Non-renewable resource prices. A robust evaluation from the stationarity perspective

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NON-RENEWABLE RESOURCE PRICES. A ROBUST EVALUATION FROM THE STATIONARITY PERSPECTIVE

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ABSTRACT

The bulk of the literature investigating persistence properties of non-renewable resource prices series has focused on application of unit root tests. This paper contributes to the debate, applying a methodology which allows (1) robust detection of the presence and (if so) the number of changes, (2) inference on stationarity of the series, and (3) estimation of change locations. In contrast to previous papers, the analysis is carried out from the perspective of stationarity testing, incorporating quadratic trends and the possibility of smooth changes. For a classical database, we find significant evidence of trend stationarity in most of the series, suggesting that shocks are mostly of a transitory nature. Exceptions are silver and natural gas, with stationarity being rejected for all the specifications considered in the paper. Finally, the knowledge of the stochastic characteristics of the series allows robust detection of change points which appear to be related to economic events.

Keywords: non-renewable resource prices, structural changes, stationarity test, sequential procedure.

1. INTRODUCTION

There is a large body of literature which investigates the time series properties of non-renewable resource prices. The reasons for this interest include both theoretical and econometric issues.

From a theoretical point of view, if prices are trend stationary, shocks dissipate and policy efforts to restore price following a shock are unwarranted. On the contrary, in the case of a stochastic trend, policy intervention is sensible in order to overcome the permanent effect of a shock.

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Researching the potential stationarity of real non-renewable resource prices can be vital in an assessment of theories validity. One of the models more debated is the Hotelling model. In a world of certainty, the Hotelling model predicts that non-renewable resource prices are trend stationary; while in an uncertain context, according to Slade (1988), prices may be difference stationary. A number of papers[2] have examined this issue in an effort to understand which theory or theories best describe the observed behaviour. In this respect, Slade (1988) represents one of the first attempts to analyze time series properties of natural resource prices in order to evaluate the Hotelling model; applying unit root tests and considering a linear trend model, Slade finds evidence of stochastic trends. After Slade´s (1982) assessment that the progress effect can lead to a U-shaped price path, Agbeyegbe (1993) and Berck and Roberts (1996) extended the unit root analysis incorporating a quadratic trend, and Ahrens and Sharma (1997) and Lee *et al*. (2006) considered breaks and found further evidence against the unit root hypothesis. Using a different methodology - Kalman filter methods- Pindyck (1999) estimated a model where prices revert to a quadratic trend that shifts over time.

In the field of energy, time series properties of prices have been analysed in order to investigate the efficient market hypothesis. Lee and Lee (2009) found evidence in favour of the broken stationarity hypothesis, implying that energy prices are not characterized by an efficient market. Maslyuk and Smyth (2008) focused on crude oil, and highlighted reasons to analyse the stochastic properties of its price: if oil prices are trend reverting, this is consistent with crude oil being sold in a competitive market where prices revert to long-run marginal cost, which changes only slowly. Also, some studies[3] have linked shocks to crude oil prices to output and inflation, the natural rate of unemployment, movements in stock market indices, and fluctuations in business cycles. Finally, there are links between oil price shocks and investment decisions (e.g. Dixit and Pindyck, 1994; Finn, 2000), and the price of oil occupies a central stage in theories in the area of environmental and resource economics. For instante, Sinn (2008) points out that oil is one of the main sources of carbon emissions and extends the Hotelling model in order to consider the global warming, and Holland (2008) shows that oil prices, rather than production, are a better indicator of impending resource scarcity.

Knowledge of the stochastic properties of time series is also important in econometric estimation and subsequent application of the models to forecasting and decision making.

[2] Krautkraemer (1998) includes a survey of this literature.
[3] See Maslyuk and Smyth (2008) for a review.

Berck and Roberts (1996) focused on ARMA and ARIMA models to forecast natural resource prices, but in their estimation they did not consider structural breaks. Lee *et al.* (2006) overcame this limitation, and stressed that pre-testing for unit roots and including structural breaks can improve the accuracy of forecasting non-renewable resource prices. Pindyck (1999) applied Kalman filter techniques to obtain forecasts of energy prices and stressed the relevance of knowing the stochastic properties of prices in terms of long-run forecasting and for firms making investment decisions. In the field of energy, Felder (1995) highlighted the importance of long-term fuel price forecasts in ascertaining generation planners to make correct choices in determining their fuel mix and evaluating fuel diversification strategies.

Papers which investigate persistence properties of non-renewable resource prices have focused on unit root tests results, allowing in some cases for structural breaks in the trend function. In this paper we contribute to the debate by incorporating results from new time series methodologies which provide more robust conclusions about the nature of the resource price time paths. For this we examine a classical database of 11 natural resource real prices series from 1870 to 1990. These data were analysed previously using others methodologies, thus making comparability of conclusions easier.

First, we apply stationarity tests. The above papers analysed the null hypothesis of a unit root against the alternative of trend stationarity -in some cases with a break-, but we consider the testing problem in the reverse direction: the null of trend stationarity (around linear and quadratic trends with breaks or smooth transitions) against the alternative of a unit root. So, stationarity tests complement unit root tests. Furthermore, as unit root tests are known to have low power under stationary but highly persistent processes, stationarity tests provide a useful means to confirm results from unit root tests.

In this paper we apply stationarity tests allowing for breaks and smooth transitions in the trend function, but we use a new methodology for their treatment. Some researches have shown that there is a circular testing problem between tests on the parameters of the trend function and unit root/stationarity tests, so Perron and Yabu (2009), Harvey *et al.* (2010) and Kejriwal and Perron (2010) proposed approaches that are robust to unit root and stationary errors in order to test for stability of the trend function and to obtain a consistent estimate of the true number of breaks. With this basis, our analysis begins by detecting the presence, and if so, the number of breaks in the series. For this we apply the above methodologies. In their mainstream versions these techniques consider linear trends, but the pecualirities of non-renewable resource prices time series have led us to extend the basic methodology in order to allow for nonlinear (quadratic) trends.

Once we have checked the number of changes, we apply two alternative types of stationarity tests in order to distinguish the stochastic properties of the data: (i) allowing for breaks - which occur instantaneously- and (ii) allowing for smooth transitions -whose effects are gradual, the transition between two regimes being smooth-. The latter approach is attractive since to assume that the change takes place instantaneously may be unrealistic in many economic applications, and also allows us to eliminate the very substantial size distortions which appear when we apply stationarity tests with a break when the series really exhibits smooth changes (see Landajo and Presno, 2010).

Finally, knowing the stochastic characteristics of time series is useful in order to tackle consistent estimation of the break/midpoint smooth transition dates. Concretely, with breaks in the level and/or the slope, consistent estimates of the break dates are obtained from a level or first-differenced specification according to whether a stationary process is present or not.

To summarize, this paper contributes to the debate about temporal properties of a classical database of natural resource real price series, but applying a powerful methodology that enables (i) robust detection of presence, and if so, the number of breaks in the level and/or the slope of the trend function, (ii) to carry out inferences on stationarity of the series, conditional on the presence of breaks and smooth transitions, and (iii) estimation of breaks/midpoint smooth transition locations.

The rest of the paper is structured as follows: section 2 introduces the methodology, including Monte Carlo experiments to obtain critical values adapted to the characteristics of the time series. Section 3 reports the empirical results and a discussion. The paper closes with a summary of conclusions.

2. METHODOLOGY

In this section we introduce the methodology for the analysis. First, we estimate the number of changes in time series, applying some approaches which are robust to stationary/integrated errors. Upon this basis, we examine the stochastic properties of the data via the analysis of the null of stationarity around linear and quadratic trends, with the number of changes detected in the previous stage. For this, we implement the Landajo and Presno (2010) proposal, applying two types of stationarity tests: allowing for breaks and allowing for smooth transitions. Finally, we estimate change locations.

2.1. Methods to estimate the number of changes

Information about the absence or presence (and in this case, the number) of changes is vital to devise unit root and stationarity tests with good properties. Traditionally, both kinds of tests were applied considering *a priori* the presence of one or more changes; however, it seems more suitable to research first the potential presence of such breaks, since the inclusion of dummy variables to cope with nonexistent breaks leads to reduction in the power of unit root/stationarity tests.

On the other hand, knowing the nature of persistence in the noise component is necessary in order to test for structural breaks. Inference based on a structural change test from first-differenced data -which conveys to assume a unit root- leads to tests with poor properties when the series contains a stationary component. On the other hand, application of the test on the level of the data entails different limiting distributions -so, different asymptotic critical values- depending on a unit root is present or not.

So, there is a circular problem between tests on the parameters of the trend function and unit root/stationarity tests.

Perron and Yabu (2009) solved this circular problem. They proposed an approach to assess the presence of a structural change in the linear trend function of a univariate time series without any prior knowledge as to whether the noise component is stationary or contains an autoregressive unit root. Kejriwal and Perron (2010) extended the methodology, and developed a sequential procedure that allows one to obtain a consistent estimate of the number of breaks in the linear trend function. Their proposal provides a procedure to test the trend function for breaks in slope or simultaneous breaks in slope and level, but no breaks solely in level. Harvey *et al.* (2010) filled this gap and derived tests which allow for multiple level shifts. Next we introduce these tests. All these proposals consider a linear trend, but we extend them in order to incorporate a quadratic trend to cope with nonlinearities.

The Perron and Yabu (2009) test

Perron and Yabu (2009) proposed an approach to testing the stability of the trend function based on a Feasible Quasi Generalized Least Squares procedure that uses a super-efficient estimate of the sum of the autoregressive parameters α when α=1.

They consider the data generating process:

$$
\begin{aligned}
y_t &= x_t^{'}\Psi + u_t \\
u_t &= \alpha u_{t-1} + v_t \\
v_t &= d(L)e_t
\end{aligned}
\tag{1}
$$

for t=1,…,T, where x_t is a (r x 1) vector of deterministic components, Ψ is a (r x 1) vector of unknown parameters, $d(L)=\sum_{i=0}^{\infty} d_i L^i$, $\sum_{i=0}^{\infty} i|d_i| < \infty$, $d(1) \neq 0$, $e_t \approx i.i.d.(0,\sigma^2)$, and u_0 is some constant. It is assumed that $-1<\alpha\leq 1$. If $\alpha=1$, u_t is an integrated process of orden 1 ($u_t \sim I(1)$), so y_t is a difference stationary process with a possibly broken trend; when $-1<\alpha<1$, $u_t \sim I(0)$, and the series is trend stationary with a possibly broken trend.

The null hypothesis to be tested is $R\Psi=a$, where R is a (q x r) full rank matrix and a is a (q x 1) vector, with q being the number of restrictions.

Perron and Yabu (2009) considered three linear Models including a shift: Models I and II only allow for a shift in intercept and in slope, respectively, and Model III allows for both a shift in intercept and slope at $T_b=[\lambda T]$ for some $\lambda \in (0,1)$, where [.] denotes the largest integer that is less than or equal to the argument. In our analysis, we just consider[4] Model III, where $x_t=(1,t,DU_t,DT_t)'$, $DU_t=1(t>T_1)$, $DT_t=1(t>T_1)(t-T_1)$, with 1(.) being the indicator function, and $\Psi=(\beta_0,\beta_1,\delta_1,\eta_1)'$. For the general case, the hypothesis of interest is $\delta_1=\eta_1=0$. We also consider an "unrestricted" case[5] which allows testing for stability of the slope parameter while the intercept may vary across regimes. For that, we only test whether a shift in slope is present (η_1 with δ_1 unrestricted, so the hypothesis of interest is $\eta_1=0$). In this case, critical values corresponding to Model II are used.

Since we also analyse the case of quadratic trends, we extend the procedure, to include a new model: Model III (quadratic), where $x_t=(1,t,t^2,DU_t,DT_t)'$, with $\Psi=(\beta_0,\beta_1,\beta_2,\delta_1,\eta_1)'$. The hypotheses of interest are $\delta_1=\eta_1=0$ and $\eta_1=0$ for the general and unrestricted cases, respectively. Appendix A.1. describes the test procedure.

Perron and Yabu (2009) provided asymptotic critical values for this test, although our simulations[6] (see Table 1 below) indicated that in finite samples of moderate size, critical values may differ considerably from their asymptotic counterparts; so, finite sample critical

[4] We skip Model I because the sequential procedure by Kejriwal and Perron (2010) does not allow for shifts just in intercept, so, in order to analyse this kind of change, we apply the Harvey *et al.* (2010) procedure.

[5] As shown in Kejriwal and Lopez (2010), the joint test for Model III has power against processes which are characterized by shifts only in the level and it is likely to reject the null of stability even when there is no change in the slope of the trend function. So, in order to distinguish between changes in level or slope, they recommend the "unrestricted" proposal.

[6] Matlab codes for the procedures used in this paper are avalaible from the authors upon request.

values are obtained. More precisely, we generated critical values for samples with T=100 and T=500 in Models III and III (quadratic), in the general and unrestricted versions. Based on simulations we found that the trimming parameter ε=0.05 and δ=0.5 in (3a) –see Appendix A.1.- led to good results in finite samples, so we considered these values both to obtain critical values and in applications.

Table 1 reports critical values. As a reference, the last two columns contain the asymptotic critical values (Perron and Yabu, 2009). As expected, as T increases, finite sample critical values approach the asymptotic ones, but for T=100 there are remarkable differences between both values. Concretely, for T=100 critical values are longer than asymptotic ones, and application of the latter in finite samples would lead to an increase in rejections of the null hypothesis of stability and to size distortions in the test, so, in this paper we use the finite sample critical values.

[Insert Table 1]

The Kejriwal and Perron (2010) sequential test

Kejriwal and Perron (2010) extended the Perron and Yabu (2009) test and proposed a sequential procedure that allows one to obtain a consistent estimate of the number of breaks while being agnostic to whether a unit root is present. The procedure proceeds by testing the null hypothesis of l changes against the alternative hypothesis of l+1 changes. In our analysis, given the number of sample observations, we allow a maximum of two breaks[7].

The first step of the procedure conducts the Perron and Yabu test for no break versus one break. Conditional on rejection, the estimated break date is obtained by a global minimization of the sum of squared residuals. The strategy proceeds (by using the methodology by Perron and Yabu, 2009) to test for the presence of an additional break in each of the segments obtained from the estimated partition. The test statistic for the null of one versus two breaks can be expressed as:

$$ExpW(2/1) = \max_{1 \le i \le 2}\{ExpW^{(i)}\} \qquad (2)$$

where $ExpW^{(i)}$ is the one-break test in segment i. The null hypothesis of a single change against the alternative of two is rejected if $ExpW(2/1)$ is sufficiently large.

[7] This is in accordance with Kejriwal and Perron (2010), who recommended that the maximum number of breaks should be decided with regard to the available sample size. Otherwise, the sequential test will be based on a small number of observations in each subsample, leading to low power and/or size distortions in the tests.

As in Perron and Yabu (2009), we considered Model III (for the general and unrestricted proposals), derived the quadratic case (Model III, quadratic, general and unrestricted), and generated finite sample critical values. Simulations showed good results for the trimming parameter ε=0.1 and for δ=0.1. Table 2 reports critical values and shows that small sample critical values are again longer than the asymptotic ones.

[Insert Table 2]

The Harvey et al. (2010) test for breaks in level

The sequential procedure by Kejriwal and Perron (2010) does not allow testing for multiple breaks solely in level. Harvey *et al.* (2010) filled this gap and proposed robust tests for detecting multiple breaks in level conditional on a stable underlying slope. The model is:

$$\begin{aligned} y_t &= \beta_0 + \beta_1 t + \sum_{i=1}^{n} \delta_i DU_t([\lambda_i T]) + u_t, \quad t = 1,\dots,T \\ u_t &= \rho u_{t-1} + \varepsilon_t, \quad t = 2,\dots,T \end{aligned} \tag{3}$$

$\lambda_i \in \Lambda$, where $\Lambda = [\lambda_L, \lambda_U]$, with λ_L and λ_U being trimming parameters which satisfy $0 < \lambda_L < \lambda_U < 1$.

The null hypothesis is $\delta_i = 0$ for i=1,…, n, and the alternative is that there is at least one break in level.

The test is based on the quantities:

$$\begin{aligned} M &= \max_{t \in \Lambda} \left| M_{t,[mT]} - \hat{\beta}_1 \left[\frac{m}{2} T \right] \right| \\ S_0 &= (\hat{\omega}_v)^{-1} T^{-1/2} M \\ S_1 &= (\hat{\omega}_u)^{-1} T^{1/2} M \end{aligned} \tag{4}$$

where

$$M_{t,[mT]} = \frac{\sum_{i=1}^{\left[\frac{m}{2}T\right]} y_{t+i} - \sum_{i=1}^{\left[\frac{m}{2}T\right]} y_{t-i+1}}{\left[\frac{m}{2} T \right]}$$

m is the *window width*, and must satisfy the constraint $n \le 1 + \left[\frac{\lambda_U - \lambda_L}{m} \right] = n_{\max}$, which provides an upper bound for the maximum number of breaks assumed to be present. $\hat{\beta}_1$

denotes the OLS estimator of the trend coefficient, and $\hat{\omega}_v$ and $\hat{\omega}_u$ are the long-run variance estimates appropriate for the case of $I(1)$ and $I(0)$ shocks, respectively.

The proposed test is:

$$U = \max\left\{ S_1, \left(\frac{cv_\xi^1}{cv_\xi^0} \right) S_0 \right\} \tag{5}$$

where cv_ξ^1 and cv_ξ^0 denote the asymptotic critical values of S_1 and S_0, under $I(1)$ and $I(0)$ errors respectively, at significance level ξ. The decision rule rejects the null if $U > \kappa_\xi cv_\xi^1$, where κ_ξ is a positive scaling constant. A rejection informs us that at least one level break is present.

Harvey *et al.* (2010) also proposed a sequential procedure for determining the number of level breaks, n_U. The procedure, adapted to a maximum of two breaks, is in Appendix A.2.

We extended the above procedures in order to include a quadratic trend. The model is:

$$\begin{aligned} y_t &= \beta_0 + \beta_1 t + \beta_2 t^2 + \sum_{i=1}^{n} \delta_i DU_t([\lambda_i T]) + u_t, t = 1,\ldots,T \\ u_t &= \rho u_{t-1} + \varepsilon_t,\ t = 2,\ldots,T \end{aligned} \tag{6}$$

In this case, M in (4) is replaced by

$$M = \max_{t \in \Lambda} \left| M_{t,[mT]} - \hat{\beta}_1 \left[\frac{m}{2} T \right] - \hat{\beta}_2 (2t+1) \left[\frac{m}{2} T \right] \right| \tag{7}$$

where $\hat{\beta}_2$ is the OLS estimator for the quadratic trend coefficient. This modification is also included in the sequential procedure to determine the number of breaks.

Table 3 reports finite sample critical values for linear and quadratic cases[8].

[Insert Table 3]

2.2. Stationarity analysis. The Landajo and Presno (2010) test

Once the number of changes is analysed, we apply stationarity tests allowing for breaks and smooth transitions.

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[8] Following Harvey *et al.* (2010) recommendation, we chose m=0.1 and m=0.15 for the window width, and considered λ_L = 0.15, λ_U = 0.85 and λ_L = 0.1, λ_U = 0.9 respectively. Our choices imply that the maximum number of breaks allowed in the model is n_{max}=8 and 6, respectively. Harvey *et al.* (2010) does not consider this last case, although we included it in order to analyse the possibility of changes at both ends of the sample, as in Perron and Yabu (2009) and Kejriwal and Perron (2010).

Landajo and Presno (2010) extended previous results on stationarity testing to nonlinear models which may include several endogenously determined changes. Their approach may be applied to a wide range of models, including smooth deterministic components, and some non-smooth cases (e.g., breaks) may be seen as limiting cases of the considered structures. The following error-components model is analysed:

$$y_{t,T} = \mu_t + f(t/T, \boldsymbol{\theta}) + \varepsilon_t, \tag{8}$$

$$\mu_t = \mu_{t-1} + u_t;\ \ t = 1,...,T;\ \ T = 1,2,...$$

where $f(t/T, \boldsymbol{\theta})$ is a smooth function of time (i.e. a trend) with $\boldsymbol{\theta}$ being a vector of free parameters, $\{\varepsilon_t\}$ and $\{u_t\}$ are independent zero-mean error processes with variances $E(\varepsilon_t^2) = \sigma_\varepsilon^2 > 0$ and $E(u_t^2) = \sigma_u^2 \geq 0$; $\{\mu_t\}$ starts with μ_0, which is assumed to be zero. As for the linear smooth transition models we consider logistic sigmoidal changes of the forms:

Model I: $$f(t/T, \boldsymbol{\theta}) = \beta_0 + \beta_1\, t/T + \delta_1 \left[1 + \exp\{-\gamma(t/T - \lambda)\}\right]^{-1} \tag{9}$$

Model III: $$f(t/T, \boldsymbol{\theta}) = \beta_0 + \beta_1\, t/T + (\delta_1 + \eta_1\, t/T)\left[1 + \exp\{-\gamma(t/T - \lambda)\}\right]^{-1} \tag{10}$$

$\lambda \in [0,1]$, $\gamma > 0$. λ determines the relative position of the timing of the transition midpoint T_b into the sample and γ controls the speed of transition (gradual for small γ, and converging to a break as γ increases). So, smooth transition models are a very flexible class. The above specifications allow the analysis of series affected by a smooth change in level (Model I), and both in level and slope (Model III).

Lagrange Multiplier (LM) stationarity testing relies on the following setting:

$$H_0\ :\ q \equiv \tfrac{\sigma_u^2}{\sigma_\varepsilon^2} = 0,\ H_1\ :\ q > 0 \tag{11}$$

The LM statistic to test (11) has the expression:

$$\hat{S}_T = \hat{\sigma}^{-2} T^{-2} \sum_{t=1}^{T} E_t^2 \tag{12}$$

where $E_t = \sum_{i=1}^{t} e_i$ denotes the forward partial sum of the residuals of nonlinear least squares (NLS) fitting and $\hat{\sigma}^2$ is a suitable estimator for the long-run variance of $\{\varepsilon_t\}$.

2.3. Estimation of change locations

Finally, information on stationarity of the time series can be exploited to facilitate more accurate estimation of the break dates.

Results by Perron and Zhu (2005) show that, in the presence of a break in slope, the estimates of the break dates from the level specification are consistent irrespective of the noise component is stationary or has a unit root; however, Kejriwal and Lopez (2010) concluded via Monte Carlo simulations that more accurate estimates of the break dates can be obtained by estimating a specification in first differences when a unit root is present, and lower mean squared errors are observed when estimating a level model in the $I(0)$ case.

In models with pure level shifts, consistent estimates of the break dates may be obtained using the procedure suggested by Harvey *et al*. (2010) in the unit root case, and by minimizing the sum of squared residuals from the level specification in the stationary case.

3. EMPIRICAL RESULTS

This section includes an empirical analysis of the time series properties of non-renewable resource prices. To ensure comparability between our conclusions and previous papers we selected series similar to those analysed by Slade (1982) and Berck and Roberts (1996), and identical to the data used by Ahrens and Sharma (1997) and Lee *et al.* (2006). Data are annual prices for the period between 1870 and 1990, deflated by the producer price index (1967=100), and include aluminium, bituminous coal, copper, iron, lead, natural gas, nickel, petroleum, silver, tin and zinc. In this long period of time, non-renewable resource prices have suffered changes due, among others, to macroeconomic factors -such us changes in interest rates and exchange rates-, business cycle phases -recessions and expansion periods-, or political events -such us wars or threats-, so our analysis begins with the estimation of the number of changes.

3.1. Estimation of the number of changes

In the first stage we applied tests to ascertain if breaks are present. These tests are usually applied to evaluate the joint significance of the intercept and slope dummies. However, in order to distinguish between changes in level or slope, we followed a strategy similar to the Kejriwal and Lopez (2010) proposal. The first step tests for one structural break using the Perron and Yabu (2009) procedure and considering the more general Model III. A rejection by this test can be caused by a change in level and/or slope. So, in the second stage the unrestricted test (designed to detect a break in slope while allowing the intercept to shift) is applied. A rejection by this test can be interpreted as a change in the growth rate regardless of whether the level has changed. Given evidence in favour of a break we then proceed to test for one versus two breaks using the Kejriwal and Perron (2010) test. According to the number of observations in our analysis we allow for a maximum of two breaks. Bai and Perron (1998) and Prodan (2008) point out that a potential problem associated with this sequential procedure is that single break tests may suffer from low power in finite samples in the presence of multiple breaks, especially if they show opposite signs. So, we report the results of the one versus two breaks test independently of the results from the single break test.

Conditional on a stable slope in the first step, we focus on changes in the level of the series, applying the Harvey *et al.* (2010) test in order to estimate the number of level breaks. Figure 1 illustrates the sequence.

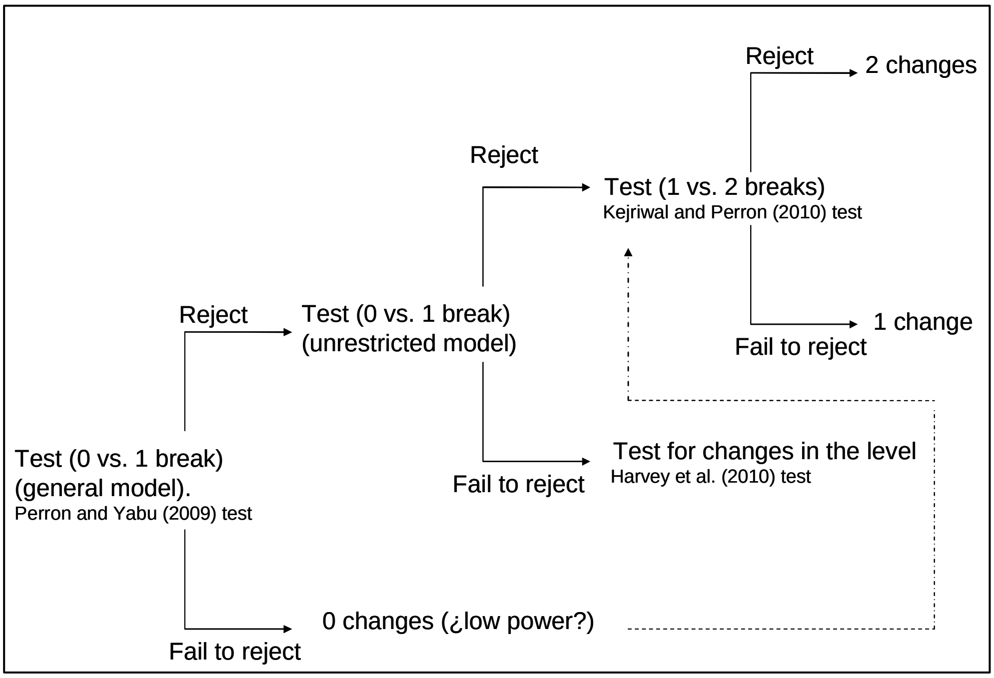

Figure 1. Sequential application of change tests.

The analysis was carried out for the linear and quadratic models. Table 4 reports results. Columns *ExpW* and *ExpW*(2/1) show figures from Perron and Yabu (2009) and Kejriwal and Perron (2010) tests respectively. Column *U* includes results from Harvey *et al.* (2010) test for m=0.15 (first row) and m=0.1 (second row), which led to identical conclusions in all cases. Column n_U reports the number of level breaks detected from the sequential test.

Conclusions about the number of changes for the linear and quadratic models are similar, and the inclusion of a quadratic trend only allows modification of results manifestly for the coal and iron series. Also, we find one pure level shift just in the coal series (lineal model). Aluminium, gas, silver and zinc series show clearly two changes, both for the linear and quadratic models, while petroleum and tin have just one. For copper, lead and nickel (for the last two ones, only in the quadratic model) we find contradictory results from *ExpW* and *ExpW*(2/1) tests, which can be explained by low power of the tests in finite samples in the presence of multiple breaks. In these cases of doubt we will show further results about stationarity for both models (0 and 2 breaks).

3.2 Stationarity analysis

Once the kind and number of changes were found, we applied the stationarity tests for the linear and quadratic specifications. For both models, we considered two types of changes: breaks and smooth transitions. The last specification is of interest since it incorporates the possibility of gradual, instead of instantaneous, changes and allows the nonlinear nature of the series to be captured.

Tables 5 and 6 display results and critical values at the 1%, 5% and 10% significance levels (columns *c.v.*) for the stationarity tests, under the break and smooth case, respectively.[9] Column "Model" indicates the specification considered and between parentheses is the number of changes detected in the previous stage. In case of doubt on the specification (change in level and/or growth rate), we chose the more general one in order to avoid distortions in the size of the test, since the inclusion of irrelevant components just leads to slight reduction in power. In order to take residual autocorrelation into account, we used the Bartlett window, with bandwidth ℓ_T selected by using the data-driven device proposed by Kurozumi (2002), with the pre-specified values $k = 0.5, 0.8, 0.9$ (in Kurozumi's notation, $\ell_T = \ell_A k$). Similar conclusions are obtained for each k value. Table 6 also includes the fitted λ and γ values[10].

In contrast to Lee *et al.* (2006), who concluded that including a quadratic trend implies few significant differences in their unit root analysis with breaks, we observed that the null of stationarity is generally favoured. In particular, for the break case, aluminium and petroleum

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[9] In order to compute critical values for the stationarity test, the Monte-Carlo-based bootstrap proposed by Landajo and Presno (2010) was used (see Appendix A.3).

[10] NLS fitting of the smooth transition models was implemented by using Levenberg-Marquardt algorithm, with the constraints $\lambda \in [0,1]$ and $0<\gamma<500$ imposed on each smooth change. A preliminary grid search over 10,000 (λ, γ) pairs was carried out before the gradient descent algorithm was initiated.

become stationary; and the same occurs for aluminium, coal and copper in the smooth analysis, although the contrary effect takes place for nickel. These changes in conclusions could be due to a decrease in size distortions as a consequence of a more suitable specification, although a factor to keep in mind is also the loss of power associated with the introduction of a new determinist component.

Results in Table 6 show that estimated speeds of transition are clearly low for the gas series. In this case, the specification of a smooth change leads to the rejection of the null hypothesis of stationarity at lower significance levels. A similar behaviour happens for silver, copper, coal and nickel series, which are characterized by a relatively smooth/medium change estimate.

For the tin series the fitted speed of transition is medium. However, in this case the stationarity test moves from rejection to non rejection of the null hypothesis when the more flexible smooth change specification is considered. A similar behaviour is observed for the petroleum series in the linear case. One explanation for this fact may be found in Landajo and Presno (2010), who point out that if the change is smooth and it is misspecified as a break, the stationarity test suffers size distortions which lead to incorrectly rejecting the null; on the contrary, the introduction of a smooth transition in series with a break just leads to slight reductions in the power of the stationarity test.

In order to carry out a confirmatory analysis, we compared our results with Lee *et al.* (2006) unit root test conclusions for the same specifications (linear or quadratic model and number of breaks). Their research concludes that series are stationary in more cases than ours, which looks somewhat unexpected, since stationarity tests tend to favour the null of stationarity. In general terms, conclusions from both tests coincide except for coal (just for the linear model), aluminium, gas, silver and tin (for both, linear and quadratic, models) series, for which opposite conclusions are found. Cheung and Chinn (1996) summarized the results of their confirmatory analysis, and concluded that contradictions due to non rejection of stationarity tests and unit root tests can be imputed to the low power of the tests. This could be the case of the aluminium series for the quadratic model and coal for the linear one. The reverse, that is, a rejection for both tests can be explained by the existence of more complex data generating processes. It could be the case of aluminium (for the linear model), gas, silver and tin (for both models). We note that most of these cases are series where the estimation of the smooth transition model displays at least one low/medium value of the speed of transition parameter. This seems to suggest the suitability of considering these smoother and more flexible models.

[Insert Table 4] [Insert Table 5] [Insert Table 6]

Due to the variety of models considered and that some conclusions vary according to model specification, we opted for applying model selection criteria for linear/quadratic and break/smooth models, considering the number of changes detected in the first stage. Concretely, we computed the Schwarz information criterion (SIC), the Akaike information criterion (AIC) and the adjusted R-Squared. Table 7 reports results. With the exception of zinc and iron, in all cases the quadratic model is selected. Also, the smooth transition model is selected for coal, copper, iron, gas, petroleum and tin series. Excepting petroleum, all these series have at least one change with low/medium speed of transition, and some of them are marked as problematic in the break-based confirmatory analysis. This appears to support the presence of nonlinear patterns in the relative prices of natural resources. For the selected models, the null of stationarity is not rejected at 5% significance, except for gas and silver; at 10% significance the null is also rejected for lead, nickel and tin.

Prevalence of nonlinear features in relative prices of primary commodities is documented in the literature[11]. Balagtas and Holt (2009) studied the dataset[12] compiled by Pfaffenzeller *et al.* (2007), which includes 24 relative primary commodity price series, among them some non-renewable resourses: aluminium, copper, lead, silver, tin and zinc. Balagtas and Holt (2009) conducted tests of the linear unit root model against models belonging to the family of smooth transition autoregressions (STAR). In their analysis they found that the null is rejected for most prices of primary commodities, among them, all the series corresponding to non-renewable resourses. They postulate that nonlinearity is due to impossibility of negative storage.

Harvey *et al.* (2011) analysed the integration properties of the same dataset with a different methodology. They generalized the Elliott *et al.* (1996) unit root test which considers a linear trend along the direction of allowing for a local quadratic trend term, and suggested a test procedure based on a conservative union of rejections decision rule. In their analysis it is confirmed the rejection of the unit root hypothesis with both tests for aluminium and zinc, and the non rejection for silver and tin; however, their results are mixed for copper and lead. In these cases, the rejection rule leads to the rejection of the null of unit root, although just at the marginal 10% for copper.

Our conclusions are largely in accordance to the above references.

[11] See Balagtas and Holt (2009) for a review.

[12] Data differ from ours, since these are indices of primary commodity prices relative to the price of manufactures, observed annually over the period 1900-2003 and measured in logarithms.

[Insert Table 7]

By way of summary, we find that the series are stationary, excepting silver and gas. In the case of tin, lead and nickel the rejection is at the marginal 10% level significance.

For the gas series, the conclusion of no stationarity is robust to all trend specifications and confirms Pindyck (1999) assertion: “state variables for coal and natural gas are estimated to be random walks or something very close to a random walk”. For the coal series, our results agree with this conclusion for the linear case, but not for the finally selected quadratic specification.

Results for another energy series –petroleum- lead to non rejection of the null of stationarity for the selected quadratic model. Previous papers found evidence for quadratic trends in petroleum series (e.g. Slade, 1982 and Lee *et al.*, 2006), and concluded that the inclusion of breaks allows rejecting the null of unit root (e. g. Postali and Picchetti, 2006 or Lee *et al.*, 2006).

Conclusions for the silver series are also robust to the model specifications considered in this research, and for all of them we reject the null of stationarity, confirming the efficient market hypothesis. Xu and Fung (2005) remarked that precious metal commodities are characterized by standard quality and storage characteristics that enable arbitrage in cross-market futures trading, so, understanding whether shocks to these prices are persistent or transitory has direct relevance to arbitrageurs and speculators in the commodity trading market. In our study it is confirmed that shocks are persistent, so prices cannot be predicted using historical data and it is not possible for investors to make profits using technical analysis. A conclusion about non-stationarity of silver series could be expected since its price, as that of gold, is determined in clearly speculative markets. Also, information criteria select the break model, which is in accordance to Mainardi´s (1998) assertion that precious metal price peaks are quickly followed by downward pressures brought about by factors such as international interest rates hikes or slack world economic activity.

In the case of tin, conclusions depend on the model. For the selected one -a quadratic trend model with one smooth change- the rejection of the null of stationarity is just at the 10% significance level; however, the rejection is at lower levels when a break is considered. In the case of non linear models, the unit root test by Balagtas and Holt (2009) rejects the null at the marginal 10% and the procedure by Harvey *et al.* (2011) leads to no reject. So, conclusions are mixed, but at the habitual 5% significance level our results seem to indicate stationarity of the tin series.

3.3. Estimation of change locations and discussion of results

Upon the above information about stationarity of the series more accurate estimates of the change dates can be obtained. According to Kejriwal and Lopez (2010), in the case of unit root the change dates are estimated from a specification in first differences, while for stationarity series a model in levels is considered. Table 8 reports change points for all the models considered in the study. In the case of smooth transition models we report estimations of λ and γ. As expected, when a smooth model is selected, at least one of the parameters of speed of transition is low/medium valued. For the specification selected according to information criteria we report parameter estimates of the complete model.

Most of the series show negative slopes and the quadratic model is selected in many cases. Krautkraemer (2005) points out that for most of the twentieth century, natural resource commodity price trends have been generally flat or decreasing, especially for minerals series. Since these are non-renewable resources, one might expect they would be more subject to increasing scarcity and therefore increasing prices; however mineral prices generally declined, with the exception of the period from 1945 until the early 1980s, when many non-renewable prices (copper, iron, nickel, silver, tin, coal, gas) showed an upward trend, particularly after the 1973 embargo. Krautkraemer (2005) points out that "this seems to match the U-shaped price curve that would occur as depletion exerted enough upward pressure on price to overcome the downward force of technological progress". However, the economy responds to price increases in a variety of ways: substitutions, research and development, new reserves are discovered, new methods for recovering resources or reducing the cost of using lower-quality reserves are found… As a result, most mineral prices declined since the early 1980s.

[Insert Table 8]

Next we comment specific results for each resource and discuss historical and economic events which took place.

Aluminium. Linear models detect a change date which matches with the outbreak of World War I in Europe in 1914. Then, shortages of aluminium metal began to appear, and prices rose because of the increased demand for aluminium in war materials. In March 1918, the president of the U.S. imposed price controls on aluminium metal, and its use for military equipment and essential civilian needs was placed under Government regulation. This fact could mark the other turning point, detected around the end of World War I.

However, the quadratic trend models detect changes before, at the end of the 19th century and in the early 1900´s. The first date matches with the use of innovations, such as the Hall-

Heroult process, which led to the mass commercial production of aluminium; as production levels continued to increase, producers kept the price low to encourage its use by consumers. This way, in the early 1900's, producers held aluminium metal prices at a low steady level in order to compete against copper in the electrical industry and other appliances (Plunkert, 1999).

Copper. In this case a quadratic trend is selected. Our results agree with Slade (1982), who compares linear and quadratic trends, and finds the latter provides the best fit for copper prices. The trend is quadratic, falling for a time and then rising.

For the selected model, the change midpoints are detected at 1898 and 1982. The first change is quite sharp and may be related to the period of depression by the end of the 19^{th} century. However, in 1982 the change has a medium speed. Edelstein (1999) points out that when the recession began in 1981, world mine production was reaching peak levels, and the resulting oversupply depressed copper prices (not sharply, according to our results) for 5 years.

For the other specifications, a change in 1918 is detected, corresponding to World War I. During war time copper was most needed, so some studies detect structural breaks in the First, and even in the Second World War.

Iron. A linear model with two smooth changes (with midpoints around 1874 and 1956) is selected. The first change is quite sharp and coincides with the *Long Depression* which began with the *Panic of 1873*. Concretely, some researches show that the iron industry as a whole felt the effects of the depression between 1875 and 1886. At the time, railroad-building industry and iron were closely related: the first one peaked in 1871 and the second one reached its highest price in 1872. So, the fall in railroad construction in 1875 entailed that both consumption and prices of iron declined. Following Stürmer (2011), the *Long Depression* exhibited a negative aggregate demand shock, which had effects on the iron prices.

The change in 1956 could be related to the period after the Korean War.

Lead. Information criteria select a quadratic model with breaks in 1947 and 1982, which coincide with previous studies, such us Kellard and Wohar (2006) or Yang *et al.* (2012). The first change could be related to the period after World War II, when total demand for lead accelerated with electronic developments (e.g. primary television and video display tubes) and demand for leaded gasoline. Smith (1999) points out that with the near phaseout of lead in gasoline, paints, solders, and water systems, and the imposition of expensive environmental production controls, the industry experienced hard times beween 1982 and

1986. Also, lead consumption declined substantially at the beginning of the eighties due to recession.

Nickel. Models show robust conclusions about change points, although a quadratic model with two breaks (in 1973 and 1988) is finally selected.

Stainless steel production and nickel prices are closely related. In fact, in the late 1990's, stainless steel production accounted for more than 60% of world nickel consumption and was the primary factor in nickel pricing (Kuck, 1999). So, nickel prices, reflecting consumption, rose slightly from 1970 until 1975, when the cumulative effect of opening several new production facilities began to be felt. In 1975, U.S. demand for nickel weakened, partly because of the termination of military operations in Vietnam and the crisis of the early 1970´s.

In the eighties, price peaked in 1988 and declined afterwards. Kuck (1999) points out three factors which were responsible for this increase: the substantial and unforeseen increase in demand for stainless steel, reduction in world production capacity because of low metal prices during the early and mid-1980's and the decreased availability of stainless steel scrap.

Silver. All the models detect changes at the beginning of the 80´s. It coincides with the exceptional speculative movement occurring in 1979-1980, when the Hunt brothers attempted to corner the silver market. Parameter estimates show a sharp increase followed by a negative slope. This fall in prices after the break point appears as a reaction to the high levels obtained beforehand.

Tin. A smooth change with the midpoint in 1976 is detected[13]. Carlin (1999) remarks that during the 29-year run of the tin agreements (1956-1985), the International Tin Council supported the price of tin by buying and selling tin from its buffer stockpile; however, the buffer stockpile was not sufficiently large, mainly to defend the artificial ceiling prices, and tin prices rose, especially from 1973 through 1980 when rampant inflation plagued the American and many foreign economies. 1976 is precisely the midpoint of this period of increase in prices. This date is roughly in accordance to Lee *et al.* (2006) -who detect a break in 1974 which they relate to the energy crisis of the early 1970s-, and Kellard and Wohar (2006) -in 1975-. As Kellard and Wohar, we observe that after an initial ratchering up of prices, the trend slope is negative. As in the case of silver, this fall in prices seems to be a reaction to the previous high levels. Stürmer (2011) ascribes the increase of prices to a

[13] As remarked previously, results from stationarity testing in tin series are mixed, so we also estimated the change point under non-stationarity for the selected model, finding a change midpoint in 1977, which is very similar to the one found in the stationary case.

specific demand shock that might be explained by sustained purchases of tin by the international buffer stock until its collapse in 1985.

Zinc. Changes are detected around World War I, and are related to the importance of zinc in the war industry. With the onset of World War I in 1914, the demand for zinc ammunition products -bronze and brass shell casings- tripled the value of zinc. However, as the war ended so did the boom.

For energy series (petroleum, coal and natural gas), information criteria select the quadratic model, which is in accordance to Pindyck (1999) specification. He points out that a quadratic U-shaped trend line is consistent with models of exhaustible resource production that incorporate exploration and accumulation of proved reserves over time, as well as technological change.

Coal. The selected model estimates a smooth change at the beginning of the 1960´s and a fast one in 1974. The "Study of Coal Prices" by the U.S. government found that the second change was due to the OPEC oil embargo started in December 1973, which raised prices for substitutes (coal and natural gas). Other factors were the anticipation of the United Mine Workers' strike during the second half of 1974 and the continuing increase in labor costs, a trend which had begun in 1970.

Following Ellerman (1994), the trends in the price of coal roughly coincide with the dominant realities of the industry: loss of market share to oil and natural gas during the 1950s and 1960s, rising crude oil prices in the 1970s, and over-capacity in the 1980s. He points out these conditions probably contributed to the observed changes in price, but changing productivity is the major explanatory factor for the trend in coal prices in U.S. since World War II.

Gas. Different changes are found depending on the specific structures (breaks/smooth transitions) considered. The break model captures the first oil shock and the period of the full liberation of the U.S. gas market. From 1954 to 1978, the price of natural gas transported through the interstate pipeline system was regulated by the Federal Power Commission, and prices changed very little from year to year. A partial deregulation of wellhead prices occurred with the Natural Gas Policy Act in 1978. But in the meantime, prices began to rise in the mid-1970s, a period of turmoil in international energy markets as a result of the first oil shock. So, when full de-regulation finally became effective in 1985, gas prices had risen, creating a long-term market surplus, the 'gas bubble'. Prices suqsequently retreated. Starting in 1984, the Federal Energy Regulatory Commission initiated a series of orders[14] intended to restructure the buy-sell relationship among production, transmission and distribution companies.

Lee and Lee (2009) also detect structural breaks in many countries around 1985, which they relate to the 1985 crash in oil prices.

Petroleum. Information criteria select a quadratic model. This is in accordance with Ahrens and Sharma (1997), Lee *et al.* (2006) and Li and Thompson (2010), who emphasized the importance of allowing for a nonlinear specification when examining the time series properties of oil price.

All the models detect a change in 1980-1981, coinciding with the Iranian Revolution and Iran-Iraq War, which caused oil prices to peak towards the end of 1981 as well as important effects on the world economy[15]. Kilian (2009) points out that the increase in the real price of oil after 1979 appears to be driven mainly by the superimposition of a sharp increase in precautionary demand in 1979 (due to the political uncertainty in the Middle East: Khomeini's arrival in Iran, the Iranian hostage crisis and the Soviet invasion of Afghanistan) on a slower-moving strong increase in real economic activity that started two years earlier, with only minor contributions from oil supply shocks.

Subsequently world petroleum consumption declined in the early 1980s due mainly to the development of new technologies, oil substitution by other energies (especially in power generation) and more efficient energy use. Although Saudi Arabia shut down production in 1981-1985, the nominal and the real price of oil declined significantly; in 1986, the Saudis abandoned those efforts, causing the price of oil to collapse.

Parameter estimates in Table 8 agree with these events, and show that after a large increase, oil prices experienced a negative trend, the adjustment being relatively fast.

4. CONCLUSIONS

This paper employs a powerful time series methodology in order to investigate the stochastic properties and the change points of a database of 11 nonrewable resource real prices. For this we have considered four model specifications which combine linear and quadratic trends with potential breaks and smooth transitions between regimes.

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[14] For instance, order no. 380 released utility buyers (such as the local distribution companies) from the commitment to purchase the transportation capacity they reserve; as Davoust (2008) shows, this led to a deep fall in average wellhead prices.

[15] In fact, the National Bureau of Economic Research characterizes the economic difficulties at this time as being two separate economic recessions, with the first one, due to the Iranian Revolution ending in July 1980, but followed very quickly by a new shock beginning in July 1981 with the Iran-Iraq War.

Our results indicate that most of the series are stationary, but there are two clear exceptions: natural gas and silver. This fact means that real price shocks on these resources are mostly permanent in nature, following that their markets are efficient in the weak sense, so prices cannot be predicted using historical data and it is not possible for investors to make profits using technical analysis. Also, both resources share the characteristic that their prices were regulated and after the deregulation suffered a "bubble": in 1980, when the Hunt brothers tried to corner the silver market and in the mid-eighties, when full de-regulation in gas market finally became effective. In contrast to others papers, we find that oil prices are stationary around a quadratic trend. As Pindyck (1999) noted, this is consistent with crude oil being sold in a competitive market where prices revert to long-run marginal cost, which changes only slowly. In this case, technical analysis is useful in order to predict prices and making profits.

Demarcation between stationary and non-stationary resource real prices series also has implications in terms of stabilization policies. Reinhart and Wickham (2004) argue that design and feasibility of stabilization and hegding strategies depend very much on the nature of shocks. Both are useful in dealing only with temporary and, preferably, short-lived shocks, while permanent shocks require adjustment and, possibly, the implementation of structural policies. Also, if a shock is temporary, but its effects are widespread and persist for many years or the price series has a varying trend, price stabilization may be equally costly and difficult to implement. From our analysis, silver and gas are difference stationary and so stabilization policies would be ineffective, and for the rest of series, these policies may be difficult to implement. This fact would explain, for instance, the gradually selling off of the tin buffer stock (see Ghoshray, 2011).

Information about stochastic properties of the series also allowed more accurate estimates of the change dates in prices, which are related to economic and historical events. Following Kilian (2009), some of the changes could be related to supply, aggregate demand and specific demand shocks. An example of the first one is the negative shock to supply which increased the real price of oil at the beginning of the eighties. Aggregate demand shocks are characterized for being relatively similar for all the resources. Instances include the *Long Depression*, World Wars I and II and the subsequent reconstruction, the industrial expansion of South Korea and Japan in the 1960s or the recessions in 1974 and 1981, and they seem to explain changes in copper, iron, lead or zinc prices. Specific demand shocks evolve differently across markets, and include precautionary demand, demand shocks due to the spread of technological innovation or non-linearities in the intensity of use. Stürmer (2011) noted that positive commodity-specific demand shocks exhibit inmediate, large and persistent positive effects on real prices, and this could be the case of lead, gas, petroleum, silver or tin. Also, in many series we find a sharp increase in price levels followed by a negative change in trend, which arises as a reaction to the high prices. Research and development, innovation in production methods, use of substitutes, discovery of new reserves, among other factors, would explain this fact.

Finally, along the analysis we have considered some models: linear/quadratic and breaks/smooth transitions. Information criteria confirm suitability of quadratic and smooth transition models in many of the series, and so the neccesity of applying stationarity tests adapted to these nonlinearities. However, the above tests are parametric, and in some cases, conclusions vary with the trend specification. An interesting avenue for future research would be to extend the analysis in order to allow for nonparametric stationarity testing, such as the recent proposal by Landajo and Presno (2012). Nonparametric methods provide increased flexibility, as they do not require a priori specification of a fixed parametric structure for the trend function.

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TABLES

Table 1. Perron and Yabu (2009) test. Finite sample and asymptotic critical values.

	T=100		*T*=500		*Asymptotic*	
	α=0	α=1	α=0	α=1	α=0	α=1
Model III						
90%	3.1644	3.6845	2.6683	3,04970	2.51	2.82
95%	4.0131	5.1254	3.3964	3,8810	3.12	3.36
99%	6.2493	20.9171	5.0738	12,5198	4.78	4.76
Model III unrestricted						
90%	1.6534	1.9696	1.5143	1.6641	1.34	1.40
95%	2.2766	3.0167	2.0423	2.4588	1.90	1.93
99%	4.1969	13.1699	3.4173	13.2114	3.07	3.27
Model III (quadratic)						
90%	3,2577	3,790	2.6681	3.0934	-----	-----
95%	4,2117	5,146	3.3491	3.8542	-----	-----
99%	6,5818	14,329	5.0565	8.4882	-----	-----
Model III (quadratic) unrestricted						
90%	1,6315	2,085	1.5091	1.7092	-----	-----
95%	2,3153	3,178	2.0917	2.3248	-----	-----
99%	4,3529	11,374	3.3234	5.9285	-----	-----

5,000 replications. ε=0.05; δ=0.5

Table 2. Kejriwal and Perron (2010) test. Finite sample and asymptotic critical values.

	T=100		*T*=500		*Asymptotic*	
	α=0	α=1	α=0	α=1	α=0	α=1
Model III						
90%	4.8002	4.5112	3.1204	3.2812	2.96	3.26
95%	5.9687	6.0204	3.8413	3.9506	3.67	3.85
99%	9.3103	21.2810	5.8604	5.4421	5.21	5.15
Model III unrestricted						
90%	2.322	2.312	1.8235	1.7652	1.75	1.82
95%	3.562	3.331	2.4927	2.3702	2.32	2.41
99%	6.263	8.232	4.0152	3.7879	3.79	3.76
Model III (quadratic)						
90%	5.32932	5.1782	3.2625	3.2606	-----	-----
95%	6.8828	7.0421	4.0928	4.0200	-----	-----
99%	10.8247	24.6765	5.8838	5.6563	-----	-----
Model III (quadratic) unrestricted						
90%	2.7601	2.8740	1.7755	1.8058	-----	-----
95%	3.8446	3.9938	2.3763	2.3945	-----	-----
99%	6.7711	12.5337	4.0526	3.8243	-----	-----

5,000 replications. ε=0.1; δ=0.1

Table 3. Harvey *et al.* (2010) test. Finite sample critical values.

	S_1	S_0	κ_ξ	S_1	S_0	κ_ξ
Linear model						
90% (ξ=0.1)	0.5139	20.6963	1.057	0.5588	17.1472	1.029
95% (ξ=0.05)	0.5612	22.067	1.064	0.6129	18.2202	1.031
99% (ξ=0.01)	0.6717	24.8387	1.086	0.7239	20.7237	1.030
Quadratic model						
90% (ξ=0.1)	0.5091	20.8609	1.081	0.5426	17.5263	1.026
95% (ξ=0.05)	0.5634	22.5771	1.061	0.5922	18.6203	1.029
99% (ξ=0.01)	0.6600	25.0302	1.127	0.6881	21.7276	1.058
	m=0.1; $\lambda_L = 0.15$; $\lambda_U = 0.85$; n_{max}=8			m=0.15; $\lambda_L = 0.1$; $\lambda_U = 0.9$; n_{max}=6		

T=100; 5000 replications

Table 4. Estimation of number of breaks. Linear and quadratic cases.

	LINEAR							QUADRATIC						
	ExpW (Model III)	*ExpW* (Model III; unrestricted)	*ExpW*(2/1) (Model III)	*ExpW*(2/1) (Model III; unrestricted)	Number of breaks	*U*	Level breaks n_U	*ExpW* (Model III)	*ExpW* (Model III; unrestricted)	*ExpW*(2/1) (Model III)	*ExpW*(2/1) (Model III; unrestricted)	Number of breaks	*U*	Level breaks n_U
Aluminium	31.761^{b}	30.185^{b}	36.441^{b}	3.409^{a}	2			21.218^{b}	16.591^{b}	22.897^{b}	0.126	2		
Coal	61.797^{b}	1.140	7.201^{b}	2.261		0.8747^{b} 0.9675^{b}	1	62.648^{b}	4.411^{b}	7.516^{b}	0.422	2		
Copper	1.763	0.165	5.116^{a}	4.186^{b}	0/2	0.3398 0.3591	0	1.897	0.683	79.856^{b}	78.885^{b}	0/2	0.3398 0.4112	0
Iron	4.943^{a}	4.064^{b}	18.877^{b}	4.849^{b}	2			1.616	0.643	6.089^{a}	-0.095	0	0.3803 0.4846	0
Lead	3.999^{a}	0.323	1.856	0.544	0	0.2750 0.3515	0	3.286	0.111	13.605^{b}	12.283^{b}	0/2	0.2750 0.3364	0
Gas	60.821^{b}	9.319^{b}	100.978^{b}	75.331^{b}	2			51.112^{b}	21.990^{b}	32.961^{b}	31.996^{b}	2		
Nickel	5.994^{b}	5.888^{b}	31.466^{b}	9.045^{b}	2			2.916	1.868	22.010^{b}	6.090^{b}	0/2	0.4439 0.5658	0
Petroleum	15.565^{b}	5.181^{b}	1.686	1.070	1			11.964^{b}	6.202^{b}	0.940	0.217	1		
Silver	37.639^{b}	7.735^{b}	22.582^{b}	17.827^{b}	2			33.908^{b}	27.014^{b}	26.324^{b}	25.165^{b}	2		
Tin	17.413^{b}	12.862^{b}	4.656	3.512^{a}	1			19.924^{b}	17.241^{b}	2.979	1.988	1		
Zinc	19.672^{b}	1.568	58.105^{b}	57.251^{b}	2			20.622^{b}	0.677	39.211^{b}	39.198^{b}	2		

ε=0.05; δ=0.5 (Perron and Yabu test) ε=0.1; δ=0.1 (Kejriwal and Perron test). Column *U*: *m*=0.15 (first row), *m*=0.1 (second row) for the Harvey *et al.* (2010) test.
$^{a, b}$ denote significance at 10% and 5%, respectively.

Table 5. Stationarity test. Break case.

	LINEAR							QUADRATIC						
	Model	*k*=0.5	*k*=0.8	*k*=0.9	c.v. 10%	c.v. 5%	c.v. 1%	Model	*k*=0.5	*k*=0.8	*k*=0.9	c.v. 10%	c.v. 5%	c.v. 1%
Aluminium	III(2)	0.1308^{b}	0.1209^{b}	0.1209^{b}	0.0912	0.1093	0.1632	III(2)	0.0447	0.0474	0.0474	0.0591	0.0691	0.0893
Coal	I(1)	0.0811	0.0903	0.1177^{b}	0.0948	0.1155	0.1827	III(2)	0.0254	0.0307	0.0307	0.0439	0.0533	0.0713
Copper	(0) III(2)	0.2160^{c} 0.0513^{a}	0.1422^{b} 0.0513^{a}	0.1422 0.0513^{a}	0.1050 0.0503	0.1279 0.0571	0.1777 0.0723	(0) III(2)	0.0897^{b} 0.0276	0.0698^{a} 0.0276	0.0698^{a} 0.0276	0.0631 0.0354	0.0743 0.0413	0.0916 0.0536
Iron	III(2)	0.0366	0.0366	0.0366	0.0502	0.0582	0.0738	(0)	0.0479	0.0479	0.0472	0.0729	0.0876	0.1207
Lead	(0)	0.0881	0.0826	0.0826	0.1077	0.1295	0.1829	(0) III(2)	0.0926^{b} 0.0395^{a}	0.0864^{b} 0.0395^{a}	0.0864^{b} 0.0395^{a}	0.0615 0.0391	0.0734 0.0458	0.0995 0.0586
Gas	III(2)	0.1395^{c}	0.1023^{b}	0.1023^{b}	0.0796	0.0961	0.1332	III(2)	0.0661^{b}	0.0603^{c}	0.0603^{c}	0.0529	0.0606	0.0773
Nickel	III(2)	0.0756^{a}	0.0704	0.0704	0.0736	0.0883	0.1161	(0) III(2)	0.0496 0.0554^{a}	0.0497 0.0507^{a}	0.049 0.0507^{a}	0.0719 0.0506	0.0860 0.0576	0.1211 0.0742
Petroleum	III(1)	0.1659^{b}	0.1532^{b}	0.1532^{b}	0.1007	0.1205	0.1977	III(1)	0.0570	0.0549	0.0549	0.0635	0.0761	0.0961
Silver	III(2)	0.2868^{c}	0.1648^{c}	0.1574^{b}	0.0970	0.1200	0.1675	III(2)	0.1035^{c}	0.0848^{b}	0.0848^{b}	0.0619	0.0712	0.1000
Tin	III(1)	0.1313^{b}	0.1255^{b}	0.1255^{b}	0.0966	0.1190	0.1616	III(1)	0.0882^{b}	0.0868^{b}	0.0868^{b}	0.0593	0.0706	0.0961
Zinc	III(2)	0.0315	0.0327	0.0327	0.0582	0.0708	0.0921	III(2)	0.0317	0.0330	0.0330	0.0421	0.0486	0.0597

$^{a, b, c}$ denote significance at 10%, 5% and 1%, respectively.

Table 6. Stationarity test. Smooth transition case.

	LINEAR								QUADRATIC							
	Model		*k*=0.5	*k*=0.8	*k*=0.9	c.v. 10%	c.v. 5%	c.v. 1%	Model		*k*=0.5	*k*=0.8	*k*=0.9	c.v. 10%	c.v. 5%	c.v. 1%
Aluminium	III(2)	$\hat{\lambda}_1 = 0.020; \hat{\gamma}_1 = 101.23$ $\hat{\lambda}_2 = 0.154; \hat{\gamma}_2 = 228.65$	0.1174[c]	0.1110[a]	0.1110[a]	0.0902	0.1114	0.1592	III(2)	$\hat{\lambda}_1 = 0.040; \hat{\gamma}_1 = 26.03$ $\hat{\lambda}_2 = 0.156; \hat{\gamma}_2 = 228.65$	0.0347	0.0356	0.0356	0.0425	0.0500	0.0670
Coal	I(1)	$\hat{\lambda}_1 = 0.853; \hat{\gamma}_1 = 184.44$	0.0866	0.0957[b]	0.1094[b]	0.0886	0.1089	0.1532	III(2)	$\hat{\lambda}_1 = 0.756; \hat{\gamma}_1 = 44.82$ $\hat{\lambda}_2 = 0.865; \hat{\gamma}_2 = 228.64$	0.0235	0.0259	0.0259	0.0358	0.0424	0.0576
Copper	III(2)	$\hat{\lambda}_1 = 0.409; \hat{\gamma}_1 = 228.65$ $\hat{\lambda}_2 = 0.940; \hat{\gamma}_2 = 58.80$	0.0567[b]	0.0561[b]	0.0561[b]	0.0395	0.0452	0.0589	III(2)	$\hat{\lambda}_1 = 0.238; \hat{\gamma}_1 = 174.26$ $\hat{\lambda}_2 = 0.924; \hat{\gamma}_2 = 44.81$	0.0270	0.0270	0.0270	0.0299	0.0345	0.0452
Iron	III(2)	$\hat{\lambda}_1 = 0.040; \hat{\gamma}_1 = 174.26$ $\hat{\lambda}_2 = 0.823; \hat{\gamma}_2 = 15.12$	00227	0.0227	0.0227	0.0377	0.0443	0.0604								
Lead									III(2)	$\hat{\lambda}_1 = 0.635; \hat{\gamma}_1 = 174.26$ $\hat{\lambda}_2 = 0.936; \hat{\gamma}_2 = 174.26$	0.0398[a]	0.0398[a]	0.0398[a]	0.0351	0.0404	0.0544
Gas	III(2)	$\hat{\lambda}_1 = 0.196; \hat{\gamma}_1 = 15.12$ $\hat{\lambda}_2 = 0.865; \hat{\gamma}_2 = 44.81$	0.0446[c]	0.0453[c]	0.0453[c]	0.0228	0.0261	0.0340	III(2)	$\hat{\lambda}_1 = 0.770; \hat{\gamma}_1 = 58.81$ $\hat{\lambda}_2 = 0.938; \hat{\gamma}_2 = 77.14$	0.0691[c]	0.0619[b]	0.0619[b]	0.0389	0.0457	0.0620
Níkel	III(2)	$\hat{\lambda}_1 = 0.805; \hat{\gamma}_1 = 15.12$ $\hat{\lambda}_2 = 0.979; \hat{\gamma}_2 = 101.22$	0.0406[a]	0.0399[a]	0.0399[a]	0.0386	0.0458	0.0617	III(2)	$\hat{\lambda}_1 = 0.825; \hat{\gamma}_1 = 15.12$ $\hat{\lambda}_2 = 0.979; \hat{\gamma}_2 = 101.22$	0.0414[b]	0.0406[b]	0.0406[b]	0.0283	0.0324	0.0428
Petroleum	III(1)	$\hat{\lambda}_1 = 0.920; \hat{\gamma}_1 = 81.85$	0.1273[a]	0.1142[a]	0.1142[a]	0.0931	0.1155	0.1614	III(1)	$\hat{\lambda}_1 = 0.922; \hat{\gamma}_1 = 213.78$	0.0567	0.0533	0.0533	0.0611	0.0731	0.1010
Silver	III(2)	$\hat{\lambda}_1 = 0.019; \hat{\gamma}_1 = 6.69$ $\hat{\lambda}_2 = 0.905; \hat{\gamma}_2 = 228.65$	0.0335[b]	0.0335[b]	00355[b]	0.0281	0.0322	0.0419	III(2)	$\hat{\lambda}_1 = 0.917; \hat{\gamma}_1 = 228.65$ $\hat{\lambda}_2 = 0.924; \hat{\gamma}_2 = 228.64$	0.0950[b]	0.0950[b]	0.0950[b]	0.0611	0.0728	0.1001
Tin	III(1)	$\hat{\lambda}_1 = 0.867; \hat{\gamma}_1 = 52.10$	0.0477	0.0495	0.0495	0.0772	0.0945	0.1368	III(1)	$\hat{\lambda}_1 = 0.868; \hat{\gamma}_1 = 61.72$	0.0524[a]	0.0525[a]	0.0525[a]	0.0487	0.0579	0.0786
Zinc	III(2)	$\hat{\lambda}_1 = 0.379; \hat{\gamma}_1 = 228.65$ $\hat{\lambda}_2 = 0.393; \hat{\gamma}_2 = 228.64$	0.0334	0.0334	0.0334	0.0544	0.0648	0.0888	III(2)	$\hat{\lambda}_1 = 0.379; \hat{\gamma}_1 = 228.65$ $\hat{\lambda}_2 = 0.392; \hat{\gamma}_2 = 228.64$	0.0331	0.0331	0.0331	0.0386	0.0442	0.0565

[a, b, c] denote significance at 10%, 5% and 1%, respectively.

Table 7. Results of model selection criteria.

<table>
<tr><th></th><th></th><th colspan="2">BREAK LINEAR</th><th colspan="2">SMOOTH LINEAR</th><th colspan="2">BREAK QUADRATIC</th><th colspan="2">SMOOTH QUADRATIC</th></tr>
<tr><td>Aluminium</td><td>NºChanges</td><td colspan="2">2</td><td colspan="2">2</td><td colspan="2">**2**</td><td colspan="2">2</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">496.3</td><td colspan="2">502.03</td><td colspan="2">**485.4**</td><td colspan="2">491.27</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">476.35</td><td colspan="2">477</td><td colspan="2">**462.9**</td><td colspan="2">463.77</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.897</td><td colspan="2">0.898</td><td colspan="2">**0.91**</td><td colspan="2">0.913</td></tr>
<tr><td>Coal</td><td>NºChanges</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">2</td><td colspan="2">**2**</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">11.26</td><td colspan="2">10.94</td><td colspan="2">-116.30</td><td colspan="2">**-126.49**</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">-2.71</td><td colspan="2">-3.04</td><td colspan="2">-141.47</td><td colspan="2">**-157.25**</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.7809</td><td colspan="2">0.7815</td><td colspan="2">0.9325</td><td colspan="2">**0.9417**</td></tr>
<tr><td>Copper</td><td>NºChanges</td><td>0</td><td>2</td><td>0</td><td>2</td><td>0</td><td>2</td><td>0</td><td>**2**</td></tr>
<tr><td></td><td>SIC</td><td>565.24</td><td>501.30</td><td>565.24</td><td>505.38</td><td>547.50</td><td>491.34</td><td>547.50</td><td>**496.49**</td></tr>
<tr><td></td><td>AIC</td><td>556.85</td><td>478.93</td><td>556.85</td><td>477.42</td><td>536.32</td><td>466.18</td><td>536.32</td><td>**465.74**</td></tr>
<tr><td></td><td>Adj. R^2</td><td>0.255</td><td>0.624</td><td>0.255</td><td>0.6617</td><td>0.3766</td><td>0.664</td><td>0.3766</td><td>**0.6979**</td></tr>
<tr><td>Iron</td><td>NºChanges</td><td colspan="2">2</td><td colspan="2">**2**</td><td colspan="2">0</td><td colspan="2">0</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">563.92</td><td colspan="2">**557.09**</td><td colspan="2">584.72</td><td colspan="2">584.72</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">542.76</td><td colspan="2">**530.64**</td><td colspan="2">571.50</td><td colspan="2">571.50</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.6393</td><td colspan="2">**0.7121**</td><td colspan="2">0.5115</td><td colspan="2">0.5115</td></tr>
<tr><td>Lead</td><td>NºChanges</td><td colspan="2">0</td><td colspan="2">0</td><td>0</td><td>**2**</td><td>0</td><td>2</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">258.57</td><td colspan="2">258.57</td><td>262.48</td><td>**207.57**</td><td>262.48</td><td>218.99</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">247.39</td><td colspan="2">247.39</td><td>248.50</td><td>**182.41**</td><td>248.50</td><td>188.24</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">-0.0045</td><td colspan="2">-0.0045</td><td>-0.0057</td><td>**0.473**</td><td>-0.0057</td><td>0.416</td></tr>
<tr><td>Gas</td><td>NºChanges</td><td colspan="2">2</td><td colspan="2">2</td><td colspan="2">2</td><td colspan="2">**2**</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">218.53</td><td colspan="2">188.78</td><td colspan="2">190.51</td><td colspan="2">**178.98**</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">200.32</td><td colspan="2">166.01</td><td colspan="2">170.02</td><td colspan="2">**153.94**</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.9621</td><td colspan="2">.9799</td><td colspan="2">0.9754</td><td colspan="2">**0.9808**</td></tr>
<tr><td>Nickel</td><td>NºChanges</td><td colspan="2">2</td><td colspan="2">2</td><td>0</td><td>**2**</td><td>0</td><td>2</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">462.39</td><td colspan="2">457.61</td><td>504.81</td><td>**453.48**</td><td>504.81</td><td>461.69</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">443.53</td><td colspan="2">434.04</td><td>493.03</td><td>**432.27**</td><td>493.03</td><td>435.77</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.5960</td><td colspan="2">0.6502</td><td>0.2109</td><td>**0.6542**</td><td>0.2109</td><td>0.6462</td></tr>
<tr><td>Petroleum</td><td>NºChanges</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">**1**</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">109.62</td><td colspan="2">200.33</td><td colspan="2">76.94</td><td colspan="2">**66.10**</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">92.90</td><td colspan="2">183.60</td><td colspan="2">57.43</td><td colspan="2">**46.59**</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.5964</td><td colspan="2">0.1406</td><td colspan="2">0.7021</td><td colspan="2">**0.7278**</td></tr>
<tr><td>Silver</td><td>NºChanges</td><td colspan="2">2</td><td colspan="2">2</td><td colspan="2">**2**</td><td colspan="2">2</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">1043.55</td><td colspan="2">1048.1</td><td colspan="2">**922.56**</td><td colspan="2">955.81</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">1021.18</td><td colspan="2">1020.1</td><td colspan="2">**897.40**</td><td colspan="2">925.06</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.7120</td><td colspan="2">0.7188</td><td colspan="2">**0.8972**</td><td colspan="2">0.8728</td></tr>
<tr><td>Tin</td><td>NºChanges</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">**1**</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">705.23</td><td colspan="2">796.89</td><td colspan="2">697.99</td><td colspan="2">**681.95**</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">689.25</td><td colspan="2">780.91</td><td colspan="2">679.35</td><td colspan="2">**663.30**</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">0.7486</td><td colspan="2">0.4030</td><td colspan="2">0.7730</td><td colspan="2">**0.8049**</td></tr>
<tr><td>Zinc</td><td>NºChanges</td><td colspan="2">**2**</td><td colspan="2">2</td><td colspan="2">2</td><td colspan="2">2</td></tr>
<tr><td></td><td>SIC</td><td colspan="2">**274.39**</td><td colspan="2">332.77</td><td colspan="2">279.16</td><td colspan="2">335.43</td></tr>
<tr><td></td><td>AIC</td><td colspan="2">**252.02**</td><td colspan="2">304.81</td><td colspan="2">253.99</td><td colspan="2">304.67</td></tr>
<tr><td></td><td>Adj. R^2</td><td colspan="2">**0.5127**</td><td colspan="2">0.2576</td><td colspan="2">0.5085</td><td colspan="2">0.3253</td></tr>
</table>

Table 8. Change dates and parameter estimates.

	BREAK LINEAR	SMOOTH LINEAR	BREAK QUADRATIC	SMOOTH QUADRATIC
Aluminum	1914; 1917	1917; 1919 $\hat{\lambda}_1 = 0.235$; $\hat{\gamma}_1 = 246.9$; $\hat{\lambda}_2 = 0.255$; $\hat{\gamma}_2 = 203.1$	**1899; 1908** $\hat{\beta}_0 = 277.8$; $\hat{\beta}_1 = -3432.1$; $\hat{\beta}_2 = 101.6$ $\hat{\delta}_1 = -13.3$; $\hat{\eta}_1 = 3479.1$; $\hat{\delta}_2 = -38.5$ $\hat{\eta}_2 = -228.4$	1899;1909 $\hat{\lambda}_1 = 0.040$; $\hat{\gamma}_1 = 26.0$; $\hat{\gamma}_2 = 228.6$ $\hat{\lambda}_2 = 0.156$
Coal	1974	1973 $\hat{\lambda}_1 = 0.853$; $\hat{\gamma}_1 = 184.4$	1958; 1974	**1961-2;1974** $\hat{\lambda}_1 = 0.756$; $\hat{\gamma}_1 = 44.8$; $\hat{\lambda}_2 = 0.865$ $\hat{\gamma}_2 = 228.6$ $\hat{\beta}_0 = 4.5$; $\hat{\beta}_1 = -5.7$; $\hat{\beta}_2 = 12.8$ $\hat{\delta}_1 = -17.8$; $\hat{\eta}_1 = 18.2$; $\hat{\delta}_2 = 78.5$; $\hat{\eta}_2 = -83.7$
Copper	1919; 1981	1919; 1984 $\hat{\lambda}_1 = 0.409$; $\hat{\lambda}_2 = 0.940$; $\hat{\gamma}_1 = 228.6$; $\hat{\gamma}_2 = 58.8$	1918; 1975	**1898; 1982** $\hat{\lambda}_1 = 0.238$; $\hat{\gamma}_1 = 174.3$; $\hat{\lambda}_2 = 0.924$ $\hat{\gamma}_2 = 44.8$ $\hat{\beta}_0 = 58.0$; $\hat{\beta}_1 = -145.9$; $\hat{\beta}_2 = 300.8$ $\hat{\delta}_1 = 67.7$; $\hat{\eta}_1 = -202.6$; $\hat{\delta}_2 = -369.4$; $\hat{\eta}_2 = 327.8$
Iron	1875; 1924	**1874; 1956** $\hat{\lambda}_1 = 0.040$; $\hat{\gamma}_1 = 174.3$; $\hat{\lambda}_2 = 0.823$ $\hat{\gamma}_2 = 15.1$ $\hat{\beta}_0 = 83.5$; $\hat{\beta}_1 = 3282$ $\hat{\delta}_1 = 29.4$; $\hat{\eta}_1 = -3345.1$; $\hat{\delta}_2 = 339.111$; $\hat{\eta}_2 = -272.018$	1875; 1949	1875-76; 1951-52 $\hat{\lambda}_1 = 0.052$; $\hat{\gamma}_1 = 246.9$; $\hat{\lambda}_2 = 0.784$ $\hat{\gamma}_2 = 8.9$
Lead			**1947; 1982** $\hat{\beta}_0 = 14.9$; $\hat{\beta}_1 = -4.2$; $\hat{\beta}_2 = -0.8$ $\hat{\delta}_1 = 5.6$; $\hat{\eta}_1 = -8.9$; $\hat{\delta}_2 = -7.6$; $\hat{\eta}_2 = 97.2$	1947; 1983 $\hat{\lambda}_1 = 0.635$; $\hat{\gamma}_1 = 174.3$; $\hat{\lambda}_2 = 0.936$ $\hat{\gamma}_2 = 174.3$

Gas	1974; 1984	1985; 1987 $\hat{\lambda}_1 = 0.902$; $\hat{\gamma}_1 = 23.8$; $\hat{\lambda}_2 = 0.942$ $\hat{\gamma}_2 = 113.2$	1974; 1984	**1985; 1988** $\hat{\lambda}_1 = 0.902$; $\hat{\gamma}_1 = 23.8$; $\hat{\lambda}_2 = 0.942$ $\hat{\gamma}_2 = 113.2$ $\hat{\beta}_0 = 19.6$; $\hat{\beta}_1 = -28.7$ $\hat{\delta}_1 = 1166.1$; $\hat{\eta}_1 = -1114.2$; $\hat{\delta}_2 = -742.2$; $\hat{\eta}_2 = 740.4$
Nickel	1970; 1988	1976; 1989 $\hat{\lambda}_1 = 0.805$; $\hat{\gamma}_1 = 15.1$; $\hat{\lambda}_2 = 0.979$ $\hat{\gamma}_2 = 101.2$	**1973; 1988** $\hat{\beta}_0 = 99.2$; $\hat{\beta}_1 = -172.0$; $\hat{\beta}_2 = 228.8$ $\hat{\delta}_1 = 30.9$; $\hat{\eta}_1 = -605.9$; $\hat{\delta}_2 = 175.1$; $\hat{\eta}_2 = -2679.1$	1977; 1989 $\hat{\lambda}_1 = 0.825$; $\hat{\gamma}_1 = 15.1$; $\hat{\lambda}_2 = 0.979$ $\hat{\gamma}_2 = 101.2$
Petroleum	1981	1981 $\hat{\lambda}_1 = 0.924$; $\hat{\gamma}_1 = 203.1$	1980	**1981** $\hat{\lambda}_1 = 0.922$; $\hat{\gamma}_1 = 228.6$ $\hat{\beta}_0 = 5.2$; $\hat{\beta}_1 = -9.9$; $\hat{\beta}_2 = 11.1$ $\hat{\delta}_1 = 149.3$; $\hat{\eta}_1 = -150.9$
Silver	1980; 1982	1980 $\hat{\lambda}_1 = 0.911$; $\hat{\gamma}_1 = 246.9$; $\hat{\lambda}_2 = 0.915$ $\hat{\gamma}_2 = 246.9$	**1980; 1982** $\hat{\beta}_0 = -9.2$; $\hat{\beta}_1 = 23.5$ $\hat{\delta}_1 = 1325.3$; $\hat{\eta}_1 = -737.3$; $\hat{\delta}_2 = -73.9$; $\hat{\eta}_2 = 708.5$	1979; 1982 $\hat{\lambda}_1 = 0.908$; $\hat{\gamma}_1 = 246.9$; $\hat{\lambda}_2 = 0.925$ $\hat{\gamma}_2 = 246.9$
Tin	1977	1977 $\hat{\lambda}_1 = 0.866$; $\hat{\gamma}_1 = 58.8$	1974	**1976** $\hat{\lambda}_1 = 0.867$; $\hat{\gamma}_1 = 58.8$ $\hat{\beta}_0 = 77.1$; $\hat{\beta}_1 = 48.3$; $\hat{\beta}_2 = 29.8$ $\hat{\delta}_1 = 2185.5$; $\hat{\eta}_1 = -2281.1$
Zinc	**1915; 1917** $\hat{\beta}_0 = 16.2$; $\hat{\beta}_1 = 2.2$ $\hat{\delta}_1 = 60.3$; $\hat{\eta}_1 = -4491.3$; $\hat{\delta}_2 = 9.2$; $\hat{\eta}_2 = 4496.3$	1916; 1918 $\hat{\lambda}_1 = 0.379$; $\hat{\gamma}_1 = 228.645$; $\hat{\lambda}_2 = 0.393$; $\hat{\gamma}_2 = 228.644$	1915; 1917	1916; 1918 $\tilde{\lambda}_1 = 0.379$; $\hat{\gamma}_1 = 228.645$; $\hat{\lambda}_2 = 0.392$ $\hat{\gamma}_2 = 228.644$

APPENDIX

A.1. The Perron and Yabu (2009) test

For the *a priori* unknown break date case, the Perron and Yabu (2009) test involves the following steps:

1. For each break date candidate, the data are detrended by OLS to obtain residuals $\hat{u}_t$.
2. Consider autoregression:

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

where k is chosen using the Bayesian Information Criterion (BIC) (k is allowed to be in the range $[0,[12(T/100)^{1/4}]]$). The corresponding estimate is denoted by $\tilde{\alpha}$, and $\tilde{\tau}$ is the t-ratio $\tilde{\tau} = \dfrac{\tilde{\alpha} - 1}{\tilde{\sigma}_\alpha}$, with $\tilde{\sigma}_\alpha$ being its standard deviation.

If k=0, we have AR(1) errors.

The AR(1) errors case

3. In order to improve the finite sample properties of the test, Perron and Yabu use a bias-corrected version of $\tilde{\alpha}$, denoted by $\tilde{\alpha}_M$:

$$\tilde{\alpha}_M = \tilde{\alpha} + C(\tilde{\tau})\tilde{\sigma}_\alpha$$

where

$$C(\tilde{\tau}) = \begin{cases} -\tilde{\tau} \ \ if \ \ \tilde{\tau} > \tau_{pct} \\ I_p T^{-1}\tilde{\tau} - (1+r)[\tilde{\tau} + c_2(\tilde{\tau} + a)]^{-1} \ \ if \ \ -a < \tilde{\tau} \le \tau_{pct} \\ I_p T^{-1}\tilde{\tau} - (1+r)\tilde{\tau}^{-1} \ \ if \ \ -c_1^{1/2} < \tilde{\tau} \le -a \\ 0 \ \ if \ \ \tilde{\tau} \le -c_1^{1/2} \end{cases} \tag{2a}$$

$c_1=(1+r)T$; $c_2 = [(1+r)T - \tau_{pct}^2(I_p + T)][\tau_{pct}(a + \tau_{pct}(I_p + T))]^{-1}$; a=10, τ_{pct} is a percentile of the limit distribution of $\tilde{\tau}$ when α=1. They recommend $\tau_{0.99}$ for the unknown break case. $I_p = [(p+1)/2]$, and p is the order of AR errors.

4. Next the proposal implies to use the following super-efficient estimate of α:

$$\tilde{\alpha}_{MS} = \begin{cases} \tilde{\alpha}_M \ \ if \ \ T^{\delta}|\tilde{\alpha}_M - 1| > 1 \\ 1 \ \ \ \ if \ \ T^{\delta}|\tilde{\alpha}_M - 1| \le 1 \end{cases} \tag{3a}$$

This super-efficient estimate is vital for obtaining procedures with nearly identical limit properties in the $I(0)$ and $I(1)$ cases.

5. Apply the quasi Generalized Least Squares (*GLS*) procedure with $\tilde{\alpha}_{MS}$ to obtain the estimate of Ψ:

$$(1 - \tilde{\alpha}_{MS})y_t = (1 - \tilde{\alpha}_{MS}L)x_t^{'}\Psi + (1 - \tilde{\alpha}_{MS}L)u_t, \ t = 2,...,T \tag{4a}$$
$$y_1 = x_1^{'}\Psi + u_1$$

Denote the resulting estimates by $\tilde{\Psi}$ and residuals by $\tilde{e}_t$.

Next, the Wald-statistic for testing the null hypothesis $R\Psi=a$ is constructed. Denote by $W_{RQF}(\lambda)$, where the subscript *RQF* stands for Robust Quasi Feasible GLS, the Wald statistic for a particular break fraction λ:

$$W_{RQF}(\lambda)=\left[R\left(\widetilde{\Psi}-\Psi\right)\right]'\left[s^2 R(X'X)^{-1}R'\right]^{-1}\left[R\left(\widetilde{\Psi}-\Psi\right)\right] \tag{5a}$$

where $X=\left\{x_t^{\widetilde{\alpha}_{MS}}\right\}$, $x_t^{\widetilde{\alpha}_{MS}}=(1-\widetilde{\alpha}_{MS}L)x_t$ for t=2,…,T; $x_1^{\widetilde{\alpha}_{MS}}=x_1$; $s^2=T^{-1}\sum_{t=1}^{T}\widetilde{e}_t^2$.

6. Finally, for an unknown break date, the test statistic is evaluated for each break date candidate for a range of possible breaks. Perron and Yabu (2009) consider several functionals of the Wald test, but recommend the application of the Exp functional:

$$ExpW=\log\left[T^{-1}\sum_{\lambda\in\Lambda}\exp\left(\frac{1}{2}W_{RQF}\left(\lambda'\right)\right)\right] \tag{6a}$$

where $\Lambda=\left\{\lambda';\varepsilon\leq\lambda'\leq 1-\varepsilon\right\}$, ($\lambda$' denotes a generic break fraction used to compute a particular value of the Wald test). ε>0 is a trimming parameter.

The AR(p) errors case

A modification is introduced in step 5, where the Wald statistic is replaced by

$$W_{RQF}(\lambda)=\left[R\left(\widetilde{\Psi}-\Psi\right)\right]'\left[\widetilde{h}_v(\lambda)R(X'X)^{-1}R'\right]^{-1}\left[R\left(\widetilde{\Psi}-\Psi\right)\right] \tag{7a}$$

$\widetilde{h}_v(\lambda)$ is an estimate of (2π times) the spectral density function of $v_t=(1-\alpha L)u_t$ at frequency zero. Its construction depends on the nature of the errors, I(0) or I(1).
In the I(0) case -when $\left|\widetilde{\alpha}_{MS}\right|<1$ - the kernel-based estimator

$$\widetilde{h}_v(\lambda)=T^{-1}\sum_{t=1}^{T}\hat{v}_t^2(\lambda)+2T^{-1}\sum_{j=1}^{T-1}\omega(j,m)\sum_{t=j+1}^{T}\hat{v}_t(\lambda)\hat{v}_{t-j}(\lambda) \tag{8a}$$

is used, where $\hat{v}_t$ are the OLS residuals from (4a). The function $\omega(j,m)$ is the quadratic spectral kernel and the bandwidth m is selected according a plug-in method, using an AR(1) approximation.
When $\widetilde{\alpha}_{MS}=1$, the above estimator can be obtained from the regression $\hat{v}_t=\sum_{i)1}^{k}\zeta_i\hat{v}_{t-i}+e_{tk}$, with k selected according to the BIC criteria. Denoting $\hat{\zeta}(L)=1-\hat{\zeta}_1 L-...-\hat{\zeta}_k L^k$ and $\hat{\sigma}_{ek}^2=(T-k)^{-1}\sum_{t=k+1}^{T}\hat{e}_{tk}^2$,

$$\widetilde{h}_v(\lambda)=\hat{\sigma}_{ek}^2/\hat{\zeta}(1)^2 \tag{9a}$$

With I(1) errors, and for models which involve a change in intercept (Models I and III), in order to attain a test with good properties, $\widetilde{\mu}_1$ is replaced by $\widetilde{\mu}_1^*$, where $\widetilde{\mu}_1^*=\widetilde{h}_v^{1/2}\hat{\zeta}(L)\widetilde{\mu}_1(T_1)/\hat{\sigma}_{ek}$.
The limiting distribution of the test is different for the I(0) and I(1) cases, but relevant quantiles are similar in both cases for the *Exp* functional. So, Perron and Yabu (2009) recommend taking the larger critical value in order to bring a powerful robust statistic under both stationary and integrated errors.

A.2. The Harvey *et al.* (2010) sequential procedure

If $S_1 > \kappa_\xi cv_\xi^1$, we assume that there is a first-level break at $\widetilde{t}_1 = \arg\max_{t\in\Lambda}(\hat{\omega})^{-1} T^{-1/2}\left|M_{t,[mT]} - \hat{\beta}_1\left[\frac{m}{2}T\right]\right|$. Then, as the possibility of more than one break in the interval $\Lambda_1 = \left[\widetilde{t}_1 - [mT]\right] + 1, \widetilde{t}_1 + [mT] - 1\ ]$ is excluded, the possibility of a further break occurring in the remaining portion of Λ, Λ-Λ_1, is examined.

If $\max_{t\in\Lambda-\Lambda_1,T}(\hat{\omega})^{-1} T^{-1/2}\left|M_{t,[mT]} - \hat{\beta}_1\left[\frac{m}{2}T\right]\right| \le cv_\xi^1$, the procedure based on S_1 selects one break; otherwise two breaks are selected. The number of breaks is denoted by $n_1^{'}$.

A similar procedure, based on S_0, allows one to select $n_0^{'}$ breaks.

The final number of breaks selected by the sequential procedure is $n_U = \max\left(n_1^{'}, n_0^{'}\right)$.

A.3. Monte Carlo Algorithm for the limiting critical values of the Landajo and Presno (2010) pseudo-LM stationarity test under smooth transition models

1. Fit by NLS the trend $f(t/T,\theta)$ in the null model (8).

2. Set the number of bootstrap resamples (b). Set the bootstrap sample size at T (the sample size) and create the $T\times d$ matrix of pseudo-regressors:

$$X_T = \left[\nabla_\theta f\left(1/T,\hat{\theta}_T\right)^{'}, \nabla_\theta f\left(2/T,\hat{\theta}_T\right)^{'}, \ldots, \nabla_\theta f\left(1,\hat{\theta}_T\right)^{'}\right]^{'}.$$

3. Draw an independent sample $\varepsilon^{(B)} = (\varepsilon_1, \ldots, \varepsilon_T)^{'}$ from a $N(0,1)$ population independent of $\hat{\theta}_T$.

4. Compute the bootstrap pseudo-residuals: $e^{(B)} = \left(I_T - X_T\left(X_T^{'}X_T\right)^{-1}X_T^{'}\right)\varepsilon^{(B)}$.

5. Compute the bootstrap pseudo-LM test statistic: $S_{\hat{\theta}_T}^{(B)} = \sigma_{e^{(B)}}^{-2} T^{-2} \sum_{t=1}^{T}\left(\sum_{i=t+1}^{T} e_i^{(B)}\right)^2$, where $\sigma_{e^{(B)}}^2 = T^{-1} e^{(B)'} e^{(B)}$.

6. Repeat steps (2)-(5) for b independent samples, and compute the sample percentiles of $S_{\hat{\theta}_T}^{(B)}$.