Breaking the Dynamic of Relative Primary Commodity Prices in Levels and Volatilities since 1650.

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Abstract

In this paper, we examine two important aspects of the dynamic of relative primary commodity prices, the secular trend and the short run volatility, employing 25 series, some of them starting as far back as 1650 and powerful panel data stationarity tests allowing for endogenous multiple structural breaks. These two aspects may have potentially severe consequences for the conduct of sustainable macro-economic and social stability policies particularly, for resource-rich countries relying on exporting one or few commodities for the bulk their export earnings. All the series have been found stationary but the results on the Prebish-Singer hypothesis, stating that relative commodity prices follow a downward secular trend, is mixed but with a majority of negative trends. We also investigate the dynamic of the volatility of the 25 relative primary commodity prices allowing for data driven number of breaks and dates. We found that primary commodity prices are highly volatile, often time varying and has been generally increasing in recent years which pose many challenges to policy makers.

1 Introduction

This paper investigates two of the challenges faced by policy makers when conducting macro, fiscal and social policies in resource-rich developing countries. The dynamic of relative primary commodity prices can be decomposed into essentially three components. The secular trend which has been considered as declining over time by Prebish (1950) and Singer (1950), the long cycles that affect relative primary commodity prices and finally their volatility which has been found often time varying and generally increasing in recent years (cf. Hadri

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(2011) for an analysis of the implications of these components for policymakers). In this paper we do not examine the long cycles component for lack of space. However, we investigate the Prebish-Singer hypothesis and the volatility of relative primary commodity prices using recent panel data technology. The first step in testing the Prebish-Singer hypothesis is to test for the stationarity of the series. This is important in the sense that depending if the series is stationary or not we must use the appropriate regression to test the Prebish-Singer Hypothesis. Let y_t be the logarithm of the relativel commodity price generated by a stationary process around a time trend then we must use the following equation:

$$y_t = \alpha + \beta t + \varepsilon_t, \ t = 1, \ldots, T, \tag{1}$$

where t is a linear trend and the random variable ε_t is stationary with mean 0 and variance σ_ε^2. The parameter of interest is the slope β, which is predicted negative under the PS hypothesis. If the real commodity prices were generated by a so called difference-stationary (DS or $I(1)$) model, implying that y_t is non-stationary then we should employ the following regression:

$$\Delta y_t = \beta + v_t, \ t = 1, \ldots, T, \tag{2}$$

where v_t is stationary . It is well known, now, that if y_t is a DS process, then using equation (1) to test the null hypothesis: $\beta = 0$ will result in acute size distortions, leading to a wrong rejection of the null when no trend is present, even asymptotically. Alternatively, if the true generating process is given by equation (1) and we base our test on equation (2). Our test becomes inefficient and less powerful than the one based on the correct equation. Therefore, when testing the PS hypothesis we have first to test the order of integration of our relative commodity prices in order to use the right regression. In this paper we use Hadri and Rao (2008) panel stationarity test in order to test jointly for the stationarity of our series in order to increase the power of the test relatively to its time series counterpart and to incorporate the information contained in the cross sectional dependence of our series. It is well known that there are generally positive and significant correlations between real primary commodity prices. Pindyck and Rotemberg (1990) noted this strong correlation in the real prices of unrelated commodities which they called "Excess co-movement". They found that even after controlling for current and expected future values of macroeconomic variables this excess co-movement remains. We use very long series, some of them starting in 1650 and therefore, it is highly likely that they will show multiple breaks. Since the pioneering work of Perron (1989) it is widely accepted that the failure of taking into account structural breaks is likely to lead to a significant loss of power in unit root tests. Similarly, stationarity tests ignoring the existence of breaks diverge and thus are biased toward rejecting the null hypothesis of stationarity in favour of the false alternative of a unit root hypothesis. This is due to severe size distortion caused by the presence of breaks (see *inter alia* Lee *et al.* (1997). Therefore in our panel stationarity tests we allow for endogenous multiple breaks not only in order to avoid biases in our tests but also to exploit the information on the breaks and find out whenever possible the causes of these breaks and the change of the signs in the piecewise regressions of the trend. The second step deals with testing the significance and finding the sign of the slopes of the appropriate regressions in order to find out if the Prebish-Singer hypothesis is not rejected by the data. The consequences of the acceptance of the Prebish-Singer hypothesis are very important particularly for developing countries, because many of them depends on only a few primary commodities to generate most of their export earnings. This overwhelming commodity reliance has serious policy consequences. The country concerned might have to explore diversifying its export portfolio to include manufactures and services for which it has comparative advantages.

The second part of the paper examines the volatility of primary commodity prices. It is well known that primary commodity prices are highly volatile (c.f. Mintz (1967), Reinhart and Wickham (1994) and for oil, Dvir and Rogoff (2009). High volatility in the prices of real commodity prices is an important cause of economic and social instability particularly in developing countries. In this paper, using long series some of them starting as far as 1650 we test for data driven structural breaks employing Bai and Perron (1998) methodology. As in the first part, we try to identify the causes of these breaks. The other innovation in this paper comparatively to most previous papers is that not only we are using very long series but we are also using relative primary commodity prices instead of indices made after aggregation of commodity prices and by so doing we avoid the aggregation bias and the generally ad-hoc weighting rule to combine the commodity prices involved.

2 Panel stationarity tests with multiple structural breaks

In this paper we extend Hadri and Rao (2008) to deal with multiple breaks. In Hadri and Rao (2008) we considered four possibilities of effects that a single break may cause on the deterministic parts of the model under the null hypothesis. Model 0 has a break in the level (α_i) and no trend ($\beta_i = 0$). Model 1 allows for a break in the level and a time trend without a break ("crash model" in Perron's terminology) and Model 2 permits a break in the slope only. In Model 3, a break is admitted in both the level and the slope. Model 3 is the most general model which encompasses the three other models. Model 3 is specified as follows:

$$\text{Model 3:} \quad y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \gamma_i DT_{it} + \epsilon_{it}, \tag{3}$$

with

$$r_{it} = r_{it-1} + u_{it}, \tag{4}$$

where y_{it}, $i = 1, ..., N$ individuals and $t = 1, ..., T$ time periods, are the observed series for which we wish to test stationarity. For all i, $\alpha_i^{\prime}s$, $\beta_i^{\prime}s$, $\delta_i^{\prime}s$ and $\gamma_i^{\prime}s$ are unknown parameters. r_{it} is a random walk with initial values $r_{i0} = 0$ $\forall i$. Under the null hypothesis of y_{it} being stationary r_{it} reduces to zero and Model 3 becomes:

$$y_{it} = \alpha_i + \delta_i D_{it} + \beta_i t + \gamma_i DT_{it} + \epsilon_{it},$$

For testing the Prebish-Singer hypothesis on the basis of the general to specific methodology we shall be using solely Model 3.

Within the panel data framework, two models among the four models proposed in Hadri and Rao (2008) were able to allow for multiple breaks (see also Carrion-i-Silvestre, Del Barrio and López-Bazo (2005), thereafter CDL). Each of the two models is based on different break effects, i.e. breaks in the level and no trend (model 0) and breaks in both the level and the trend (model 3). The general model considered here can be written as follows:

$$y_{i,t} = \alpha_{i,t} + \beta_i t + \varepsilon_{i,t},$$

$$\alpha_{i,t} = \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \sum_{k=1}^{m_i} \gamma_{i,k} D(T_{b,k}^i)_t + \alpha_{i,t-1} + \nu_{i,t},$$

where $\nu_{i,t} \sim i.i.d(0, \sigma_{v,i}^2)$, $\varepsilon_{i,t}$ is allowed to be serially correlated. $\{\nu_{i,t}\}$ and $\{\varepsilon_{i,t}\}$ are assumed to be mutually independent across i and over t. This assumption is relaxed later to allow for cross-sectional dependence. $D(T_{b,k}^i)_t$ and $DU_{i,k,t}$ are defined as $D(T_{b,k}^i)_t = 1$ for $t = T_{b,k}^i + 1$ and 0 elsewhere, and $DU_{i,k,t} = 1$ for $t > T_{b,k}^i$ and 0 elsewhere with $T_{b,k}^i$ denoting the kth date of break for the ith individual, $k = 1, ..., m_i$. The null hypothesis is specified as $\sigma_{v,i}^2 = 0$ for all i, under which we obtain:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} D(T_{b,k}^i)_t + \nu_{i,t}. \tag{5}$$

Hence, model 0 is obtained when $\beta_i = \gamma_{i,k} = 0$, and model 3 is defined if $\beta_i \neq 0$ and $\gamma_{i,k} \neq 0$, α_i is the initial value of $\alpha_{i,t}$.

The proposed test statistic, which is based on Hadri (2000) LM test, is expressed as:

$$LM(\lambda) = N^{-1} \sum_{i=1}^{N} (\hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}_{i,t}^2), \tag{6}$$

where $\hat{S}_{i,t}^2 = \sum_{j=1}^{t} \hat{\varepsilon}_{i,t}$ denotes the partial sum of OLS estimated residuals $\hat{\varepsilon}_{i,t}$. For each i, $\lambda_i = (\lambda_{i,1}, ..., \lambda_{i,m_i})^{\prime} = (T_{b,1}^i/T, .., T_{b,m_i}^i/T)^{\prime}$ indicates the locations of the breaks over T. Since autocorrelation is allowed in the residuals, $\hat{\omega}_i^2$ is a consistent long-run variance (LRV) estimate of $\hat{\varepsilon}_{i,t}$ for each i. To obtain a consistent estimor of $\hat{\omega}_i^2$, we use a nonparametric method jointly with the boundary condition rule suggested by Sul *et al.* (2003) which is shown to be effective in avoiding inconsistency problems in the KPSS-type test. Using appropriate moments and applying a Central Limit Theorem (CLT), the limiting distribution of the statistic (6) is shown to be a standard normal, that is,

$$Z(\lambda) = \frac{\sqrt{N}(LM(\lambda) - \bar{\xi})}{\bar{\varsigma}} \Longrightarrow N(0,1),$$

with

$$\bar{\xi} = N^{-1}\sum_{i=1}^{N}\xi_i,\ \overline{\varsigma^2} = N^{-1}\sum_{i=1}^{N}\varsigma_i^2.$$

The asymptotic mean and variances for each individual have been provided in CBL (2005) as follows:

$$\xi_i = A\sum_{k=1}^{m_i+1}(\lambda_{i,k} - \lambda_{i,k-1})^2;\ \varsigma_i^2 = B\sum_{k=1}^{m_i+1}(\lambda_{i,k} - \lambda_{i,k-1})^4.$$

The values of A and B equal the values of moments in Hadri (2000), that is, for model 0, $A = \frac{1}{6}$, $B = \frac{1}{45}$; for model 3, $A = \frac{1}{15}$, $B = \frac{11}{6300}$.

In the situation where break dates are unknown, the SSR procedure is employed to estimate the break points, that is, the estimated break dates are obtained by minimizing the sum of squared residuals. To estimate multiple break dates we employ the method of Bai and Perron (1998) that computes the global minimization of the SSR, so that all the break dates are estimated via minimizing the sequence of individual $SSR(T_{b,1}^i, ..., T_{b,m_i}^i)$ computed from (5)

$$(\hat{T}_{b,1}^i, ..., \hat{T}_{b,m_i}^i) = \arg\min_{T_{b,1}^i,...,T_{b,m_i}^i} SSR(T_{b,1}^i, ..., T_{b,m_i}^i).$$

2.1 Testing the presence of multiple structural changes

In order to obtain a consistent estimation of the number and dates of the breaks we have first to test for the presence of breaks in the series of interest. Bai and Perron (1998) suggest a sup Wald type tests for the null hypothesis of no change against an alternative containing an arbitrary number of changes.They also propose a sequential test. In this paper, we use the Double maximum tests which have the advantage that a prespecification of a particular number of breaks are not required before testing the significance of the breaks. Therefore, we can test with the null hypothesis of no structural break against an unknown number of breaks with given bound M of number of breaks. It is pointed out by Perron (2005) that Double Maximum tests can play a significant role in testing for structural changes and it is most useful tests to apply when determing if structural changes are present. In addition, it is also shown in Bai and Perron (2005) by simulations that the double maximum tests is as powerful as the best power that can be chieved using the test that accounts for the correct number of breaks. For the Double maximum tests, the UDmax and WDmax are used and are defined as follows:

$$UD\max F_T(M,q) = \max_{1\leq m\leq M} \sup_{(\lambda_1,...,\lambda_m)\in\Lambda_\epsilon} F_T(\lambda_1,...,\lambda_m;q)$$

$$WD\max F_T(M,q) = \max_{1\leq m\leq M} \frac{c(q,\alpha,1)}{c(q,\alpha,m)} \times \sup_{(\lambda_1,...,\lambda_m)\in\Lambda_\epsilon} F_T(\lambda_1,...,\lambda_m;q)$$

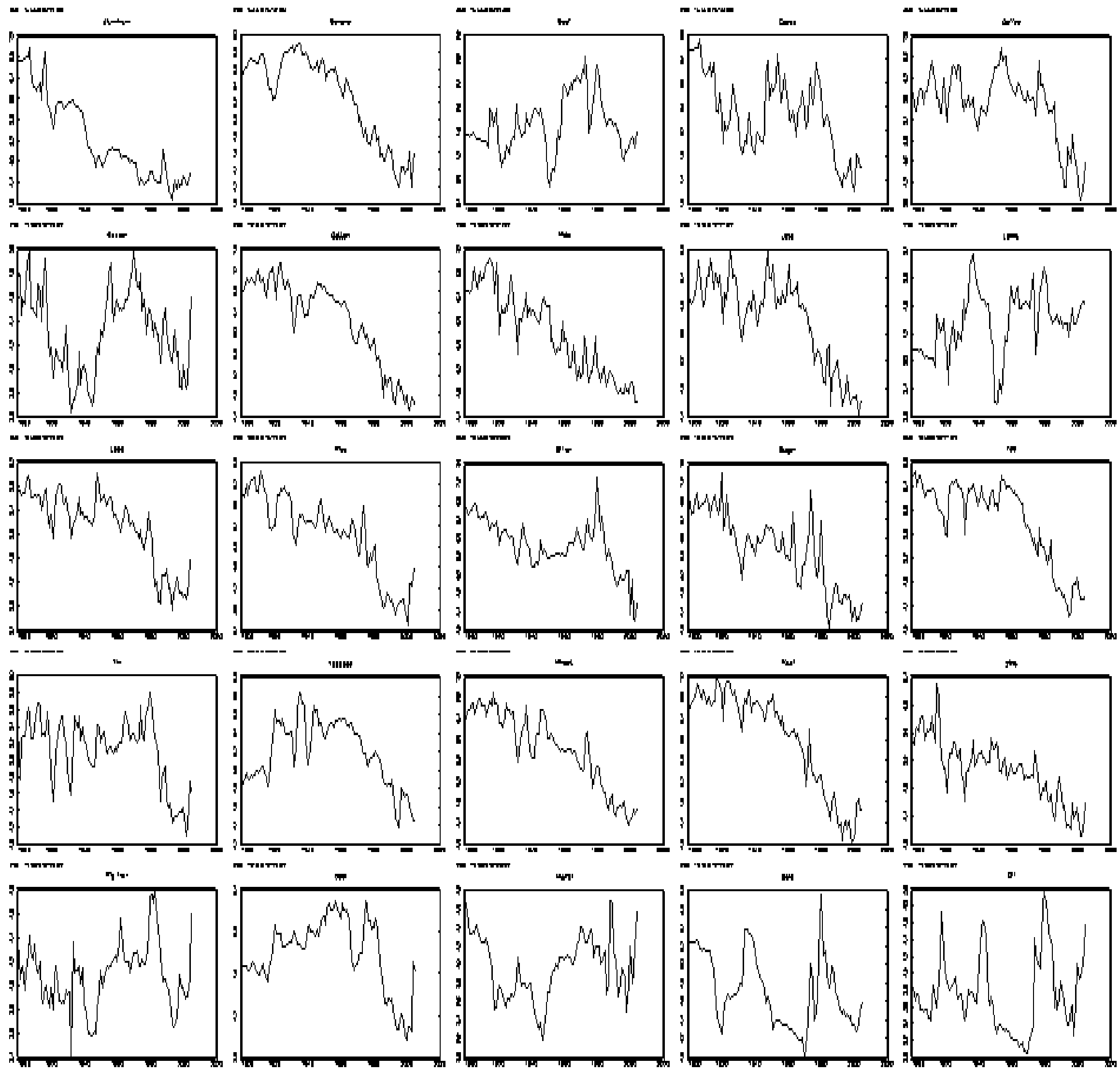
The $UDmax$ is an equal version of Double maximum tests which assuming equal weights to the possible number of structural changes. And $WDmax$ applies weights to the invidividual tests such that the marginal p-values are equal across values of number of breaks. The values of these two tests are reported in the appropriate Tables. All the $UDmax$ and $WDmax$ tests are significant at 1% signicance level . This clearly shows that at least one structural break is present for any of the real primary commodity price.

3 Data

We employ 25 *relative commodity prices* constructed by Harvey, Kellard Madsen and Wohar (2010)[2]. They calculate these relative commodity prices by deflating the nominal commodity series with their manufacturing value-added price index. Eight relative commodity prices cover the period 1650-2005. These are: Beef, Lamb, Lead, Sugar, Wheat, Wool, Coal and Gold. We call this set 1.The relative prices of Aluminum, Cocoa, Coffee, Copper, Cotton, Hide, Rice, Silver, Tea, Tin, Tobacco, Zinc, Pig Iron, Nickel and oil cover the period 1872-2005. We call set 2, the set including all the commodity prices for which we have observations during the period 1872-2005 including set 1. Finally, the relative commodity prices of Banana and Jute cover the period 1900-2005. We call set 3, the balanced panel including all the 25 relative commodity prices covering the period 1900-2005. Fig 1 plots the natural logarithm of the 25 relative commodity prices covering the period 1900-2005. Tabl1 gives the cross-sectional correlations between all the commodity prices.

[2] We thank David Harvey for providing the data.

Fig 1



Plot of relative commodity prices

4 Empirical Results

4.1 Testing the Prebish-Singer hypothesis

4.1.1 Testing the stationarity of relative commodity prices

The first step when testing the Prebish-Singer hypothesis is to test for the stationarity of the series in order to use the right equation to estimate the significance and the sign of the coefficient of the time trend β. As explained above, we employ a panel stationarity tests allowing for serial correlation, cross-sectional dependence and endogenous multiple breaks. The maximum breaks allowed are specified as $m\max = 5$ and 8. But we report only $m\max = 5$ as the difference between the two is negligeable. The numbers of breaks are determined by using the modified Schwarz Information Criterion (LWZ). The Bootstrap method is employed to correct for cross-sectional dependence. The critical values, with numbers of replications equal to 5000, are reported in the Tables below. The correction for cross-sectional dependence is essential as the relative commodity prices have been shown in Table 1 to be highly correlated.

The following Tables summarize the results of break $m\max = 5$ estimations. To make the best use of the information contained in the data, we consider three sets of data. In Table 2 we report the results of the panel stationarity tests for 25 commoditiy prices for the period 1900-2005. We first test for the presence of structural breaks in the series using $UD\max$ and $WD\max$. Both tests are significant at 1% significance level. This clearly shows that at least one structural break is present for all the relative primary commodity prices. (simliar results apply for the other sets and therefore we do not report the critical values). Then we determine the number of breaks and the break dates. The bootstrap critical values show clearly that the null hypothesis of joint stationarity of the series is not rejected at the the 5% and 10% levels. In Tables 3 and 4 we carry the same tests for respectively set 1 and set 2 and for both the null hypothesis of joint stationarity of the series is not rejected at the the 5% and 10% levels. Finally, Table 5, Table 6 and Table 7 report the piecewise regressions for respectively set 3, set 1 and set 2.

Table 1: Cross-sectional correlations between all the commodity prices

1.0																					
0.7	1.0																				
−0.2	−0.1	1.0																			
0.5	0.5	0.0	1.0																		
0.4	0.7	0.0	0.7	1.0																	
0.2	0.0	0.3	0.6	0.4	1.0																
0.7	0.9	−0.1	0.7	0.8	0.2	1.0															
0.9	0.8	−0.2	0.6	0.6	0.1	0.9	1.0														
0.6	0.9	−0.0	0.6	0.8	0.3	0.9	0.8	1.0													
−0.3	−0.2	0.7	−0.4	−0.3	−0.2	−0.3	−0.3	−0.3	1.0												
0.7	0.9	−0.0	0.7	0.8	0.3	0.9	0.8	0.9	−0.3	1.0											
0.8	0.9	−0.1	0.7	0.7	0.2	0.9	0.8	0.9	−0.3	0.9	1.0										
0.6	0.5	0.2	0.7	0.6	0.4	0.6	0.6	0.6	−0.1	0.6	0.6	1.0									
0.7	0.7	−0.1	0.7	0.6	0.3	0.9	0.8	0.8	−0.3	0.8	0.9	0.7	1.0								
0.7	0.9	−0.0	0.7	0.8	0.2	0.9	0.8	0.9	−0.2	0.9	0.9	0.6	0.7	1.0							
0.4	0.6	0.3	0.7	0.7	0.4	0.7	0.5	0.7	0.0	0.7	0.7	0.8	0.6	0.7	1.0						
0.1	0.6	0.2	0.2	0.6	−0.1	0.6	0.3	0.6	0.1	0.6	0.5	0.3	0.4	0.7	0.5	1.0					
0.8	0.9	−0.1	0.7	0.7	0.2	0.9	0.9	0.9	−0.3	0.9	0.9	0.7	0.9	0.9	0.6	0.5	1.0				
0.8	0.9	−0.2	0.6	0.7	0.1	0.9	0.9	0.9	−0.3	0.9	0.9	0.6	0.8	0.9	0.6	0.6	0.9	1.0			
0.8	0.8	−0.1	0.7	0.6	0.4	0.9	0.9	0.8	−0.3	0.9	0.9	0.7	0.9	0.8	0.7	0.4	0.9	0.8	1.0		
−0.1	−0.1	0.4	0.3	0.2	0.5	−0.1	−0.2	0.0	0.1	0.0	0.0	0.4	0.0	0.0	0.4	0.0	−0.1	−0.1	0.0	1.0	
0.1	0.6	0.2	0.4	0.7	0.1	0.6	0.3	0.6	0.0	0.6	0.5	0.4	0.4	0.6	0.6	0.8	0.5	0.6	0.4	0.2	1.0
0.1	−0.2	0.2	0.3	−0.0	0.7	−0.2	−0.2	−0.2	0.0	−0.1	0.0	0.2	0.0	−0.1	0.1	−0.4	−0.2	−0.2	0.0	0.6	−0.
0.5	0.3	0.0	0.3	0.1	−0.1	0.2	0.4	0.1	0.1	0.2	0.4	0.5	0.4	0.2	0.4	−0.1	0.3	0.3	0.4	0.2	0.0
−0.1	−0.2	0.1	−0.1	−0.2	−0.3	−0.1	0.0	−0.3	0.2	−0.2	−0.1	0.1	0.0	−0.2	0.1	−0.1	−0.1	−0.1	−0.1	0.1	0.0

Table 2. Summary of estimated numbers and location of structural breaks
(m max=5)
(25 commodities from 1900-2005, set 3)

Commodities	Estimated Break Dates (m max = 5)					$UDmax$	$WDmax$
	TB_1	TB_2	TB_3	TB_4	TB_5		
Aluminum	1918	1941				78.26	171.84
Banana	1916	1931	1971			238.01	425.41
Beef	1950	1965				140.58	177.83
Cocoa	1947	1973	1989			85.27	187.22
Coffee	1949	1987				131.79	175.55
Copper	1947	1975				111.57	141.14
Cotton	1930	1946				319.80	568.25
Hide	1921	1952				32.57	35.92
Jute	1947					104.15	209.73
Lamb	1935	1950	1965			285.48	427.24
Lead	1947	1982				120.11	151.94
Rice	1982					75.66	113.09
Silver	1940	1979				139.94	177.02
Sugar	1925	1965	1982			31.01	68.08
Tea	1922	1954	1986			321.52	571.30
Tin	1986					75.54	95.56
Tobacco	1918	1968				497.30	629.10
Wheat	1946					34.91	57.25
Wool	1948	1991				187.97	237.78
Zinc	1918	1948				23.42	46.14
Pig Iron	1933	1948	1987			56.43	100.28
Coal	1966	1984				166.29	365.12
Nickel	1931	1950	1991			142.47	312.81
Gold	1917	1934	1957	1979		288.03	632.42
Oil	1946	1974	1991			76.22	122.49

Panel Stationarity test	Statistics Value	Bootstrap Critical Values	
		10%	5%
Homogeneous variance	5.498	12.521	12.911
Heterogeneous variance	3.009	4.939	5.414

Table 3. Summary of estimated numbers and location of structural breaks (m max=5)
(8 commodities from 1650-2005, set 1)

Commodities	Estimated Break Dates (m max = 5)				
	TB_1	TB_2	TB_3	TB_4	TB_5
Beef	1793	1876	1952		
Lamb	1793	1894	1947		
Lead	1721	1793	1851	1946	
Sugar	1833				
Wheat	1837	1945			
Wool	1793	1875	1947		
Coal	1892	1952			
Gold	1793	1913			

Panel Stationarity test	Statistics Value	Bootstrap Critical Values	
		10%	5%
Homogeneous variance	0.176	2.706	3.290
Heterogeneous variance	2.207	2.526	3.096

Table 4. Summary of estimated numbers and location of structural breaks (m max=5)
(23 commodities from 1872-2005, set 2)

Commodities	Estimated Break Dates (m max = 5)				
	TB_1	TB_2	TB_3	TB_4	TB_5
Aluminum	1891	1918	1940		
Beef	1949	1969			
Cocoa	1907	1946	1985		
Coffee	1949				
Copper	1898	1946	1974		
Cotton	1945				
Hide	1920	1951			
Lamb	1934	1955			
Lead	1946	1981			
Rice	1981				
Silver	1939	1978			
Sugar	1928	1981			
Tea	1922	1953	1985		
Tin	1985				
Tobacco	1894	1917	1967		
Wheat	1945				
Wool	1947	1982			
Zinc	1917	1947			
Pig Iron	1948	1985			
Coal	1964	1984			
Nickel	1899	1949			
Gold	1916	1938	1958	1978	
Oil	1915	1973			

Panel Stationarity test	Statistics Value	Bootstrap Critical Values	
		10%	5%
Homogeneous variance	1.849	4.380	5.103
Heterogeneous variance	2.624	3.988	4.619

4.1.2 Piecewise regressions

After determing the presence, the numbers and the locations of structral breaks for the above relative commodity prices, we consider piecewise regressions to examine the signs, the significance and change of signs over time of the slopes of these regressions. The log of the relative commodity prices are used in the regressions. For each commodity we fit a linear trend model, i.e., $y_t = \alpha + \beta t + \varepsilon_t$ before and after the break dates. The results are summarized in the Tables below for the three sets considered in this paper. $\hat{\beta}_m$ represents the estimated slope for the linear regression model before the m^{th} structural break. The values in bracket are the p-values for the corresponding parameters.

Table 5. Piecewise regression results ($m\,$max=5)
(25 commodities from 1900-2005, set 3)

Commodities	Piecewise Regression				
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$
Aluminum	-0.03*(0.01)	-0.01(0.18)	-0.01*(0.00)		
Banana	0.01(0.00)	0.04(0.00)	-0.02*(0.00)	-0.02*(0.00)	
Beef	0.01(0.00)	0.12(0.00)	-0.03*(0.00)		
Cocoa	-0.04*(0.00)	-0.02*(0.00)	-0.05*(0.00)	0.004(0.32)	
Coffee	-0.006*(0.02)	-0.02*(0.00)	-0.044*(0.00)		
Copper	-0.02*(0.00)	0.02(0.00)	-0.02*(0.00)		
Cotton	0.00(0.19)	0.01(0.21)	-0.04*(0.00)		
Hide	0.02(0.00)	-0.001(0.39)	-0.02*(0.00)		
Jute	-0.01*(0.00)	-0.04*(0.00)			
Lamb	0.02(0.00)	-0.07*(0.00)	0.12(0.00)	-0.01*(0.01)	
Lead	-0.01*(0.00)	-0.02*(0.00)	-0.01(0.17)		
Rice	-0 .01*(0.00)	-0.01(0.21)			
Silver	-0.02*(0.00)	0.02(0.00)	-0.08*(0.00)		
Sugar	-0.004(0.27)	-0.002(0.30)	0.04(0.09)	-0.02*(0.00)	
Tea	-0.04*(0.00)	-0.004(0.18)	-0.05*(0.00)	-0.01(0.12)	
Tin	0.001(0.18)	-0.02*(0.00)			
Tobacco	0.004(0.07)	0.003(0.049)	-0.03*(0.00)		
Wheat	-0.02*(0.00)	-0.03*(0.00)			
Wool	-0.006*(0.00)	-0.05*(0.00)	0.02(0.05)		
Zinc	0.02(0.03)	0.00(0.49)	-0.02*(0.00)		
Pig Iron	-0.014*(0.00)	-0.04*(0.00)	0.01(0.00)	0.003(0.36)	
Coal	0.01(0.00)	0.02(0.01)	-0.02*(0.01)		
Nickel	-0.04*(0.00)	-0.04*(0.00)	0.01(0.00)	0.03(0.02)	
Gold	-0.02*(0.00)	0.02(0.00)	-0.05*(0.00)	0.01(0.02)	-0.03*(0.00)
Oil	0.01(0.00)	-0.02*(0.00)	-0.02(0.17)	0.05(0.00)	

Table 6. Piecewise regression results (m max=5)
(8 commodities from 1650-2005, set 1)

Commodities	Piecewise Regression				
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$
Beef	0.002(0.00)	0.014(0.00)	-0..002*(0.03)	-0.01*(0.02)	
Lamb	0.001(0.00)	0.014(0.00)	0.02(0.00)	0.018(0.00)	
Lead	-0.01*(0.00)	0.00(0.05)	0.01(0.00)	-0.01*(0.00)	-0.03*(0.00)
Sugar	-0.003*(0.00)	-0.02*(0.00)			
Wheat	0.00(0.00)	-0.01*(0.00)	-0.03*(0.00)		
Wool	-0.002*(0.00)	0.02(0.00)	-0.01*(0.00)	-0.05*(0.00)	
Coal	0.001(0.00)	0.01(0.00)	-0.02*(0.00)		
Gold	0.001(0.001)	0.01(0.00)	-0.003*(0.01)		

Table 7. Piecewise regression results (m max=5)
(23 commodities from 1872-2005, set 2)

Commodities	Piecewise Regression				
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$
Aluminum	-0.03*(0.003)	-0.07*(0.00)	-0.01(0.18)	-0.012*(0.00)	
Beef	0.00(0.358)	0.10(0.00)	-0.04*(0.00)		
Cocoa	0.01(0.002)	-0.04*(0.00)	-0.01*(0.04)	-0.02*(0.012)	
Coffee	-0.01*(0.00)	-0.04*(0.00)			
Copper	-0.02*(0.00)	-0.02*(0.00)	0.02(0.00)	-0.02*(0.00)	
Cotton	-0.01*(0.00)	-0.04*(0.00)			
Hide	0.002(0.14)	-0.001(0.39)	-0.02*(0.00)		
Lamb	0.001(0.16)	-0.10*(0.00)	0.00(0.46)		
Lead	-0.004*(0.00)	-0.02*(0.00)	-0.01(0.17)		
Rice	-0.01*(0.00)	-0.01(0.21)			
Silver	-0.024*(0.00)	0.02(0.00)	-0.08*(0.00)		
Sugar	-0.02*(0.00)	-0.003(0.22)	-0.02*(0.00)		
Tea	-0.03*(0.00)	-0.01*(0.01)	-0.05*(0.00)	-0.01(0.12)	
Tin	0.004(0.00)	-0.02*(0.00)			
Tobacco	0.05(0.00)	-0.00(0.35)	0.003(0.05)	-0.03*(0.00)	
Wheat	-0.012*(0.00)	-0.03*(0.00)			
Wool	-0.01*(0.00)	-0.05*(0.00)	-0.02*(0.02)		
Zinc	0.001(0.294)	0.00(0.49)	-0.02*(0.00)		
Pig Iron	-0.01*(0.00)	0.01(0.00)	-0.004(0.32)		
Coal	0.01(0.00)	0.01(0.17)	-0.012*(0.05)		
Nickel	-0.07*(0.00)	-0.02*(0.00)	0.002(0.16)		
Gold	0.00(0.37)	0.04(0.00)	-0.05*(0.00)	0.02(0.01)	-0.04*(0.00)
Oil	-0.02*(0.00)	-0.02*(0.00)	-0.02*(0.02)		

4.1.3 Analysis of the results of the Prebish-Singer testing

Table 2 and Table 5 report the results for set 3. Table 2 indicates the timing and the number of breaks for the 25 primary commodities whereas Table 5 shows the corresponding significance and sign of the slopes of the piecewise regressions. Four commodities have 1 break, thirteen have 2 breaks, seven register 3 breaks and only one (gold) has 4 breaks. On the total of 80 slopes, 41 are negative and significant, 11 are negative but insignificant, 21 are positive and significant finally, 7 are positive and unsignificant. Table 3 and Table 6 concern set 1. One commodity has one break (sugar), three commodities have 2 breaks, three other commodities are affected by 3 breaks and one commodity has 4 breaks. For 27 slopes, 13 are negative and significant, 13 other are positive and significant and one is positive but unsignificant.Table 4 and Table 7 deal with set 2. Five commodities have one break, twelve have 2 breaks, five have 3 breaks and one commodity has four breaks. There are 71 slopes. fourty four are negative and significant, 7 are negative but unsignificant, 11 are positive and significant and 9 are positive but unsignificant. These results seem to indicate that in the majority of cases the PS hypothesis is not rejected.

It will be interesting to match the breaks to some events that happened in the past. For the investigation of the drivers of the breaks, we shall consider for each commodity price only its longest series. To find the causes of the breaks, a historical analysis of primary commodity markets is indispensable. Radetzki (2011) shows that the share of the primary sector in GDP has declined steadily overtime in advanced economies. Recently, most of the total consumption growth of primary commodities took place in emerging economies like China. For instance, its share of total consumption growth in this century was 50%. In the case of copper China's utilization between 2000 and 2008 corresponds to 113% of total increase Cochilco (2009). More amazing, China's import growth of iron ore between 2000 and 2009 corresponded to 125% of total import growth (UNCTAD, 2010). The decline of the share of the commodity sector in GDP can also be explained by the growing hability to create man made substitutes. Despite the important decline of its share in GDP, the primary sector remains crucial for the good functioning of a modern economy. Another aspect analysed by Radetzki (2011) is the role of relentless falling transport costs in shaping and expanding primary commodity markets since the 19th century. Up to mid-19th century, shipment rates on long hauls was prohibitively high. Only high value primary commodities like coffee, cocoa, spices and precious or semi-precious metals could be transported. However, towards the end of the second-half of the 19th century, the use of the steam technology made long hauls transport more affordable and benefited primary commodities like cotton, wheat, wool ... Also, the introduction around 1880s of refrigeration made possible the transport of meat and fruit over long distances. Between 1950 and 1970 steady improvements in specialized bulk carriers lead to dramatic fall in the transport costs of heavy primary commodities like iron ore, coal, bauzite, oil... Finally, state intervention starting early 1930s and beginning to fade in 1970s may had some effects on the formation of prices of primary commodities.

Radetzki (2011) considers four main factors explaing state intrusion in primary commodity production and commerce: (1) the Great Depression of 1930s led to the price collapse of many primary commodities like wheat, sugar, rubber..., (2) the second world war provoked havoc in the supply routes of numerous commodities including sugar, wheat, coffee, tin...., (3) the breakup of colonial empires affected greatly the functioning of primary commodity markets (buying at above market prices, food aid...), (4) the period 1925 to 1975 wittnessed the wide spread belief in collectivism. But since the 1980s government control started to fade excepy notably in oil industries where it remains strong.

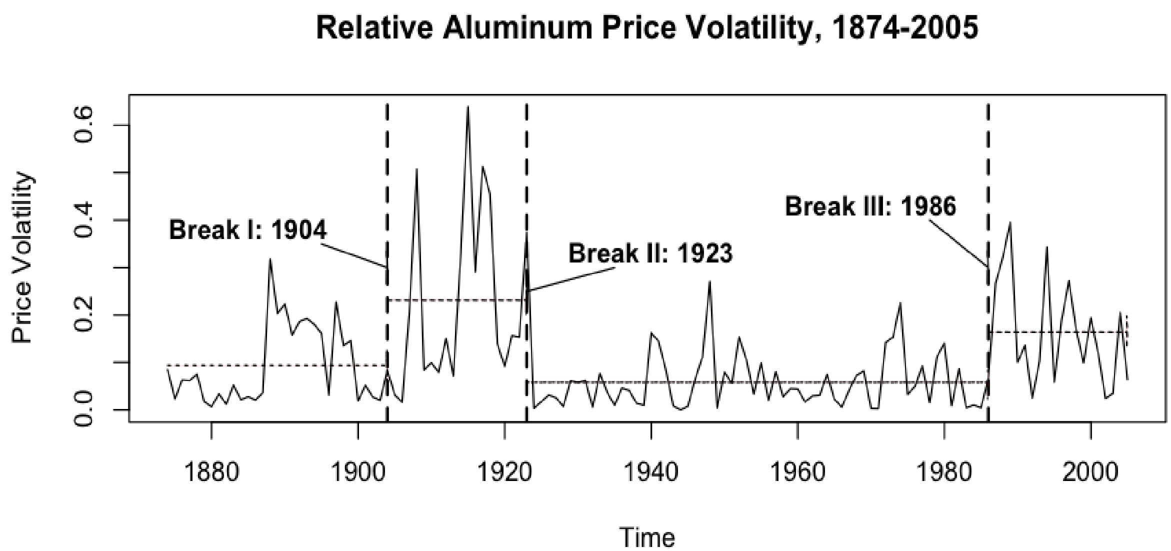
4.2 Volatility of relative commodity prices

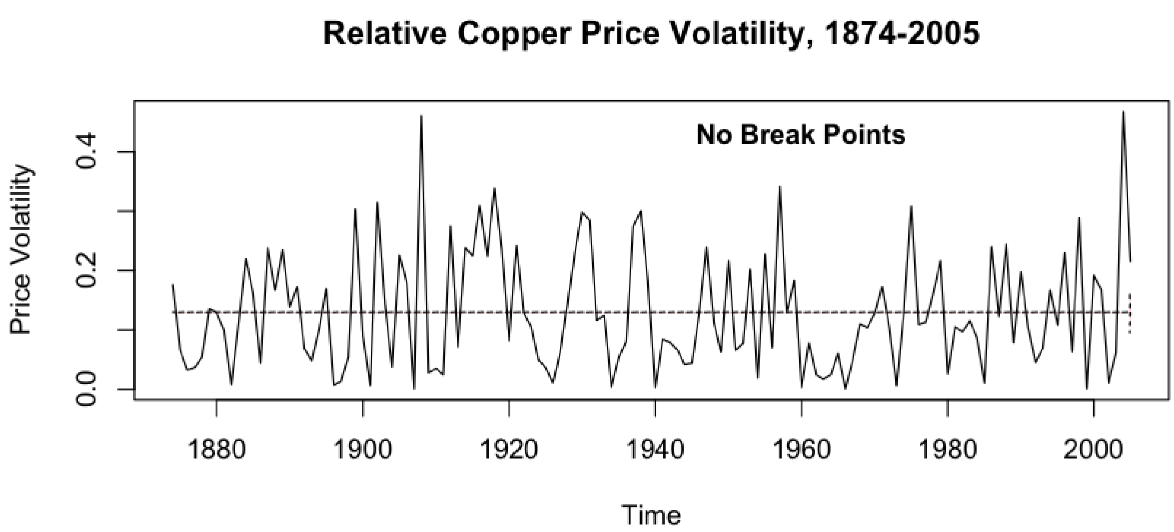
As in Dvir and Rogoff (2009), we define volatility as the mean absolute residual from a regression of a given relative primary commodity price growth on its lagged value. It is well documented that primary commodity prices are relatively highly volatile and this volatility is time varying (Mintz (1967), Reinhart and Wickham (1994) and Dvir and Rogoff (2009) for oil). Whereas prices of manufactures have been found, generally, more tranquil. In this paper, by volatility we mean short term movements of primary commidity prices to be distingushed from medium and long term cycles that are another characteristics of primary commodity prices. It has also been found that commodity price variability is big relatively to the secular trend. Cashin and McDermott (2002) describe primary commodity price volatilities as rapid, unexpected and often as large changes in primary commodity prices. They noted an increase in the amplitude of price movements around 1899. Some authors found that since the breakdown of the Bretton Woods exchange regime, real commodity prices have exhibited increasing variability since early 1970 (Chu and Morrisson (1984), Reinhart and Wickham (1994) and Cuddington and Liang (1999)). The price elasticity of demand for raw materials is generally small because its cost represents only a tiny fraction of the final product price. therefore, an increase in the demand for finished products will cause a greater increse in the demand for the primary materials used due to the necessary increase of inventories of finished product which will affect the entire production chain. On the other hand, fluctuations in supply will also contibute to price volatility. The weather is another factor that can affect the price instability of agricultural products although, its importance has diminished in recent decades due to the geographical diversification of production. Important strikes or major technical accidents can be the cause of significant decrease in mineral supply. The price elasticity of supply is generally low, particularly at around full capacity which is often the case in competitive markets. Consequently, it takes considerable time to increase supply capacity and in the interim even tiny variations in demand will result in considerable change in price. Wars or expected wars are another cause of sharp change in primary commodity prices. Since world II three commodity booms have occured, 1950, 1973 and 2003 Radetzki (2006). They were all generated by demand shocks due to rapid macroeconomic expansion.The first two commodity booms subsided in 1952 and 1974 respectively, less than two years after their birth. During the more recent boom, prices increased sharply (food prices by more than 50% and fuel prices doubled) from 2003 and lasted until the first-half of 2008. This was followed In the second-half of 2008 by a severe global contraction which stayed until the end of 2009. Then, commodity prices increased drammatically again. This commodity price recovery is thought to be due to the major emerging economies and possibly to slack monetary policy and the recent inflows of speculative capital into commodity markets. Large and unexpected movements of commodity prices can have serious consequences for the terms of trade, real income, external and fiscal balances and povertyof commodity dependent countries and have serious implications for the achievement of macro-economic stabilization and social stability. To protect the economy against such large price movements some solutions have been proposed including: stabilization funds which often have been found inadequate, finding external finance facilities which are difficult to access in these situations and hedging using financial instruments à la Mexican. On the social side, the huge increase in food and oil prices can start conflicts, riots and even revolutions like the recent so called Arab-Spring. Many measures can be adopted to alleviate the suffereing of the poor and the young. These measures have to be finely tagetted towards these groups.

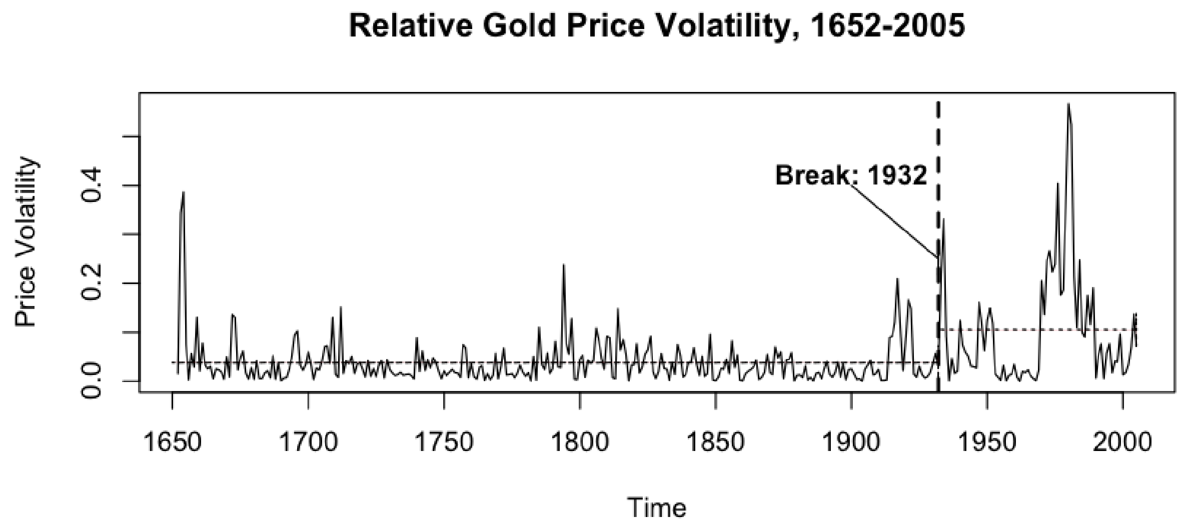
In order to find periods of high price instability, we test for multiple breaks in commodity price volatility employing the methods proposed by Bai and Perron (1998, 2003). The results are reported graphically below

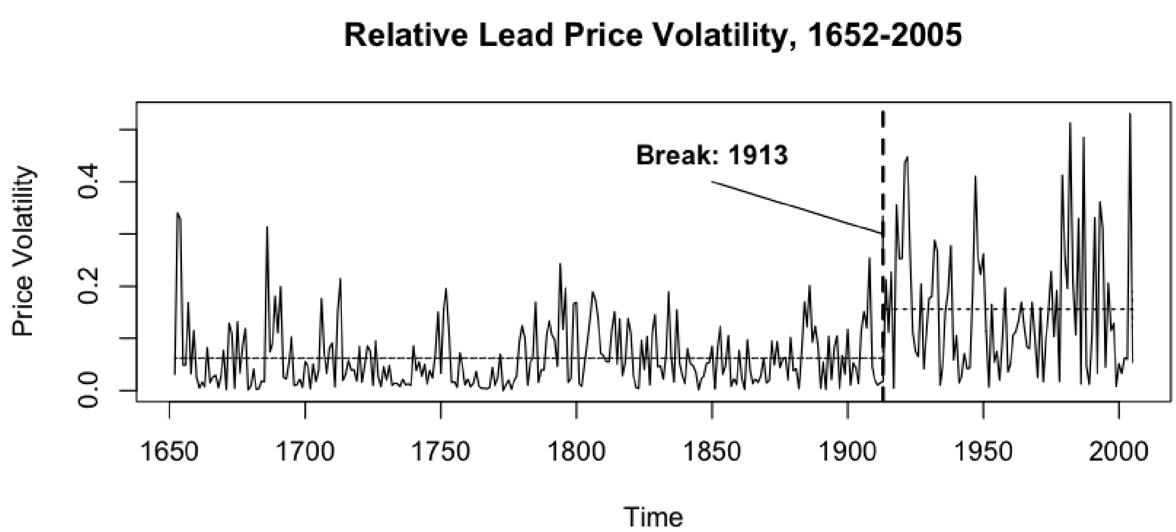
4.2.1 Analysis of the volatility results

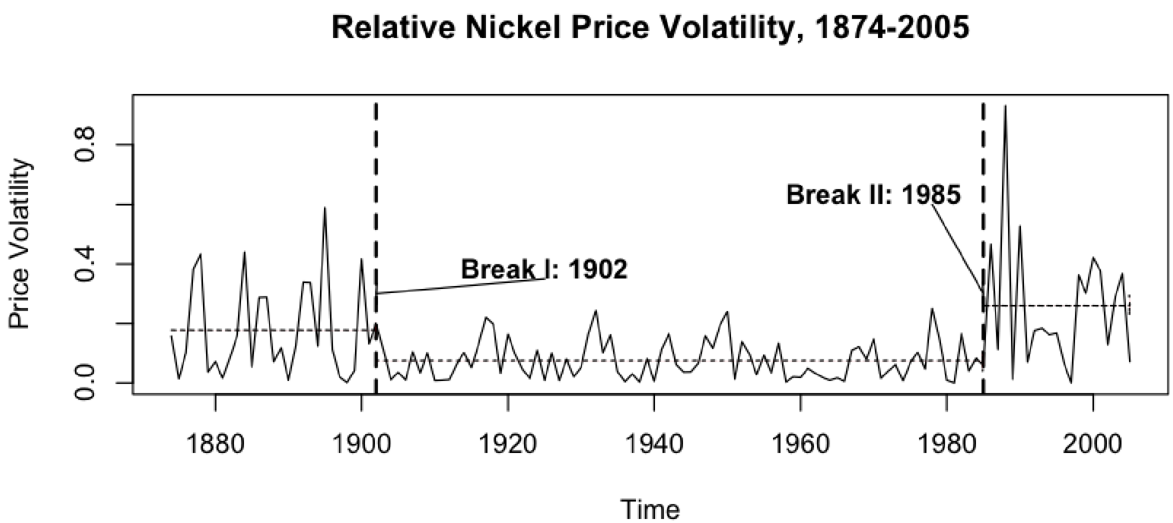
Ten price volatilities are found without breaks. this include copper, pig iron, silver, tin, banana, coffee, jute, tobacco, wheat, and oil. This is surprising particularly concerning the price volatility of oil. Dvir and Rogoff (2009) find three break points for the price volatility of oil. However, it should be noted that (1) they use real oil price whereas we use oil price relative to a price index of manufactures, (2) they consider the period 1861-2008, we use observations starting in 1874 and ending in 2005 and finally the results may depend on the various criteria used by Bai and Perron which do not always agree as note by Dvir and Rogoff (2009). Eight price volatilities are affected by one break: gold in 1932, lead in 1913, cocoa in 1913, rice in 1965, sugar in 1912, beef in 1913, lamb in 1914 and coal in 1704. Three primary commodity relative price volatilities indicates two breaks. These are; nickel (1902 and 1985), zinc (1911 and 1938), hide (1917 and 1938), wool (1713 and 1966). Finally, only aluminium has three break points in 1904, 1923 and 1986. Some more research is neede to find the cause of these breaks. In general, it seems that volatility has increased for most primary commodities in recent years.

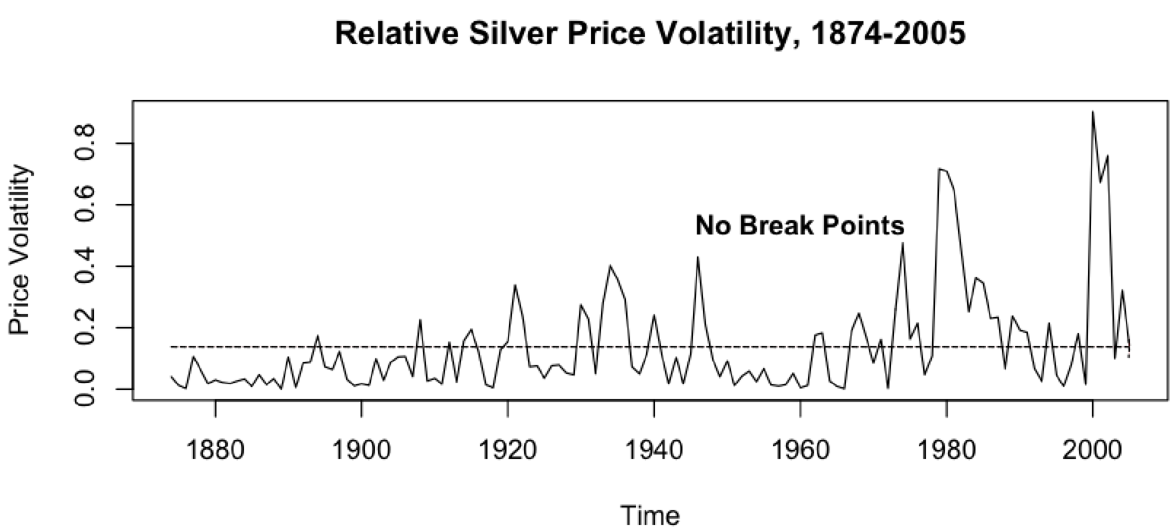

Relative Aluminum Price Volatility, 1874-2005
Price Volatility
0.0
0.2
0.4
0.6
Break I: 1904
Break II: 1923
Break III: 1986
1880
1900
1920
1940
1960
1980
2000
Time


Relative Copper Price Volatility, 1874-2005
Price Volatility
0.0
0.2
0.4
No Break Points
1880
1900
1920
1940
1960
1980
2000
Time

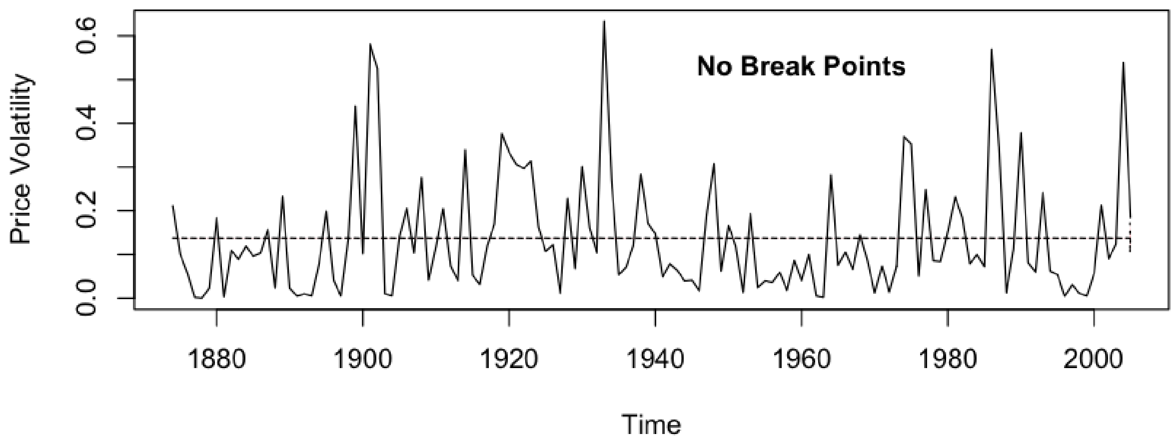

Relative Gold Price Volatility, 1652-2005
Break: 1932
Price Volatility
0.0
0.2
0.4
1650
1700
1750
1800
1850
1900
1950
2000
Time


Relative Lead Price Volatility, 1652-2005
Break: 1913
Price Volatility
0.0
0.2
0.4
1650
1700
1750
1800
1850
1900
1950
2000
Time

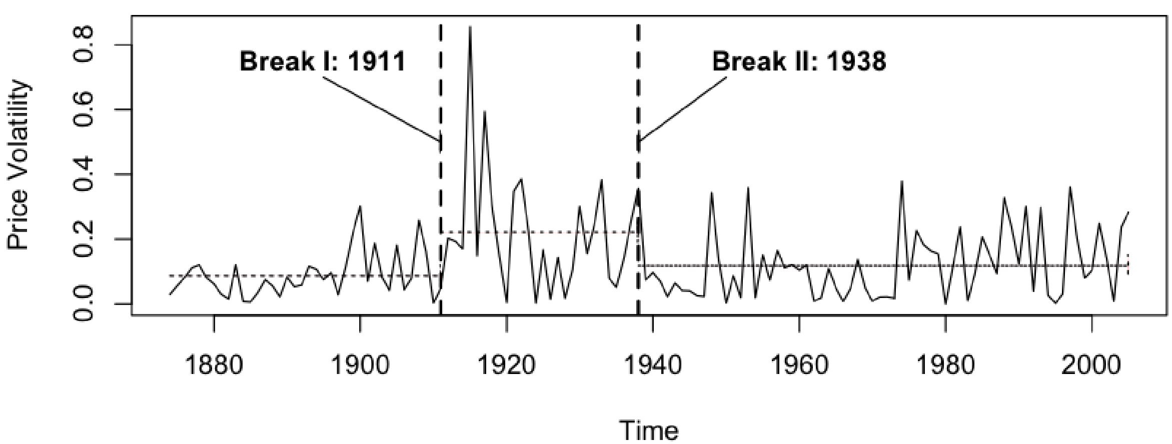

Relative Nickel Price Volatility, 1874-2005
Break I: 1902
Break II: 1985
Price Volatility
0.0
0.4
0.8
1880
1900
1920
1940
1960
1980
2000
Time


Relative Silver Price Volatility, 1874-2005
No Break Points
Price Volatility
0.0
0.2
0.4
0.6
0.8
1880
1900
1920
1940
1960
1980
2000
Time

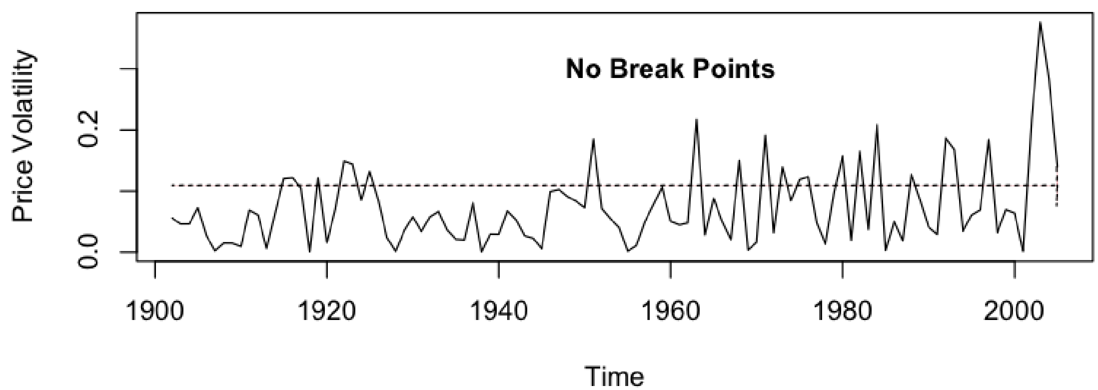
Relative Tin Price Volatility, 1874-2005



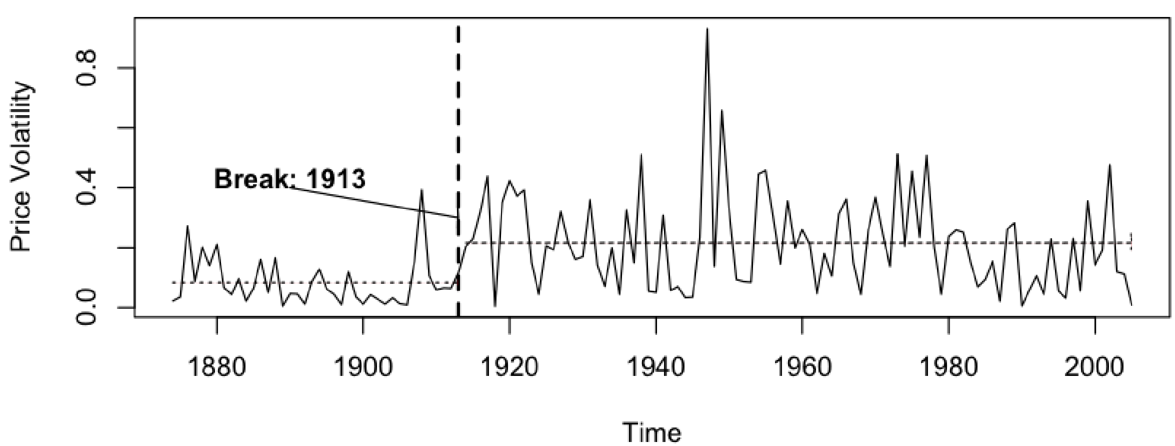
Relative Zinc Price Volatility, 1874-2005



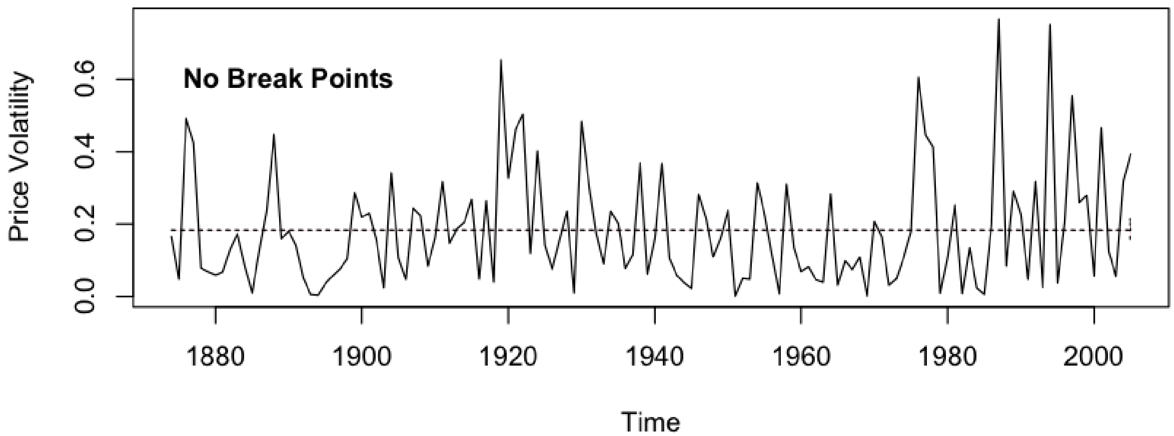
Relative Banana Price Volatility, 1902-2005



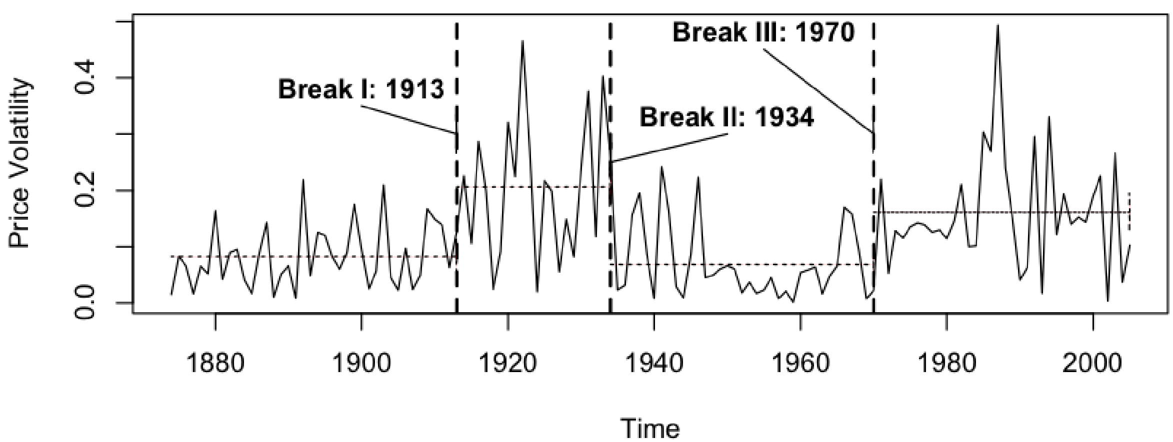
Relative Cocoa Price Volatility, 1874-2005

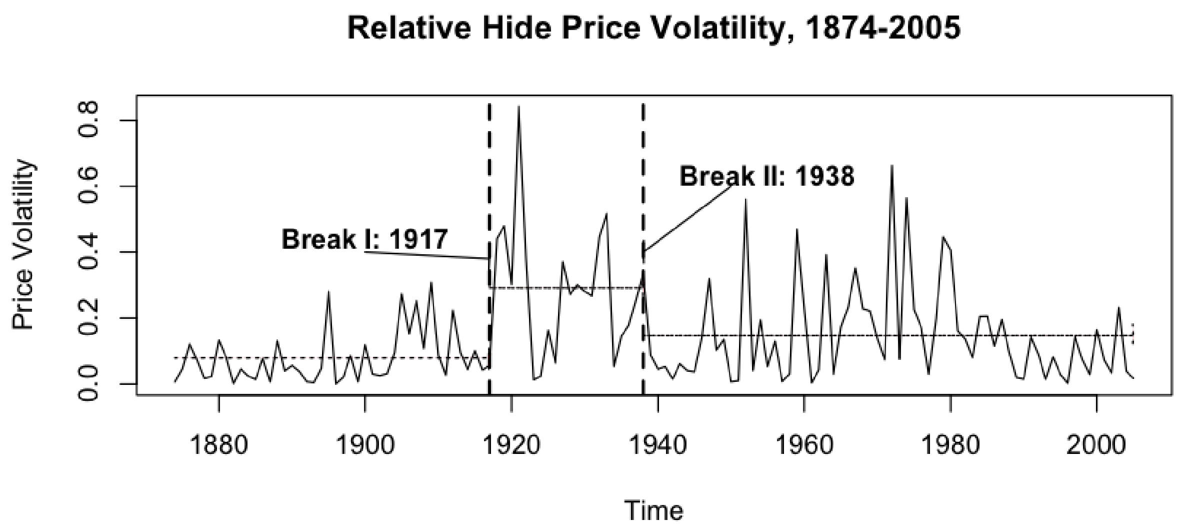


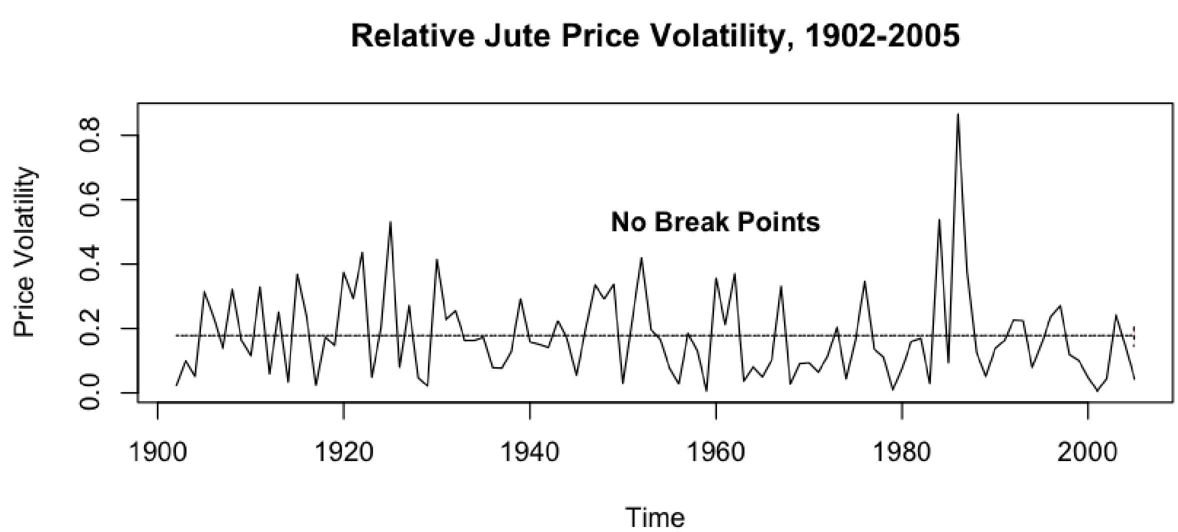
Relative Coffee Price Volatility, 1874-2005

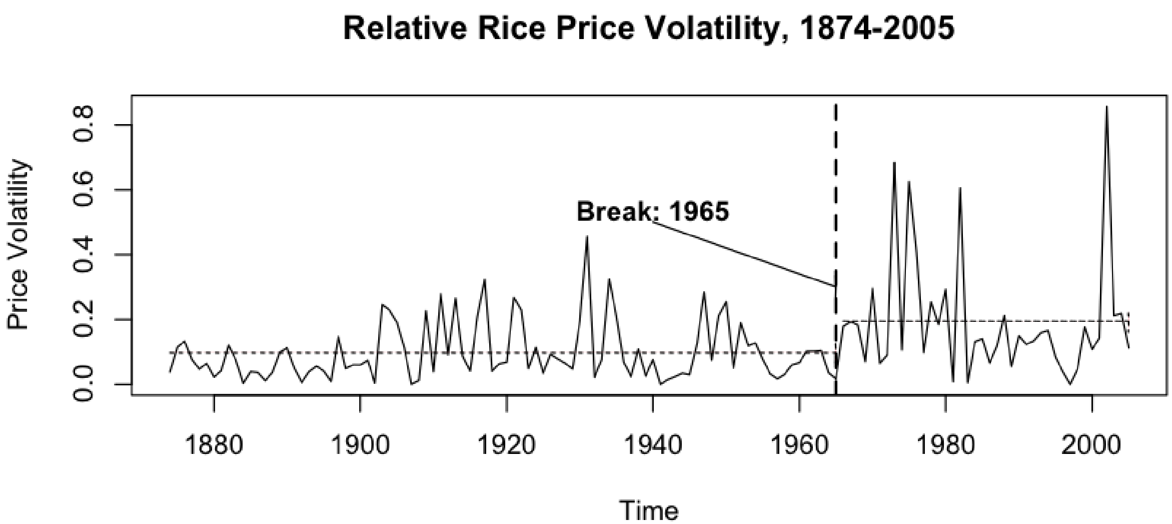


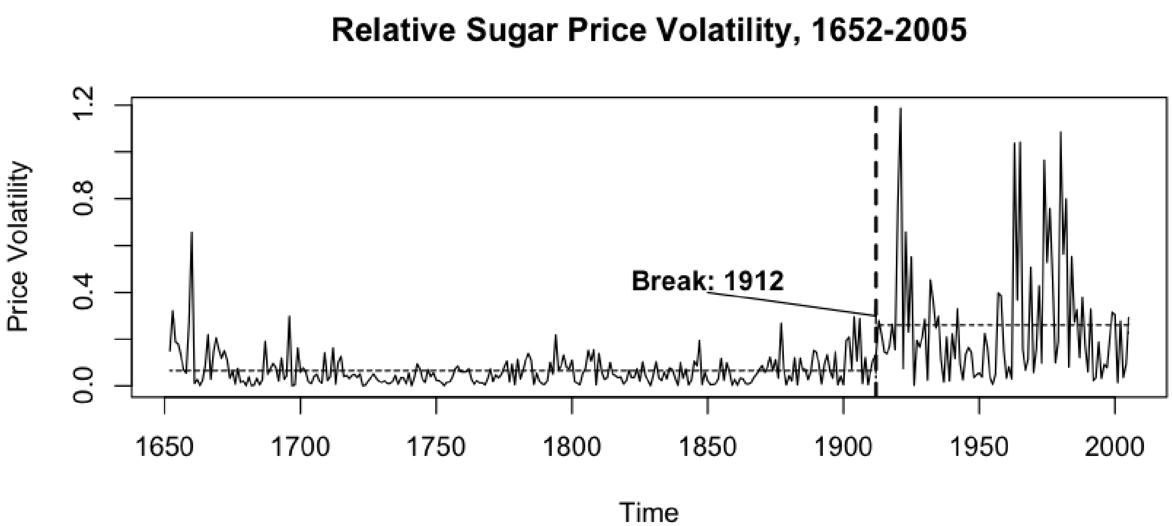
Relative Cotton Price Volatility, 1874-2005



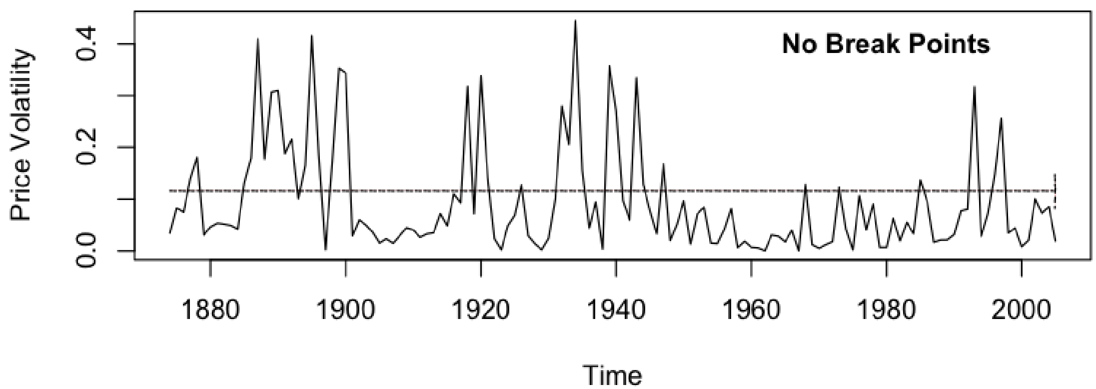

Relative Hide Price Volatility, 1874-2005
Break I: 1917
Break II: 1938
Price Volatility
0.0
0.2
0.4
0.6
0.8
1880
1900
1920
1940
1960
1980
2000
Time


Relative Jute Price Volatility, 1902-2005
No Break Points
Price Volatility
0.0
0.2
0.4
0.6
0.8
1900
1920
1940
1960
1980
2000
Time

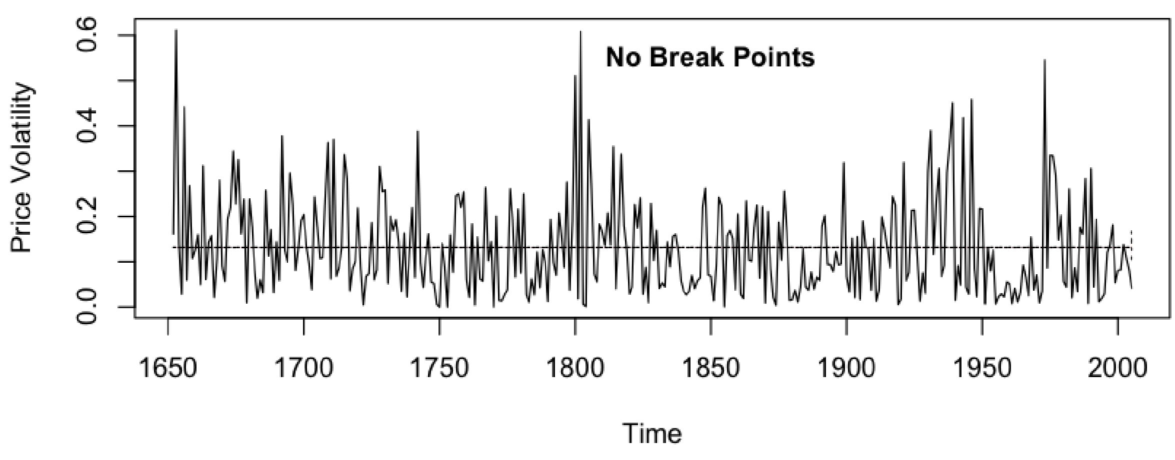

Relative Rice Price Volatility, 1874-2005
Price Volatility
0.0
0.2
0.4
0.6
0.8
Break: 1965
1880
1900
1920
1940
1960
1980
2000
Time

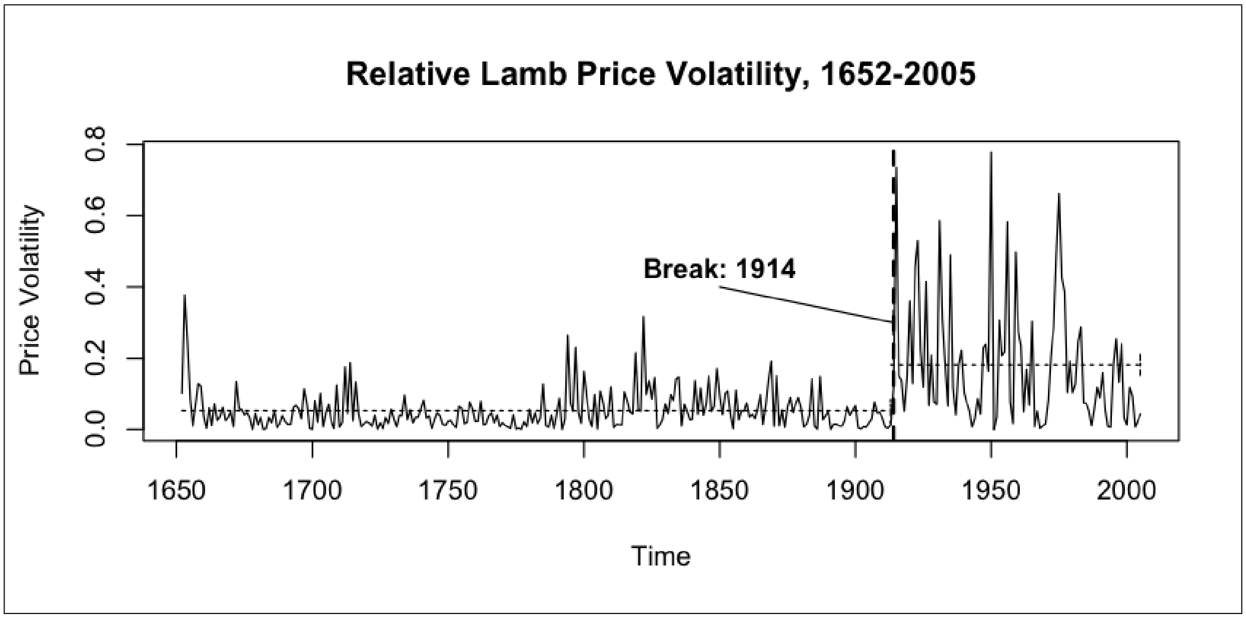

Relative Sugar Price Volatility, 1652-2005
Price Volatility
0.0
0.4
0.8
1.2
Break: 1912
1650
1700
1750
1800
1850
1900
1950
2000
Time

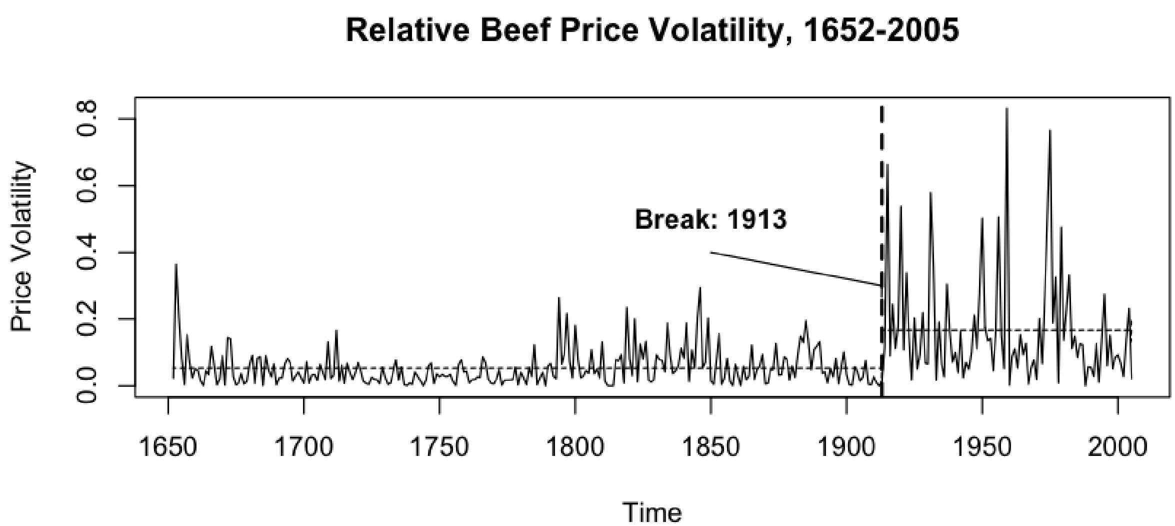
Relative Tobacco Price Volatility, 1874-2005

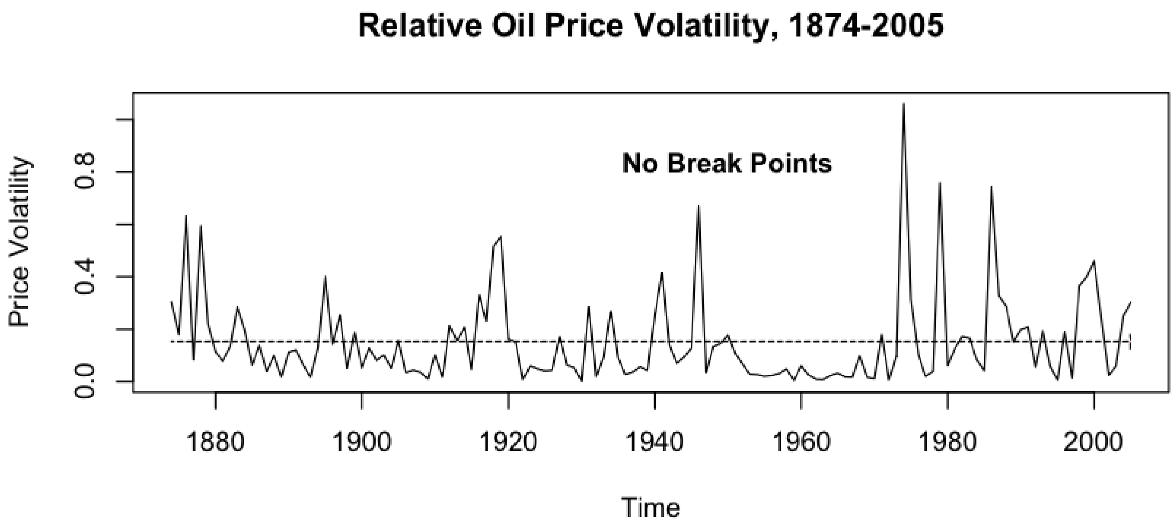


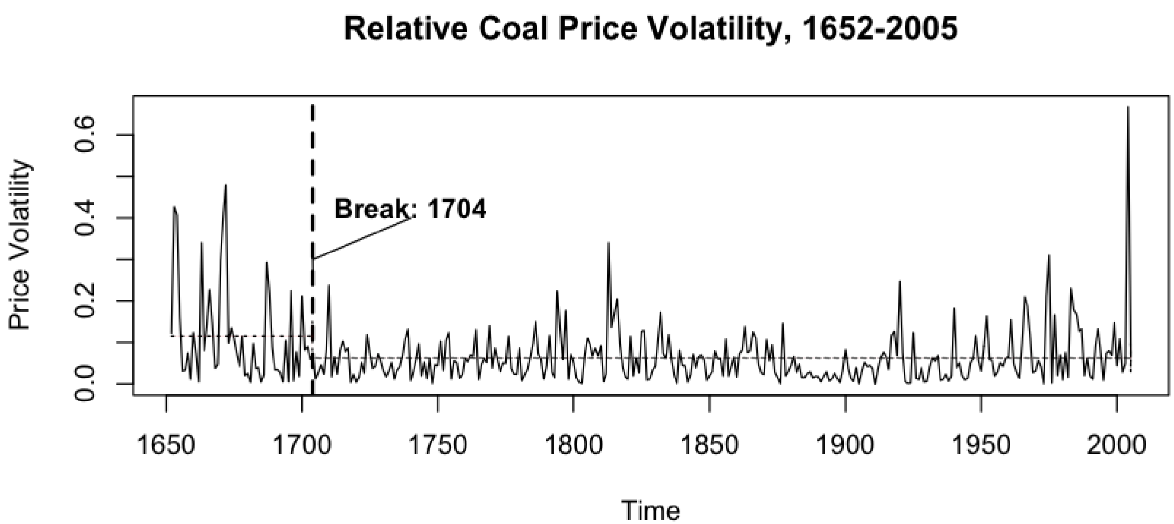
Relative Wheat Price Volatility, 1652-2005




Relative Lamb Price Volatility, 1652-2005
Price Volatility
0.0
0.2
0.4
0.6
0.8
Break: 1914
1650
1700
1750
1800
1850
1900
1950
2000
Time


Relative Beef Price Volatility, 1652-2005
Price Volatility
0.0
0.2
0.4
0.6
0.8
Break: 1913
1650
1700
1750
1800
1850
1900
1950
2000
Time


Relative Oil Price Volatility, 1874-2005
No Break Points
Price Volatility
0.0
0.4
0.8
1880
1900
1920
1940
1960
1980
2000
Time


Relative Coal Price Volatility, 1652-2005
Break: 1704
Price Volatility
0.0
0.2
0.4
0.6
1650
1700
1750
1800
1850
1900
1950
2000
Time

5 Conclusions

In this paper we commence by testing the Prebish-Singer hypothesis employing 25 relative primary commodity prices observed over more than three-and-half centuries. We find that all the series are stationary employing powerful panel stationarity tests accounting for data driven structural breaks. The results on the Prebish-Singer hypothesis tests are mixed. However, the majority of the piecewise regressions have downward slopes. We also reviewed some potential causes of structural breaks. One of the possible remedy to the secular decline of relative primary commodity prices is to diversify into manufactures and services for which the country concerned has comparative advantages.The resource-rich countries may also enter into international commodity agreements to keep relative prices of its resources at acceptable levels. Another possibility is to invest the resources rent in well run sovereign wealth funds.

We also investigate the volatility and data driven structural breaks of primary commodity prices. We discover that primary commodity prices are highly volatile with often time varying volatility. In general the volatility had the tendancy to increase during the recent years. Besides, we examine the possible drivers of changes in the volatility. This price instability can have severe economic, fiscal and social consequences. The potential tools to employ in order to lessen the negative effects of high volatility are: to set-up stabilizing funds which often have been found inadequate, finding external finance facilities which are difficult to access in these situations and hedging using financial instruments à la Mexican.

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