t - 1)] \) for \( t = 2, 3, \ldots, T \) and \( x_1^{FC} = (1, 1)' \). From the estimate \( \hat{\beta}_0 \), we can obtain the corresponding t-statistic due to the PY test as \( t_{PY} \) (see PY for details).

Harvey et al. (2007), HLT hereafter, propose the estimate of the trend \( \hat{\beta}_0 \) with the associated 100(1 - \( \alpha \))% confidence interval for \( \beta_0 \) valid for both I(1) and I(0) errors to be:

\[ \hat{\beta}_0 \pm c_{a/2}2(\bar{\omega}_0)(1 - \varphi(U, S))\bar{\omega} + \varphi(U, S)\bar{\omega} \]

(12)

where \( \bar{\omega} \) and \( \bar{\omega} \) are the long run variance estimators using the level regression of the trend function in (7) and its differenced form respectively employing the quadratic spectral kernel of Newey and West (1994) automatic bandwidth selection, adopting a non-stochastic bandwidth of \( [4(T/100)^{2/5}] \). The weight function \( \varphi(U, S) = \exp(-0.00025(U/S)^2) \), where \( U \) is the local GLS detrended t-statistic for the unit root null due to Elliott et al. (1996) and \( S \) is the standard KPSS test statistic due to Kwiatkowski et al. (1992) for the stationarity null; and \( c_{a/2} \) is such that \( P(x > c_{a/2}) = \alpha/2 \) for \( x \) following a standard normal distribution.

Since natural resource prices are known to be volatile, to establish the presence of non-stationary volatility we follow the procedure by Cavaliere and Taylor (2007). They construct a variance profile \( \hat{\sigma}_n \), which is determined by:

\[ \hat{\sigma}_n = \left[ \sum_{t=1}^{[sT]} \hat{\nu}_t^2 + (sT - [sT])\hat{\nu}_{[sT]+1}^2 \right] / \sum_{t=1}^{T} \hat{\nu}_t^2 \]  

(13)

where \( \hat{\nu}_t \) is the estimated residual of the error term of the trend function given by Eq. (7) on its own lag. The variance profile measures unconditional volatility often referred to as nonstationary volatility. The method produces a graph to determine whether the variance is constant or not. This measure is of significance to this study, as prices show relative tranquillity up to the 1970s after which volatility increased (Slade, 1991).

We build on the estimation of trends by applying the novel procedure of Yang and Wang (2017) which modifies the PY test to allow for nonstationary volatility. Yang and Wang (2017) show that when \( u_t \) is I(0), then \( t_{PY} \) converges weakly to the asymptotic null distribution. They emphasise the need to modify \( t_{PY} \) when \( |\tilde{\alpha}_M| < 1 \) and therefore propose a new modified statistic where they show (following Xu, 2012), that it can be a consistent estimator. Based on this consistent property, Yang and Wang (2017) demonstrate that the modified t-statistic, denoted \( t_{MY} \), can be employed irrespective of whether \( u_t \) is I(1) or I(0).

The modified test statistics by Yang and Wang (2017) has also been extended to the HLT test for estimating trends. For example if \( u_t \) in (7) is known to be I(0), then the conventional t-statistic for the trend estimate is given by: \( z_0 = (\hat{\beta} - \beta_0)/\hat{\sigma}_n \); and if \( u_t \) is known to be I(1), then we estimate \( \Delta \beta = \hat{\beta} + v_t \) from (7) and the conventional t-statistic for the trend estimate is given by: \( z_0 = (\hat{\beta} - \beta_0)/\tilde{\sigma}_n \). HLT show that when \( u_t \) is unknown, the robust t-statistic is given by \( z_0 = \tilde{\sigma}_n (1 - \delta)z_0 \) where \( \delta \) is a data dependent weight and meets certain assumptions (see HLT for details). Yang and Wang (2017) show that if \( u_t \) is known to be I(0), then following Xu (2012), they can modify the test statistic (see Yang and Wang, 2017 for details). The modified test statistic of the linear trend estimate is given by: \( z_n = \tilde{\sigma}_n^2 (1 - \delta)z_0 \). Yang and Wang (2017) show that the modified statistic \( z_n \) has a standard normal distribution under time varying variance. Therefore, when estimating the trend of the variable in question, one can be agnostic about the order of integration of the data once the weight \( \delta \) is established.

We employ the test proposed by Smeekes and Taylor (2012), which is a bootstrap union test for unit roots in the presence of non-stationary volatility. The test builds on the procedure by Cavaliere and Taylor (2008) who show that not only the standard ADF tests are asymptotically not correctly sized in the presence of non-stationary volatility, but also the presence or absence of a linear trend in the data series can be problematic. Harvey et al. (2009) construct a union of rejections of unit root tests with and without a deterministic linear trend and show that this union test can maintain high power and size irrespective of the true value of the trend, and then Harvey et al. (2012) extend the procedure by considering the impact of both trend and the uncertainty of initial condition simultaneously. To this end, Smeekes and Taylor (2012) extend the work of Harvey et al. (2012) by dealing with the possible presence of nonstationary volatility. This is done by considering union tests that are robust to nonstationary volatility, trend uncertainty, and uncertainty about the initial condition. In this test, the wild bootstrap shows robustness to nonstationary volatility. They consider two bootstrap union tests, ‘unit root A type’ test, denoted \( UR_{AA} \) and ‘unit
root B type test, denoted $UR_{4d}$; the former test, that is $UR_{4d}$ does not include a deterministic trend in the test, while the latter, that is, $UR_{4d}$ does include a trend in the bootstrap data generating process.

A limitation of the Smeekes and Taylor (2012) approach is that the trend is specified to be linear or a constant. This assumption can be restrictive and it is quite possible that the underlying trend can be more complex and better approximated by a structural break. Taking this into consideration, in the final stage of the analysis, we test for unit roots in the presence of a possible break in trend and at the same time allowing for nonstationary volatility. To this end, we make use of the procedure developed by Cavaliere et al. (2011). To conduct the procedure we modify Eq. (7) and allow for a structural break with some further conditions as follows:

$$p_t = \mu_0 + \rho_0 t + \xi_0 DT(\tau_0) + u_t, \quad t = 1, 2, ..., T.$$  

$$u_t = \psi_1 u_{t-1} + \xi_t, \quad t = 2, 3, ..., T.$$  

where $\xi_t = C(L)\xi_t$, and $\psi_0 = \varphi \xi_t$ and the assumptions are the initial condition in (15) satisfies $T^{-1/2}n_t \rightarrow 0$; the lag polynomial satisfies $C(z)z \neq 0$, $\forall z \leq 1$ and $\sum_{j=0}^{\infty} j c_j < \infty$; $z_t \sim IID(0, 1)$; $E|z_t|^r < K < \infty$ for some $r \geq 4$; $\varphi = \omega(t/T)$ where $\omega$ is non-stochastic and strictly positive. The trend break in (14) is given by $DT(\tau_0) = 1(1 < [\tau_0 T]/(T - [\tau_0 T]))$, so that the potential trend break is given by $[\tau_0 T]$ with associated unknown break fraction $\tau_0$ and the fixed trend break magnitude $\xi_0$. We assume $\tau_0 \in \Lambda = [\tau_l, \tau_r]$ where $\tau_l$ and $\tau_r$ are the trimming parameters such that $0 < \tau_l < \tau_r < 1$ and so that no breaks are permissible outside this interval $\Lambda$. Following Cavaliere et al. (2011) a wild bootstrap based implementation of M-type unit root tests is carried out which are robust to a class of nonstationary volatility processes. Cavaliere et al. (2011) construct a test of stationarity using $MZa, MZb, \text{and } MZr$, to test for the presence of a unit root in the presence of a break in trend and nonstationary volatility, which we employ in this study.

5. Data and empirical results

The data used in this study has been compiled by David Jacks,\(^6\) constructed from spot prices for commodities with at least 5 billion dollars of production in 2011. The price data is measured at an annual frequency and comprises of 12 metals, out of which 9 of them are base metals (being aluminium, chromium, copper, lead, manganese, nickel, steel, tin, zinc), and 3 are precious metals (being gold, silver, and platinum). The price data is constructed using the annual Sauerbeck/Statist (SS) series and the annual Grilli and Yang (GY) series. The annual unit values of mineral production provided by the United States Geological Survey (USGS) date from 1900. The time span is 1900–2017 covering 118 observations. The price data is expressed in US dollars and deflated by the US Consumer Price Index. The subsequent analysis of the data is carried out in logarithms. The issue of variability in the data is central to this study, and Stuermer (2018) notes that large swings in commodity prices can occur at low frequency. Positive demand shocks can cause an increase in metal prices, thereby prompting an investment into exploration of new deposits and technical change (Jacks and Stuermer, 2020), which can take many years, or even decades (Radetski and Wärell, 2016), thereby justifying the use of low frequency data over a long period.\(^7\) A plot of the different metal prices are shown in Fig. 1 below.

Some features of the data are noticeable such as the heterogeneity of the data for different metals. There is no apparent commonality between precious metals or base metals. The variability can be noticed in the metal prices where large swings are present in the data. Large sharp upward spikes seem to be more prevalent than downward spikes and no obvious secular trend seems to be noticed from the plots. Some basic statistics for the data series employed in this study are shown in Table 1.

Not surprisingly, there is a high degree of autocorrelation in all the metal prices, a common feature of commodity prices in general (see Deaton and LaRouque, 1992). There is considerable variability in the data as shown by the coefficient of variation, which can be noticed in the coefficient of variation shown in Fig. 1. Most of the prices show positive skewness, which is a sign that positive spikes tend to be in number and pronounced than negative spikes; this can be expected given that metal prices tend to spike when reserves are low or when mining taking place in difficult areas to reach. We also find significant kurtosis in most metals, a sign that the price data contains extreme values. These features of the data are compatible with the plots of data shown in Fig. 1.

At this stage, we proceed to examine the presence of unconditional volatility in the data. We start by estimating the variance profile of the commodity prices. The procedure due to Cavaliere and Taylor (2007) provides a graphical approach to establish whether there exists time varying variance in the data series. The variance profile for selected metal prices are shown in Fig. 2 below:

The dashed diagonal line in each of the graphs of metal prices represents a constant variance process. The solid line moving around the dashed line is the variance profile of the data. If the metal prices straddle around the dashed line very closely, that

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6 Special thanks to David Jacks (see website, http://www.sfu.ca/~djacks/data/index.html) for making the data available.

7 With high frequency data it is possible to address information flows and speculative activity (Brunetti and Gilbert, 1995). The use of high frequency data can be useful towards the possible predictability of metal returns, especially during downward trends and crisis periods. This would be useful from the investors’ viewpoint, to better understand and optimise their investment decisions. We thank an anonymous referee for raising this point. However, for reasons provided, the focus in this paper is on low frequency and long period time series data. Chen (2010) notes that metal prices remain highly volatile using annual data where much of the within year variability is smoothed out. Using higher frequency data is beyond the scope of this study, but there is a scope to do this in future work. We leave this as an area for future research.
Fig. 1. Time series plot of commodity price indices. Note: The commodity prices are indices expressed in US dollars and deflated by the US CPI (shown on the vertical axis). The data is in annual frequency covering the period 1900–2017 (shown on the horizontal axis).
would be an indication of prices being close to constant variance. However, for all the metal prices considered, we find evidence of persistent deviation from this dashed line which signals time varying variance; albeit, the deviation from the dashed line can vary for the different metals. This is particularly true for gold, silver, nickel and manganese.

We now proceed to estimate the underlying time trend of the metal prices. To highlight the importance of variability in metal prices (as shown by the variance profile), we estimate the time trend using robust methods allowing for time varying variance using the modified statistic, and then compare the results with robust trend estimation that does not allow for time varying variance. In both cases however, the trend estimates are robust to the underlying order of integration of the data. The results are reported in Table 2 below:

Table 2
Descriptive statistics.

<table>
<thead>
<tr>
<th></th>
<th>AR (1)</th>
<th>AR (2)</th>
<th>CV.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminium</td>
<td>0.90</td>
<td>0.78</td>
<td>0.87</td>
<td>1.97***</td>
<td>6.36***</td>
</tr>
<tr>
<td>Copper</td>
<td>0.84</td>
<td>0.66</td>
<td>0.40</td>
<td>0.87***</td>
<td>3.55</td>
</tr>
<tr>
<td>Chromium</td>
<td>0.84</td>
<td>0.76</td>
<td>0.53</td>
<td>1.19***</td>
<td>4.53***</td>
</tr>
<tr>
<td>Manganese</td>
<td>0.74</td>
<td>0.60</td>
<td>0.40</td>
<td>1.87***</td>
<td>9.70***</td>
</tr>
<tr>
<td>Nickel</td>
<td>0.79</td>
<td>0.56</td>
<td>0.41</td>
<td>1.42**</td>
<td>5.38**</td>
</tr>
<tr>
<td>Steel</td>
<td>0.81</td>
<td>0.64</td>
<td>0.24</td>
<td>0.31</td>
<td>2.70</td>
</tr>
<tr>
<td>Tin</td>
<td>0.89</td>
<td>0.77</td>
<td>0.44</td>
<td>1.44***</td>
<td>5.98***</td>
</tr>
<tr>
<td>Zinc</td>
<td>0.67</td>
<td>0.34</td>
<td>0.41</td>
<td>2.39***</td>
<td>11.42***</td>
</tr>
<tr>
<td>Gold</td>
<td>0.91</td>
<td>0.78</td>
<td>0.57</td>
<td>1.67***</td>
<td>5.61***</td>
</tr>
<tr>
<td>Platinum</td>
<td>0.88</td>
<td>0.75</td>
<td>0.38</td>
<td>1.08***</td>
<td>3.28</td>
</tr>
<tr>
<td>Silver</td>
<td>0.73</td>
<td>0.54</td>
<td>0.67</td>
<td>3.65***</td>
<td>22.51***</td>
</tr>
</tbody>
</table>

Note: AR(p) denotes autoregressive process of order p where p is set equal to 1 and 2, respectively. CV is the coefficient of variation measure by the ratio of the standard deviation to the mean. *** denotes rejection of the null hypothesis at the 1 per cent significance level.

The two bootstrapped union tests, the $UR_{48}$ and $UR_{49}$ deliver the same results. The unit root null is rejected in the cases of chromium, lead, manganese, nickel, steel, tin, zinc and silver. This implies that these metal prices do not contain stochastic trends. Therefore, if these prices deviate from their mean or trend, which is assumed to have no break, then such deviations will correct over time. The metal prices that do not reject the null of a unit root imply that they contain stochastic trends, and any shocks to these prices are not going to dissipate, or in other words would be permanent in nature, or more likely to be long-lived.

A limitation of the above analysis is that the trend is assumed to be linear or constant. Indeed, more complex trend functions can exist such as the possibility of a broken trend. We therefore consider the possibility of a trend break in prices when testing for unit root in the presence of nonstationary volatility. Accordingly, we conduct the unit root test, due to Cavaliere et al. (2011) that allows for non-stationary volatility as well as a possible trend break. The results are shown in Table 3 below:
The unit root tests statistics along with the bootstrapped critical values at conventional levels of significance are reported. We can conclude that if at least one of the computed t-statistic for each of the unit root tests $M_{Za}, M_{Zt}$ and $M_{SB}$ are less than the bootstrapped critical values then the unit root null can be rejected. Thus, we can conclude that in 8 out of the 12 metal prices,

Fig. 2. Variance profile of metal prices
Source: Authors calculations based on the 'variance profile' procedure by Cavaliere and Taylor (2007). The calculations are based on Eq. (13), on page 13 under Section 4.
the unit root null is rejected at conventional levels of significance. These include aluminium, chromium, lead, manganese, nickel, steel, tin and zinc. When compared to the test results using the Smeekes and Taylor (2012) procedure, we find that the results are consistent except for 2 metal prices – aluminium and silver. While the unit root null is not rejected in the case of silver using the Cavaliere et al. (2011) procedure, we do find rejection of the null using the procedure of Smeekes and Taylor
Apart from these two anomalies the two unit root tests are robust to nonstationary volatility do corroborate the results. We can therefore conclude that metal prices in general do not contain stochastic trends and therefore any shocks are unlikely to be permanent. Overall, summing up the results (2012). In the case of aluminium, we have a different anomaly; the unit root null is rejected using the Cavaliere et al. (2011) procedure but is not rejected using the test of Smeekes and Taylor (2012). Apart from these two anomalies the two unit root tests that are robust to nonstationary volatility do corroborate the results. We can therefore conclude that metal prices in general do not contain stochastic trends and therefore any shocks are unlikely to be permanent. Overall, summing up the results.

### Table 2
Robust linear trend estimation results.

| Metal   | $\delta$ | $z_{\delta}$ | $z^m_{\delta}$ | $|A_M|$ | $t_{PY}$ | $t^m_{PY}$ |
|---------|----------|--------------|---------------|--------|---------|-----------|
| Aluminium | 0.031    | -3.351a      | -3.750a       | 0.758  | -14.906a | -10.536a  |
| Chromium | 0.000    | 0.366        | 0.366         | 0.834  | 1.709   | 1.72      |
| Copper   | 0.000    | -0.326       | -0.326        | 0.849  | -2.593a | -1.626    |
| Lead     | 0.163    | -0.497       | -1.016        | 0.876  | -1.986b | -1.262    |
| Manganese | 0.148   | 0.497        | 0.853         | 0.795  | 1.654a  | 1.064     |
| Nickel   | 0.000    | -0.662       | -0.662        | 0.836  | -3.567a | -2.213b   |
| Steel    | 0.231    | 0.160        | 0.452         | 0.832  | -0.197  | -0.118    |
| Tin      | 0.177    | 0.013        | -0.046        | 0.874  | -0.124  | -0.076    |
| Zinc     | 0.542    | -0.762       | -1.428        | 0.742  | -1.223  | -0.890    |
| Gold     | 0.000    | 0.350        | 0.350         | 0.890  | 1.617   | 1.053     |
| Platinum | 0.012    | 0.304        | 0.311         | 0.880  | 1.742c  | 1.089     |
| Silver   | 0.000    | -0.067       | -0.067        | 0.877  | -0.806  | -0.572    |

Note: The superscripts $a$, $b$, and $c$ denote rejection of the null at the 1%, 5% and 10% significance levels respectively. The symbols $\delta$ and $|A_M|$ denote the data dependent weight and super-efficient estimate as described in Section 4. The statistics $z_{\delta}$ and $z^m_{\delta}$ are the robust and modified robust t-statistics respectively, due to HLT. The statistics $t_{PY}$ and $t^m_{PY}$ are the robust and modified robust t-statistics respectively, due to PY, as described in Section 4.

### Table 3
Unit root tests robust to nonstationary volatility.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>UR4A Statistic</th>
<th>UR4B Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminium</td>
<td>-1.85</td>
<td>-1.96 [0.146]</td>
</tr>
<tr>
<td>Chromium</td>
<td>-2.09</td>
<td>-1.94 [0.054][a]</td>
</tr>
<tr>
<td>Copper</td>
<td>-1.90</td>
<td>-2.03 [0.146]</td>
</tr>
<tr>
<td>Lead</td>
<td>-2.01 [0.063][b]</td>
<td>-1.98 [0.061][c]</td>
</tr>
<tr>
<td>Manganese</td>
<td>-2.45</td>
<td>-2.13 [0.039][b]</td>
</tr>
<tr>
<td>Nickel</td>
<td>-2.21</td>
<td>-2.08 [0.069][b]</td>
</tr>
<tr>
<td>Steel</td>
<td>-2.28</td>
<td>-1.96 [0.036][b]</td>
</tr>
<tr>
<td>Tin</td>
<td>-2.53</td>
<td>-2.00 [0.011][b]</td>
</tr>
<tr>
<td>Zinc</td>
<td>-3.15</td>
<td>-1.96 [0.001][b]</td>
</tr>
<tr>
<td>Gold</td>
<td>-1.62</td>
<td>-2.00 [0.296]</td>
</tr>
<tr>
<td>Platinum</td>
<td>-1.95</td>
<td>-1.98 [0.0114]</td>
</tr>
<tr>
<td>Silver</td>
<td>-2.02</td>
<td>-1.96 [0.083][b]</td>
</tr>
</tbody>
</table>

Note: The superscripts $a$, $b$, and $c$ denote rejection of the null hypothesis of a unit root at the 1%, 5% and 10% significance levels respectively. Numbers in square brackets indicate p-values. ‘Unit root type A’, denoted UR4A and ‘unit root type B’ test, denoted UR4B are the two bootstrap union tests, as described in Section 4.

### Table 4
Unit root tests robust to nonstationary volatility and a trend break.

<table>
<thead>
<tr>
<th>Metal</th>
<th>M2a Bootstrapped Critical Value</th>
<th>MSB Bootstrapped Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1%</td>
<td>5%</td>
</tr>
<tr>
<td>Aluminium</td>
<td>-24.08$^a$</td>
<td>-38.42</td>
</tr>
<tr>
<td>Chromium</td>
<td>-28.33$^c$</td>
<td>-31.28</td>
</tr>
<tr>
<td>Copper</td>
<td>-10.73</td>
<td>-24.04</td>
</tr>
<tr>
<td>Lead</td>
<td>-14.42</td>
<td>-25.69</td>
</tr>
<tr>
<td>Manganese</td>
<td>-31.24$^{a.c}$</td>
<td>-33.59</td>
</tr>
<tr>
<td>Nickel</td>
<td>-19.12</td>
<td>-31.60</td>
</tr>
<tr>
<td>Steel</td>
<td>-14.75</td>
<td>-27.44</td>
</tr>
<tr>
<td>Tin</td>
<td>-13.47</td>
<td>-23.78</td>
</tr>
<tr>
<td>Zinc</td>
<td>-26.78$^{a.c}$</td>
<td>-23.18</td>
</tr>
<tr>
<td>Gold</td>
<td>-8.05</td>
<td>-27.95</td>
</tr>
<tr>
<td>Platinum</td>
<td>-11.46</td>
<td>-22.44</td>
</tr>
<tr>
<td>Silver</td>
<td>-16.10</td>
<td>-30.51</td>
</tr>
</tbody>
</table>

Note: The superscripts $a$, $b$, and $c$ denote rejection of the null hypothesis of a unit root at the 1%, 5% and 10% significance levels respectively. M2a, MSB, and M2t are the unit root test statistics.
from Tables 3 and 4, we can conclude that in general, there is little evidence that external shocks have a permanent effect on metal prices.

6. Conclusion

The issue of whether trends in metal prices are significant or not; and if they are, whether they are increasing or decreasing has been a subject of much debate. As outlined earlier, the conjectures based on the model by Tilton (2006) make it difficult to discern the underlying trends as the slope of metal prices depends on several factors. These include shifts in demand from metal consuming countries as well as the amount of reserves that are discovered, or technical progress that makes extractions possible from hard to reach areas (Cuddington and Nüllle, 2014). Based on the unpredictable shifts in demand, extraction costs, discovery of reserves, it is possible to expect that prices may be subject to upward and downward swings. An upward swing preceded by a downward swing could be mistakenly thought of as a break in trend, or over a long period of time the swings could be simply movements around some underlying long run trend that could be positive or negative. Structural breaks, while they are important, are limited to only two breaks in a data set that consists of annual data spanning a century. This makes it not only restrictive but also unrealistic that major events over a century have only manifested in at most two structural changes to the data. Besides, as alluded to earlier, while structural break tests that are robust to the order of integration in the data are available, they are not robust to nonstationary volatility. To our knowledge, no such robust procedures for structural breaks exist and therefore remains as a subject for further research.

Accordingly, the contentious issue of whether a significant trend exists in the metal price series, is examined using novel econometric methods that account for volatility. Conducting variance profile tests, we find evidence of different degrees of time varying variance. Our results of robust trend estimation that allow for nonstationary volatility show that there is limited evidence of any significant trend, and we can further establish that if time varying variance is ignored, the results would be mixed leading to a different overall conclusion. Further tests are carried out to check whether metal prices are mean or trend reverting, again accounting for nonstationary volatility with and without the possibility of a trend break. We conclude that for 9 out of the 12 metals considered in this study, the prices are stationary. This implies that most metal prices do not contain stochastic trends and any exogenous shocks to these prices are unlikely to be permanent in nature.

Our study makes a contribution by lending support to some key studies, but at the same time departing from some others. With regards to trend estimation, our results are in contrast to that of Jacks (2019) where he finds that metals prices (including other primary commodities) are on a modest rise since the 1900s. We find most of the metals prices to have no trend, and in the case of aluminium and nickel we actually find a significant negative trend. Erten and Ocampo (2013) use a sub-index of metal prices and find a downward trend from the late nineteenth century to the mid-1970s after which the trend is upward, which seems to suggest that the trend is broken. We emphasise on the presence of volatility that lead most prices to contain no significant trend, and given the difference in underlying trends in individual metal prices our results suggest that it would be better to examine the properties of individual metal prices rather than using a sub-index for metals. More importantly, a shortcoming with these studies is the assumption of the price data being non-stationary I(1) in levels, which is not necessarily the case as we find in the union based unit root tests in our study. Our results contrast with that of Chen (2010), except for aluminium. This is not surprising as our results are based on robust estimation procedures whereas in Chen (2010) the trends are estimated by simple mean changes without taking into account the underlying nature of persistence in the data. Arezki et al. (2014) adopt a different method based on panel methods and the results of their study partly match with ours. Our results lend support to a host of popular studies (e.g., Cuddington, 1992, Berck and Roberts, 1996, Harvey et al., 2010, Ghoshray et al., 2014, Sun and Shi, 2015, Winkelried, 2018). For example, our results are in line with that of Harvey et al. (2010), Ghoshray et al. (2014) and Sun and Shi (2015), where robust tests for structural breaks and trend estimation are employed; as well as lending support to Winkelried (2018) where the prevalent trend is estimated by fitting a flexible trend to the data. However, our key contribution is that we address the issue of volatility that has been acknowledged in recent studies, (e.g., Kellard and Wohar, 2006; Harvey et al., 2010; Arezki et al., 2014; Winkelried, 2018) but not dealt with. With regards to unit root tests, our results are broadly in favour of prices being stationary which supports the argument by Deaton (1999), and lends empirical support to studies by Winkelried (2018), Sun and Shi (2015), Ghoshray et al. (2014), Kellard and Wohar (2006).

The absence of unit roots in most metal prices can lead one to concur that concerns about the uncertainty of price stability may be ameliorated. For example, at a micro level it is difficult for producers to decide the quantity of metals to be extracted, and for consumers to determine their usage. If prices are expected to mean revert with time, then producers and consumers can expect prices to return from unusually high peaks or low troughs. At a macro level exporters may not find it hard to determine their usage. If prices are expected to mean revert with time, then producers and consumers can expect prices to return from unusually high peaks or low troughs. However, a slowdown of China, led to metal prices recording decreases (Ghoshray and Pundit, 2021). Gold and platinum are precious metals and have been found to contain stochastic trends, implying that shocks to these metals are likely to be long-lived. A possible departure of these precious metals from other base metal (with the exception of copper), might be due to the possibility that these metals have been found to lack the link with stock markets, where there may be predictability.
In recent years, the threat of climate change has turned our attention to renewable technologies and to reduce our dependence on fossil fuels. This has led to an interest in metals that have properties to produce solar panels, batteries and wind turbines. For example, silver is used for photovoltaics, platinum for fuel cells and catalytic converters, copper and nickel for electric vehicles and fuel cells. In order to adopt low carbon technologies, the strategic and economic importance of these metals have increased in the face of a risk of supply shortage as the demand for metals increases (Sovacool et al., 2020) and the accompanying price volatility is likely to make the risk greater. While substitution in metals can play a role in tackling scarcity, such as aluminum replacing copper in wire harnesses in the automotive industry, the substitute metal, which can initially be abundant, may turn out to be challenging to extract over time (Sovacool et al., 2020).

To conclude, the last century has been influenced by policies that have been interventionist especially after the Great Depression in the 1930s when prices of most metals collapsed. Between 1945 and 1965, commodity agreements were in place to stabilise prices, to counter the effects of the Second World War and the Korean War. While attempts were made to create price bands using buffer stocks, these policies have failed and since the 1980s, state intervention has been replaced by the free market forces. However, China’s huge appetite for commodities can create an influence on commodity prices. For example, when supply is increased through more extraction and discoveries to meet increasing demand, a slowdown in China can cause a slack in demand and while lagged effects cause supplies to increase, a downward pressure on prices occurs. The low elasticity of demand causes prices to fluctuate and we can infer that any underlying trend in metal prices may be overshadowed by this variability. Policy makers and extractive industries would need to exercise caution when formulating decisions when faced with a surging and persistent increase in demand for metals.

Conflict of interest

We can confirm there are no financial and personal relationships with other people or organisations that could inappropriately influence this work.

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