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Discerning trends in international metal prices in the presence of non-stationary volatility

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Abstract: Modelling the underlying long-run trend of metal prices is important, given that selected metals are a source of income for many countries. However, estimating the underlying trend has proven to be difficult, given the persistence and volatility of primary commodity prices—metals are no exception. Recent events have led experts to believe that trends have been undergoing large swings; whether these movements are temporary or contribute to the trend being characterized by broken piecewise trends over certain lengths of time remains a contentious issue. We combine robust econometric procedures to calculate the trend, which could be secular or broken, for selected metal prices over a century. We find support for the conjecture that, based on the unpredictable shifts in demand, extraction costs, and discovery of reserves, it is highly possible to expect that prices may be subject to large variability that overshadows any underlying trend.

Key words: trends, metal prices, volatility, persistence

JEL classification: C22, Q02, Q32

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1 Introduction

Metals are a crucial input for industrial production and are therefore important for both producing and consuming countries. In the case of many metal-exporting countries, the revenue from metal exports is often their main source of income. Likewise, for many metal-importing countries, the imports are crucial for industrialization and infrastructure development. In this paper, we analyse the long-run trend in metal prices and persistence to shocks in metal prices over a century's worth of data. This paper aims to answer two key questions. First, do we find evidence that metal prices are increasing or decreasing prices in the long run? We find support for neither case—or, in other words, we find no significant trend in metal prices. Second, are shocks to metal prices short-lived? We find that for most metal prices, the effect of any exogenous shocks is short-lived in nature.

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 will continue as long as there is capacity and the price of metals exceeds variable costs. If there is 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; at full capacity, the supply curve is vertical. At these points in time, if there is an increase in demand, the price increase will be quite high. Alternatively, there can be shifts in supply. A leftward shift in the short-run supply curve can arise due to strikes, and a rightward shift in the supply curve can result from 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 how an important feature of prices is that they exhibit rapid and often large movements. The short-run variability can be caused by the low price elasticity of demand for metals. The price elasticity of supply can be a contributing factor when capacity is almost fully utilized. Such variability in metal prices in the short run can be extremely difficult 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 over time. Similarly, an increase in extraction costs would lead to an increase in prices over time. 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 over time. However, these changes in reserves, 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. Extractive resource prices are known to be highly volatile, given the low price elasticity of demand and supply, making the estimation of the underlying trend notoriously difficult. However, as we can see, the importance of robust estimation of the underlying trend cannot be over-emphasized.

A complicating factor that clouds the interaction of demand and supply curves is that the dynamic price adjustment is nebulous. 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 it again when the price returns to its equilibrium level. In other words, it would be economical to

suffer a temporary loss, as prices would not cover variable costs (Radetski 2008). In this light, it would be imperative for policy makers and investors to know if price shocks are indeed temporary in nature.

This paper makes a robust estimation of the long-run trend of metal prices using novel econometric techniques that allow us to be agnostic to certain characteristics that are likely to exist in metal prices, the underlying nature of persistence of prices, and non-stationary volatility. We find no significant trends in metal prices, lending support to the popular quip by Deaton (1999: 27): 'What commodity prices lack in trend, they make up for in variance'. We also find that exogenous shocks to metals prices are mostly short-lived in nature. This paper is organized as follows: Section 2 gives a description of relevant recent studies; Section 3 briefly summarizes some conjecture about how metal prices may evolve over time; Section 4 provides the econometric framework; Section 5 describes the data and empirical results; and, finally, Section 6 concludes.

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 is 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'. More recently, using the well-known Lewis Model, 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 grows, 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) tends to suggest that the observed patterns of oil production and prices are not compatible with Hotelling's (1931) theory. 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 into research and development for extraction of resources and discovery of new deposits more profitable, 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 has examined the trend in commodity prices, including metal prices. The very early studies 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. A further test is applied using log-likelihood ratio to account for an abrupt change in the trend. The results from this study show that there is no significant 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

extensively used in empirical studies. They conduct a regression using OLS on the index and use a maximum likelihood test to correct for serial correlation. 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.

Perron (1988) 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). Taking note of this, Cuddington (1992) emphasizes the need, if the price data contains a unit root, to model prices as difference stationary if the shocks to the error terms are permanent. Otherwise, if no unit root is present, the price series can be modelled as trend stationary. Berck and Roberts (1996) argue that natural resource prices including metals should be difference stationary. The basis of their argument is 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; 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 in a price series, 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 leads to breaking trend estimation instead of estimating secular trends. Popular studies include that of León and Soto (1997), in which they find no trend in metal prices. They employ the single-break unit root test due to Zivot and Andrews (1992). The procedure tests for a unit root null against the alternative of a trend break. Kellard and Wohar (2006) apply the procedure of Lumsdaine and Papell (1997) by allowing for two structural breaks in the alternative hypothesis and conclude the evidence of a significant trend is mixed for metal prices. However, a problem with these studies is the asymmetric treatment of the breaks, in that the breaks are constrained to appear in the alternative hypothesis of these unit root tests. Ghoshray (2011) applies the more suitable unit root tests due to Lee and Strazicich (2003), which allow for breaks in both the null and the alternative hypotheses, obviating the problem of asymmetric treatment of breaks, and find no significant trend in metal prices. Arezki et al. (2014) show that most prices contain negative trends. Their analysis departs from previous studies in that they consider a panel data approach rather than the more extant univariate time series approach. Using low-frequency band-pass filters, Cuddington and Nülle (2014) make a case for analysing variable trends rather than constant long-run trends in real mineral prices. They find aluminium to exhibit a negative trend, nickel to exhibit a U-shaped path, and tin and zinc to show more than one turning point, causing the trends to evolve in a cyclical fashion. However, as acknowledged by Cuddington and Nülle (2014), the analysis is 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, but nonetheless, an overall declining trend can be found for most metal prices.

A problem with these extant studies is the circular problem of testing for trends. On one hand, we have no prior information regarding the presence and number of trend breaks before testing for

unit roots. Therefore, if no structural breaks are present in the data, by applying unit root tests with breaks, we are lowering the power of the test. On the other hand, before testing whether a time series process can be characterized by a broken trend, we have no prior information on persistence in the errors. Indeed, inference based on a structural change test on the level of the data depends on whether a unit root is present, while tests based on differenced data can have very poor properties when the series contains a stationary component (Vogelsang 1998). However, recent procedures allow one to be agnostic to the underlying order of integration of the data when testing for structural breaks and estimating trends. To this end, Harvey et al. (2010) provide limited evidence of trends in metal prices; Ghoshray et al. (2014) find no trend; and Sun and Shi (2015) also conclude no trend for various metal prices.

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 test the hypothesis: do discernible trends exist in metal prices in the presence of non-stationary volatility? Demand-driven episodes (e.g., mass industrialization, urbanization) 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 hypothesis: are shocks to metal prices transitory or permanent? Before we use robust procedures to test these two hypotheses, we provide a brief description of 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 Conjectures about metal prices

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

$$q^d(t) = y/p^\alpha(t) \qquad \alpha < 1 \tag{1}$$

where α 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 $q^s(t)$) 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:

$$q^s(t) = R_0\left(1 - e^{\lambda p(t)}\right) \tag{2}$$

Assuming markets clear, we set $q^d(t) = q^s(t)$ and obtain:

$$p(t)^\alpha\left(1 - e^{\lambda p}\right) = y/R_0 \tag{3}$$

While the supply curve can adjust to the right due to technological progress, investing in research and development, or making new discoveries, these tend to happen when there is sufficient time to increase capacity. For example, when existing capacity is fully utilized, 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 given by Equation (2) will tend to be

relatively flat as more metals can be extracted at higher costs (Radetski and Wårell 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. Therefore, in the medium to long term, one can expect incomes to change, leading to an increase in demand; 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:

$$p(t)^{\alpha}\left(1 - e^{\lambda p(t)}\right) = y(t)/R_0(t) \tag{4}$$

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 this 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 Equation (4) with respect to time t and obtain the following:

$$\alpha p^{\alpha-1}\frac{dp}{dt}\left(1 - e^{-\lambda p}\right) + p^{\alpha}\left(-e^{-\lambda p}\right)(-\lambda)\frac{dp}{dt} = \frac{1}{R_0^2}\left(R_0\frac{dy}{dt} - y\frac{dR_0}{dt}\right) \tag{5}$$

This can be simplified to:

$$\frac{dp}{dt}\left[\alpha\frac{p^{\alpha}}{p}\left(1 - \frac{1}{e^{\lambda p}}\right) + \lambda p^{\alpha}\frac{1}{e^{\lambda p}}\right] = \frac{y}{R_0}\left[\frac{1}{y}\frac{dy}{dt} - \frac{1}{R_0}\frac{dR_0}{dt}\right] \tag{6}$$

The term $\left[\alpha\frac{p^{\alpha}}{p}\left(1 - \frac{1}{e^{\lambda p}}\right) + \lambda p^{\alpha}\frac{1}{e^{\lambda p}}\right]$ on the right-hand side of the equation is positive; therefore, the sign of the term $\left[\frac{1}{y}\frac{dy}{dt} - \frac{1}{R_0}\frac{dR_0}{dt}\right]$ on the left-hand side of the equation will determine the change in price over time. For example, if the rate of growth of demand $\frac{1}{y}\frac{dy}{dt}$ exceeds the rate of growth of reserves $\frac{1}{R_0}\frac{dR_0}{dt}$, then we would expect $\left[\frac{1}{y}\frac{dy}{dt} - \frac{1}{R_0}\frac{dR_0}{dt}\right] > 0$, and so prices will increase with time as this results in $\frac{dp}{dt} > 0$. However, if the rate of growth of reserves—that is, $\frac{1}{R_0}\frac{dR_0}{dt}$—exceeds the rate of growth of demand—that is, $\frac{1}{y}\frac{dy}{dt}$—then we would expect $\left[\frac{1}{y}\frac{dy}{dt} - \frac{1}{R_0}\frac{dR_0}{dt}\right] < 0$ and so prices will decrease over time, as we obtain $\frac{dp}{dt} < 0$. The low elasticity of demand ($\alpha < 1$) makes the change in price more variable, contributing to the variability of metal prices over time. The upshot is that the existence or not of an underlying long-term trend in metal prices is an empirical one. However, as described earlier, the large variability of metal prices can overshadow any trend. In the next section, we describe the robust methods used to test the two hypotheses that we set out earlier.

4 Econometric methods

In the first instance, we test for structural breaks and begin by setting up the following regression:

$$p_t = \mu_0 + \beta_0 t + \sum_{i=1}^{K}\mu_i DU_{it} + \sum_{i=1}^{K}\beta_i DT_{it} + u_t, \qquad t = 1,2,\dots,T \tag{7}$$

$$u_t = \rho u_{t-1} + \varepsilon_t, \qquad t = 2,3,\dots,T \qquad u_1 = \varepsilon_1$$

where p_t denotes metal prices, and $DU_{it} = I(t > T_i)$, $DT_{it} = (t - T_i)I(t > T_i)$, and $i = 1,2, \dots, K$ are the level and trend dummies. A break in the trend occurs at time $T_i = [T\lambda_i]$, where λ_i is the break fraction and $\beta_i \neq 0$. We test for structural breaks based on the null hypothesis $H_0: \beta_i = 0$ against the alternative hypothesis $H_1: \beta_i \neq 0$. At the onset, we do not know the location and number of structural breaks in the data. The test applied is robust in the sense that the error term (u_t) can be either $I(0)$, that is $|\rho| < 1$, or $I(1)$, that is, $\rho = 1$. To this end, we make use of the procedures of Perron and Yabu (2009a), who propose a robust method to detect a break in the trend function using feasible quasi-generalized least squares (FGLS) and a further second break using a robust sequential approach due to Kejriwal and Perron (2010).

The first step tests for a single structural break in the slope of the trend function using the procedure of Perron and Yabu (2009a), which is robust to the order of integration of the data. Rejection of the null by this robust test is evidence of a structural break in the trend, and we proceed to test for one against two slope breaks using the sequential procedure proposed by Kejriwal and Perron (2010), which is an extension of the Perron and Yabu (2009a) test. We allow for a maximum of two breaks, taking into account the number of observations (118), because it is not an appropriate strategy to include too many breaks if a unit root is present (see Ghoshray et al. (2014) for details) and we choose the maximum number of permissible breaks to be equal to two.

Perron and Yabu (2009a) recommend the following exponential Wald statistic to determine the structural break (see Perron and Yabu 2009a for details):

$$exp\, W = ln\left[T^{-1} \sum_{\lambda_1 \in \Lambda_1} exp\left(1/2 W_{QF}(\lambda_1)\right)\right] \tag{8}$$

where $W_{QF}(\lambda)$ is the Wald test for a particular break function λ_1, and the subscript QF denotes the FGLS. Perron and Yabu (2009a) find that the limit distribution in the *I*(0) and *I*(1) cases are nearly identical. In the spirit of Perron and Yabu (2009a), we apply the Kejriwal and Perron (2010) sequential procedure that allows one to obtain a consistent estimate of a second trend break irrespective of whether the errors are *I*(1) or *I*(0). The procedure involves testing each of the two segments (based on finding a single break) for the presence of an additional break and determining whether the maximum of the tests is significant (see Kejriwal and Perron 2010). Formally, the test of one versus two breaks is expressed as:

$$expW(2|1) = \max_{1 \leq i \leq 2} \{expW^{(i)}\} \tag{9}$$

where $exp\, W^{(i)}$ is the one break test in segment i.

In the second stage of the empirical analysis we conduct robust estimations of the trend. If no structural breaks are found to be present in the data, then we estimate the trend function for the entire sample. However, if breaks are found to be present in the data, we delineate the sub-samples from the break points and conduct robust trend estimation for each of the regimes demarcated by the break points. To this end, we apply an appropriate econometric method of robust trend estimation due to Perron and Yabu (2009b), hereafter referred to as the PY test, which allows one to be agnostic to the nature of persistence of errors in the trend function.

Here, we briefly describe the PY procedure to estimate the trend. First, the following autoregression on the error term in Equation (7) is estimated:

$$\hat{u}_t = \alpha \hat{u}_{t-1} + \sum_{i=1}^{k} \varphi_i \hat{u}_{t-i} + e_{tk} \tag{10}$$

The residuals $\hat{u}_t$ from Equation (10) and the super-efficient estimate $\tilde{\alpha}_{MS}$ (see Perron and Yabu (2009b) for details) are used to estimate the following quasi-differenced regression:

$$(1-\tilde{\alpha}_{MS}L)y_t = (1-\tilde{\alpha}_{MS}L)x'_t\Psi^0 + (1-\tilde{\alpha}_{MS}L)u_t, \quad t = 2,3,\dots,T$$

$$y_t = x'_1\Psi + u_1 \tag{11}$$

where $\Psi^0 = (\mu_0, \beta_0)'$. Denoting the estimate $\hat{\beta}_0$ from this regression, we construct a $100(1-\alpha)\%$ confidence interval for β_0 valid for both *I*(1) and *I*(0) errors, given as follows:

$$\hat{\beta}_0 \pm c_{\alpha/2}\sqrt{(\tilde{h}_v)\{(X^{\alpha\prime}X^{\alpha})^{-1}\}} \tag{12}$$

where $c_{\alpha/2}$ is such that $P(x > c_{\alpha/2}) = \alpha/2$ for $x \sim N(0,1)$; where $X^{\alpha} = [x_{L1,1}, (1-\tilde{\alpha}_{MS})x_{L1,2}, \dots, (1-\tilde{\alpha}_{MS})x_{L1,T}]'$, and $\tilde{h}_v$ is an estimate of 2π times the spectral density function of $v_t = (1-\alpha L)u_t$ at frequency zero (see Perron and Yabu (2009b) for details). From the estimate $\hat{\beta}_0$, the corresponding *t*-statistic due to the PY test is denoted as t_{PY}.

We expand on the estimation of trends by allowing for time-varying volatility. For this, we apply the novel procedure of Yang and Wang (2017), which modifies the PY test to allow for non-stationary volatility. Yang and Wang (2017) show that when u_t is *I*(0), then t_{PY} converges weakly to the asymptotic null distribution. They emphasize 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 (see Yang and Wang (2017) for details). Based on this consistent property, Yang and Wang (2017) demonstrate that the modified *t*-statistic, denoted t_{PY}^m, 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 Harvey et al. (2007) test, hereafter referred to as the HLT test, for estimating trends. For example, if u_t is known to be *I*(0), then the conventional *t*-statistic for the trend estimate is given by $z_0 = (\hat{\beta} - \beta_0)/s_0$; if u_t is known to be *I*(1), then we estimate $\Delta y_t = \beta + v_t$ from Equation (1) and the conventional *t*-statistic for the trend estimate is given by: $z_1 = (\tilde{\beta} - \beta_0)/s_1$. Harvey et al. (2007) show that when u_t is unknown, the robust *t*-statistic is given by $z_\delta = \delta z_0 + (1-\delta)z_1$, where δ is a data-dependent weight and meets certain assumptions (see Harvey et al. (2007) 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: $z_\delta^m = \delta z_0^m + (1-\delta)z_1$. Yang and Wang (2017) show that the modified statistic z_δ^m 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 δ is established.

In the final stage, we test for unit roots in the presence of a possible break in trend and at the same time allowing for non-stationary volatility. We make use of the procedure developed by Cavaliere et al. (2011). To conduct the procedure, we consider Equation (1) and define:

$$u_t = \rho_T u_{t-1} + \eta_t, \quad t = 2,3,\dots,T \tag{13}$$

where $\eta_t = C(L)e_t$ and $e_t = \sigma_t z_t$, and the assumptions are the initial conditions in Equation (11), which are assumed to satisfy $T^{-1/2}\varepsilon_1 \xrightarrow{p} 0$; the lag polynomial satisfies $C(z) \neq 0,\ \forall\ z \leq 1$ and

$\sum_{j=0}^{\infty} jc_j < \infty$; $z_t \sim IID(0,1)$; $E|z_t|^r < K < \infty$ for some $r \geq 4$; $\sigma_t = \omega(t/T)$ where ω is non-stochastic and strictly positive. Cavaliere et al. (2011) show that a set of *M*-statistics are constructed—MZa, MSB, and $MZt\ MZt$—to test for the presence of a unit root in the presence of a possible break in trend and non-stationary volatility.

In case there is no trend break, a further test proposed by Smeekes and Taylor (2012) is employed, 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 augmented Dickey–Fuller (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; Harvey et al. (2012) extend the procedure by considering the impact of both trend and the initial condition uncertainty simultaneously. This test therefore deals with the uncertainty about the trend and the initial condition.

Finally, Smeekes and Taylor (2012) extend the work of Harvey et al. (2012) by dealing with the possible presence of non-stationary volatility. This is done by considering union tests that are robust to non-stationary volatility, trend uncertainty, and uncertainty about the initial condition. In this test, the wild bootstrap shows robustness to non-stationary volatility. They consider two bootstrap union tests, the 'unit root A type' test, denoted UR_{4A}, and the 'unit root B type' test, denoted UR_{4B}; the former test UR_{4A} does not include a deterministic trend in the test, while the latter UR_{4B} does include a trend in the bootstrap data-generating process.

5 Data and empirical results

The data used in this study were compiled by David Jacks,[1] constructed from spot prices for commodities with at least US$5 billion of production in 2011.The price data comprises 12 metals, out of which nine are base metals (aluminium, chromium, copper, lead, manganese, nickel, steel, tin, zinc) and three are precious metals (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 GY data was updated by Pfaffenzeller et al. (2007). The annual unit values of mineral production provided by the United States Geographical Survey (USGS) date from 1900. The time span is 1900 to 2017, covering 118 observations. The price data is expressed in US dollars and deflated by the US consumer price index (CPI). The subsequent analysis of the data is carried out in logarithms.

Some basic statistics for the data series employed in this study are shown in Table A1 in the Appendix. 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 Laroque 1992). There is considerable variability in the data, as shown by the coefficient of variation. Most of the prices show positive skewness, which is a sign that positive spikes tend to be greater in number and more pronounced than negative spikes, which is expected given that metal prices tend to spike when reserves are low or mining is in difficult-to-reach areas. We also find evidence of significant kurtosis in most metals, a sign that the price data contains extreme values.

[1] Special thanks to David Jacks (see www.sfu.ca/~djacks/data/index.html) for making the data available.

We start by testing for structural breaks in the data using the robust test procedures of Perron and Yabu (2009a) and Kejriwal and Perron (2010). This method is intuitive as we can be agnostic to the underlying order of integration of the data. The procedure involves testing for a single structural break in the data (using Perron and Yabu 2009a); if a break is present, then we use a sequential test (using the method of Kejriwal and Perron 2010) to determine whether a further break is present. The maximum number of breaks is set equal to two. While this may seem restrictive, the number is appropriate given the sample size (see Kejriwal and Perron 2010). The test results show that we cannot reject the null hypothesis of no structural break in favour of a single break for 10 out of the 12 metal prices. The finding of a single structural break in aluminium and chromium leads us to adopt the sequential procedure to test for the null of one break against the alternative of two breaks. However, we cannot reject the null in this case, and conclude the presence of a single break for these two metals. The estimated exponential Wald (exp*W*) test statistics and the associated number of breaks are shown in Table 1.

Table 1: Tests for multiple structural breaks

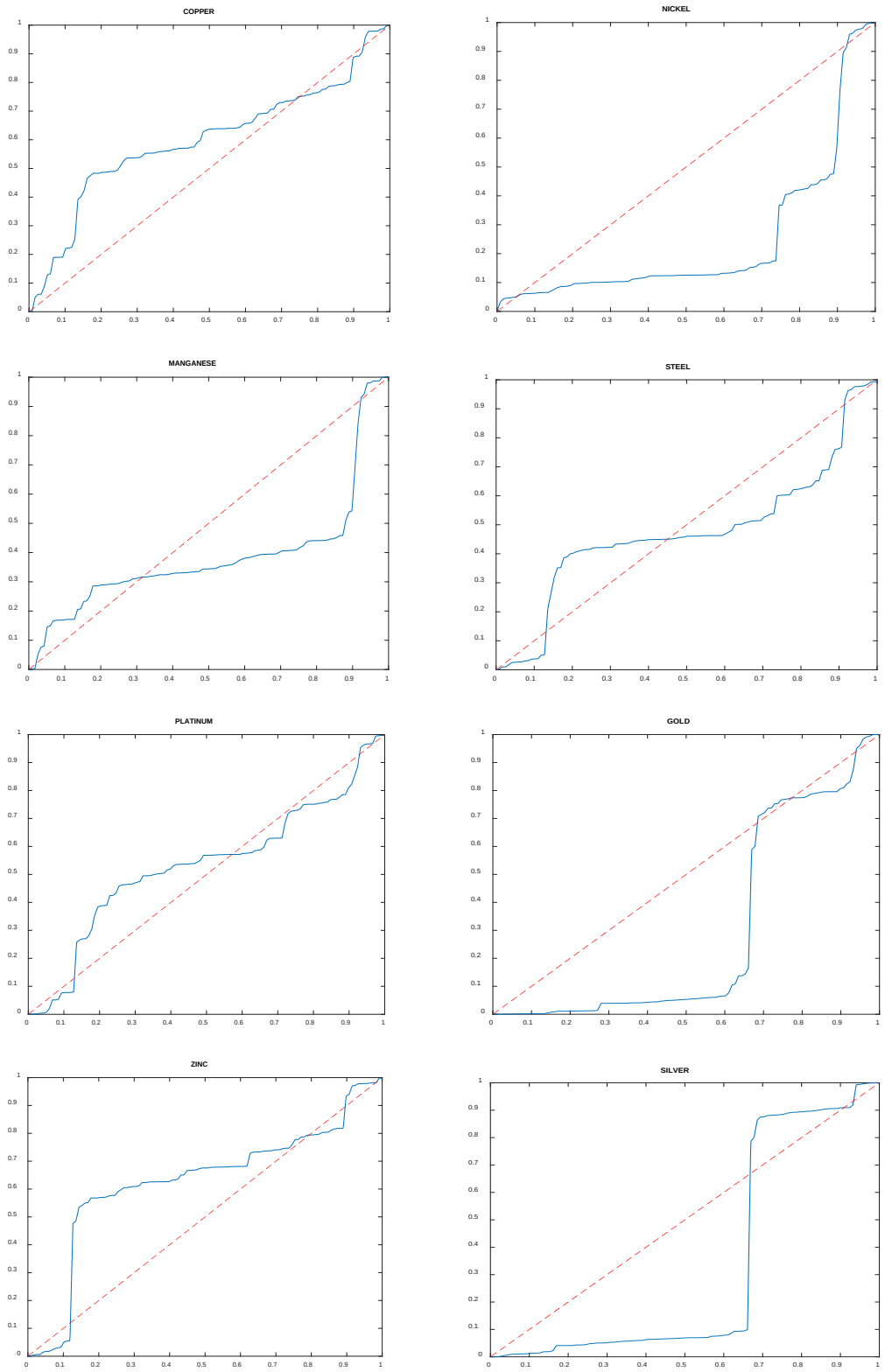
Metal prices with no breaks			Metal prices with at least one break				
	exp*W*(0|1)	Number of breaks		exp*W*(0|1)	exp*W*(1|2)	Number of breaks	(loc)
Copper	–0.034	0	Aluminium	1.54[c]	0.21	1	(1953)
Lead	–0.106	0	Chromium	3.70[a]	0.08	1	(1929)
Manganese	0.639	0					
Nickel	–0.136	0					
Steel	–0.201	0					
Tin	–0.188	0					
Zinc	0.438	0					
Gold	0.194	0					
Platinum	–0.090	0					
Silver	–0.099	0					

Note: [a] and [c] denote rejection of the null at the 1 and 10 per cent significance levels, respectively.

Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

At this stage, the presence (or not) of breaks in the metal prices is known. We next proceed to determine the nature 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 (see Cavaliere and Taylor (2007) for details). The variance profiles for selected metal prices are shown in Figure 1.

Figure 1: Variance profile of selected metal prices



Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

The dashed diagonal line in each of the 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 the dashed line closely, that is 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. At this stage we can conclude that there is not much evidence of breaks in metal prices (10 out of 12 show no breaks), and there is considerable but different levels of variability in metal prices over time.

We now proceed to estimate the underlying time trend of the metal prices. We start by examining the metal prices that do not contain any structural breaks. We can therefore expect (or not) to find a secular trend in these prices. To highlight the importance of variability in metal prices (as shown by the variance profile computed earlier), 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.

Table 2: Robust linear trend estimation results.

	HLT			PY		
	Delta	z_δ	z_δ^m	Rho	t_{PY}	t_{PY}^m
Copper	0.000	–0.327	–0.327	0.849	–2.585[a]	–1.617
Lead	0.159	–0.483	–0.361	0.849	–2.226[b]	–1.511
Manganese	0.119	0.510	0.420	0.743	2.218[b]	1.574
Nickel	0.000	–0.669	–0.669	0.838	–3.388[a]	–2.083[b]
Steel	0.227	0.154	0.074	0.815	–0.076	–0.048
Tin	0.173	0.019	0.028	0.877	–0.107	–0.064
Zinc	0.465	–0.713	–0.493	0.736	–1.306	–1.026
Gold	0.000	0.351	0.351	0.872	1.972[b]	1.318
Platinum	0.013	0.301	0.299	0.880	1.730[c]	1.082
Silver	0.000	–0.067	–0.067	0.877	–0.804	–0.571

Note: [a], [b], and [c] denote rejection of the null at the 1, 5, and 10 per cent significance levels, respectively.

Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

Two sets of tests are conducted here: the HLT tests followed by the PY tests. The HLT tests show that the data-dependent weights, denoted by ω, are found to be $0 < \omega < 1$ for 6 out of the 10 prices, thereby suggesting that the HLT robust statistic is based on a weighted combination of test statistics associated with the data being $I(0)$ or $I(1)$. The results of the modified HLT statistic will differ from that of the standard HLT statistic for these six prices. However, in the case of all metal prices, whether we choose the z_δ statistic or the z_δ^m statistic, we cannot reject the null hypothesis of no significant trend. This set of results leads us to conclude that there is no significant trend according to both the standard robust and modified robust methods. However, the PY statistic is understood to have relatively tighter confidence intervals and therefore the ability to provide precise trend estimates. Using this measure, we find the ρ estimate to be different for all 10 metal prices when comparing the modified statistic t_{PY}^m with the standard robust t_{PY} statistic. Indeed, the results show that the standard t_{PY} statistic concludes a significant trend for 6 out of the 10 metals, being copper, lead, manganese, nickel, gold, and platinum. However, the modified statistic t_{PY}^m produces a different set of results. Only one metal price (nickel) is found to be significant; the rest are statistically insignificant. The test statistics show how much the results differ when

accounting for time-varying variance. In other words, if we neglect the property of time-varying variance, we could end up with very different and potentially misleading conclusions.

Since we found trend breaks in aluminium and chromium, we proceed to estimate the broken time trends for these two metal prices. In both cases, a single structural break has been found, thereby delineating two regimes. We apply both the HLT and PY procedures along with the modified tests. The results are shown in Table 3.

Table 3: Robust broken trend estimation results.

	Pre-break date				Post-break date			
Commodity	z_δ	z_δ^m	t_{PY}	t_{PY}^m	z_δ	z_δ^m	t_{PY}	t_{PY}^m
Aluminium	–6.84[a]	–4.26[a]	–10.77[a]	–8.80[a]	–2.56[a]	–3.05[a]	–5.58[a]	–7.07[a]
Chromium	–3.93[a]	–4.55[a]	–4.83[a]	–6.60[a]	3.90[a]	3.29[a]	6.02[a]	4.89[a]

Note: [a] denotes rejection of the null at the 1 per cent significance level.

Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

We find significant time trends in each regime for both metals. In the case of aluminium, the trend estimate is negative for the entire sample. The broken trend simply suggests a change in the magnitude of the slope. From the period 1900 to 1953, the rate of decline of aluminium prices is relatively faster when compared to the period from 1954 to 2017. In the case of chromium, the slope changes from being significantly negative to being significantly positive. In contrast to aluminium, the break date is located towards the first quartile of the sample. Therefore, from the period 1900 to 1929, we find a negative trend, and from 1930 to 2017 the trend is positive. The increasing trend for chromium prices is more prevalent as it stretches across a longer time period of the sample.

Only 3 out of 12 metal prices considered are found to exhibit significant trends. In the case of nickel, the trend is secular and negative. For aluminium, the trend is broken, but negative throughout the sample period. In the case of chromium, the trend is broken and the sign of the trend changes from being negative to positive. The results suggest that, in the cases of nickel and aluminium, we can infer that positive demand shocks (e.g. changes in income growth) may have outweighed positive supply shocks (e.g. changes in reserves) in the long run. In the case of chromium, this may have occurred only up to 1929. Since then, positive demand shocks may have outweighed positive supply shocks in the long run.

We next proceed to test whether shocks to metal prices are short-lived or not. As we discussed earlier, the standard tests to determine persistence in metal prices are unit root tests. However, because of the nature of metal prices, being volatile and subject to possible structural breaks, we apply the most suitable set of tests to examine the persistence. Since we have found most prices to be volatile using the variance profile graphs, we apply the Smeekes and Taylor (2012) tests to metal prices that are likely to provide the most reliable results. For the two metal prices for which we find evidence of a single structural break, we apply the more pertinent procedure due to Cavaliere et al. (2011).

We first turn our attention to analysing the metal prices that do not exhibit a structural break. For these prices, we apply the Smeekes and Taylor (2012) procedure that tests for a unit root in the presence of non-stationary volatility. We carry out the tests on the 10 metal prices that do not exhibit a structural break. Both the UR_{4A} and UR_{4B} tests conclude that 7 out of the 10 metal prices reject the null hypothesis of a unit root. The probability values given in square brackets in Table 4 show that the null can be rejected at least at the 10 per cent significance level. This result

holds, irrespective of whether we include or do not include a linear time trend. All the results are shown in Table 4.

Table 4: Unit root tests robust to non-stationary volatility

	$UR - A$	$UR - B$
Copper	–2.029 [0.146]	–2.032 [0.150]
Lead	–2.008 [0.063][c]	–1.988 [0.061][c]
Manganese	–2.133 [0.039][b]	–2.114 [0.040][b]
Nickel	–2.079 [0.069][c]	–2.087 [0.071][c]
Steel	–1.965 [0.036][b]	–1.963 [0.036][b]
Tin	–2.003 [0.011][b]	–2.002 [0.010][c]
Zinc	–1.956 [0.001][a]	–1.951 [0.001][a]
Gold	–2.003 [0.296]	–1.993 [0.298]
Platinum	–1.987 [0.114]	–1.989 [0.113]
Silver	–1.963 [0.083][c]	–1.968 [0.084][c]

Note: [a], [b], and [c] denote rejection of the null at the 1, 5, and 10 per cent significance levels, respectively.

Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

The unit root null is rejected in the cases of lead, manganese, nickel, steel, tin, zinc, and silver. We can conclude that any shocks to these metal prices are likely to be short-lived; therefore, if these prices deviate from their mean or trend, such deviations will correct over time. The metals that do not reject the null of a unit root are copper, gold, and platinum. This implies that any shocks to these three prices are not going to dissipate quickly. The shocks, in theory, would be permanent in nature, or more likely to be long-lived.

We earlier found a structural break in aluminium and chromium. Accordingly, we conduct a unit root test, due to Cavaliere et al. (2011), that allows for non-stationary volatility as well as a trend break. The results are shown in Table 5.

Table 5: Unit root tests robust to non-stationary volatility and a structural break

	MZa	Bootstrapped critical value (10%)	MSB	Bootstrapped critical value (10%)	MZt	Bootstrapped critical value (10%)
Aluminium	–24.087[c]	–21.829	0.144[c]	0.147	–3.469[c]	–3.254
Chromium	–28.337[c]	–17.829	0.132[c]	0.163	–3.763[c]	–2.944

Note: [c] denotes rejection of the null at the 10 per cent significance level.

Source: authors' construction based on data from www.sfu.ca/~djacks/data/index.html.

The unit root tests statistics, along with the bootstrapped critical values, are reported. We can see that the computed *t*-statistic for each of the unit root tests MZa, MZt, and MSB are less than the bootstrapped critical values. Thus, we can conclude that, for both metals, the unit root null is rejected at conventional levels of significance. We can therefore conclude that shocks to both of these prices are expected to dissipate fairly quickly—in other words, shocks are likely to be transitory in nature. Overall, using the results from Tables 4 and 5, we can conclude that, in general, there is a prevalence of metal prices that show a transitory response to a shock. This is true for 9 out of 12 metals prices considered in this study.

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 shifts in demand from metal-consuming countries as well as the amount of reserves discovered or whether technical progress makes extractions possible from hard-to-reach areas (Cuddington and Nülle 2014). Based on the unpredictable shifts in demand, extraction costs, and discovery of reserves, it is highly possible to expect that prices may be subject to upward and downward swings. An upward swing preceded by a downward swing could be described 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. As mentioned earlier, metal prices are highly volatile, and it is highly possible that variance is time-varying. Accordingly, this contentious issue of whether a significant trend exists in the price series is examined using novel econometric methods. Conducting variance profile tests, we find evidence of different degrees of time-varying variance. Tests for structural breaks show that only 2 out of 12 prices show a trend break. Our results show that, based on appropriate novel procedures, there is almost no evidence of any significant trend, and it is worth pointing out that if time-varying variance is ignored the results would be mixed and therefore quite different. Further tests are carried out to check whether metal prices are mean- or trend-reverting. We find most prices are stationary, implying that shocks are transitory in nature. Overall, we find sufficient evidence to conclude that there are no significant trends in metal prices and any shocks to these prices dissipate relatively quickly over time.

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 export revenue and for importers to decide the volume to import. Fluctuations can occur that are driven by demand, and such fluctuations can be exacerbated by the low elasticity of demand, but the expectation is that prices will return to a long-run equilibrium level. This reversion to equilibrium could be persistent in the face of large increases in demand and being unable to meet this demand by increasing supply, as has been the case in response to the most recent metal price boom in the mid-2000s, largely driven by China and India (Dobbs et al. 2013). However, since the slowdown in China, metal prices have recorded decreases (Ghoshray and Pundit 2020).

To conclude, the last century has been influenced by interventionist policies, especially after the Great Depression in the 1930s, when prices of most metals collapsed. Between 1945 and 1965 commodity agreements were put in place to stabilize 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 free market forces. The variability of prices has increased especially as the middle classes grow in size in countries like China and India, where the demand for consumer goods pushes up the price for metals. However, China's huge appetite for commodities can influence commodity prices. For example, when supply is increased through more extraction and discoveries to meet increasing demand, a slowdown in China can cause a slackening in demand, and while lagged effects cause supplies to increase, downward pressure on prices occurs. The low elasticity of demand causes prices to fluctuate, and we argue that the underlying trend in metal prices is 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, as it is difficult to find a tenable recommendation to offer.

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Appendix

Table A1: Descriptive statistics

	AR(1)	AR(2)	CV	Skewness	Kurtosis
Aluminium	0.90	0.78	0.87	1.97***	6.36***
Copper	0.84	0.66	0.40	0.87***	3.55
Chromium	0.84	0.76	0.53	1.19***	4.53***
Lead	0.84	0.67	0.36	0.02	2.66
Manganese	0.74	0.60	0.40	1.87***	9.70***
Nickel	0.79	0.56	0.41	1.42***	5.38***
Steel	0.81	0.64	0.24	0.31	2.70
Tin	0.89	0.77	0.44	1.44***	5.98***
Zinc	0.67	0.34	0.41	2.39***	11.42***
Gold	0.91	0.78	0.57	1.67***	5.61***
Platinum	0.88	0.75	0.38	1.08***	3.28
Silver	0.73	0.54	0.67	3.65***	22.51***

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.

Source: authors' construction.