

Breaking the Prebisch-Singer Hypothesis in Levels and Volatilities

Presenter: **Kaddour Hadri**, Queens' University Belfast
R. Arezki and P. Loungani, IMF, Y. Rao, Liverpool University

Understanding International Commodity Price Fluctuations

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- Changes in relative commodity prices can be decomposed into: **secular trend**, **cycles** over medium and long horizon and short-run **volatility**.
- Each movement may affect adversely the conduct of a sustainable macro, fiscal and social policies in the economies concerned.
- This is more so for resource-rich countries relying on exporting one or few commodities for the bulk of their export earnings.
- In this paper, we shall examine the secular trend and the short-run volatility, employing 25 series, some of them starting as far back as 1650 and panel data stationarity tests allowing for endogenous multiple structural breaks, cross-sectional dependence and serial correlation.
- Whenever possible we shall try to find the cause(s) of these breaks.

- Introduction
- Panel stationarity tests with multiple structural breaks
- Data
- Testing the Prebisch-Singer hypothesis
- Volatility of relative commodity prices
- Conclusions

- Test the **Prebisch-Singer hypothesis** using panel data stationarity tests accounting for the well known **comovement** of relative commodity prices and allowing for **endogenous structural breaks**.
- We would like also to exploit the information on the breaks.
- The consequences of the acceptance of the Prebisch-Singer hypothesis are very important for developing countries.
- The countries concerned might have to **explore diversifying** their export portfolio to include manufactures and services for which they have comparative advantages. Apply effectively Hartwick rule by investing the rents generated by the primary commodities in worthwhile and competitive reproducible capital to ensure long-run sustainability including well run sovereign funds. Enter **international commodity agreements**.

- In a second part, we examine the **volatility of primary commodity prices**. High volatility of commodity prices is an important cause of economic and social instability particularly in developing countries.
- We test for data driven structural breaks employing Bai and Perron (1998) methodology. We also try to identify the causes of these breaks.
- How to protect against unpredictable volatility: (1) **stabilization funds** to insure against future shocks. (2) **Hedging** strategies using financial instruments. (3) **External finance facilities** for credit rationed commodities exporting countries affected by negative temporary shocks.
- It should be noted that we are using relative primary commodity prices instead of indices avoiding hence the aggregation bias and the generally ad-hoc weighting rule to combine the commodity prices involved.

Panel stationarity tests with multiple structural breaks

The most general model with one break is specified as follows:

$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \gamma_i DT_{it} + \epsilon_{it} \quad (1)$$

with

$$r_{it} = r_{it-1} + u_{it}, \quad (2)$$

where y_{it} , $i = 1, \dots, N$ individuals and $t = 1, \dots, T$ time periods, are the observed series for which we wish to test stationarity. For all i , α_i 's, β_i 's, δ_i 's and γ_i '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:

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

Panel stationarity tests with multiple structural breaks

The model with multiple breaks considered here can be written as follows:

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

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

where $v_{i,t} \sim i.i.d(0, \sigma_{v,i}^2)$, $\varepsilon_{i,t}$ is allowed to be serially correlated. $\{v_{i,t}\}$ 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 k th date of break for the i th individual, $k = 1, \dots, m_i$. The null hypothesis is specified as $\sigma_{v,i}^2 = 0$ for all i , under which we obtain:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_j t + \sum_{k=1}^{m_i} \gamma_{i,k} D(T_{b,k}^i)_t + \varepsilon_{i,t}. \quad (3)$$

α_i is the initial value of $\alpha_{i,t}$.

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

$$LM(\lambda) = N^{-1} \sum_{i=1}^N (\hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^T \hat{S}_{i,t}^2), \quad (4)$$

where $\hat{S}_{i,t}^2 = \sum_{j=1}^t \hat{\varepsilon}_{i,t}$ denotes the partial sum of OLS estimated residuals $\hat{\varepsilon}_{i,t}$. $\hat{\omega}_i^2$ is a consistent long-run variance (LRV) estimate of $\hat{\varepsilon}_{i,t}$ for each i . The limiting distribution of the statistic (4) is,

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

with

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

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

A and B are given in Hadri (2000), $A = \frac{1}{15}$, $B = \frac{1!}{6300}$.

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 $SSR(T_{b,1}^i, \dots, T_{b,m_i}^i)$ computed from (3)

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

Testing the presence of multiple structural changes

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. Using the Double maximum test by Bai and Perron (1998) we test the null hypothesis of no structural break against an unknown number of breaks with given bound M of number of breaks. For the Double maximum tests, the $UDmax$ and $WDmax$ are used and are defined as follows:

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

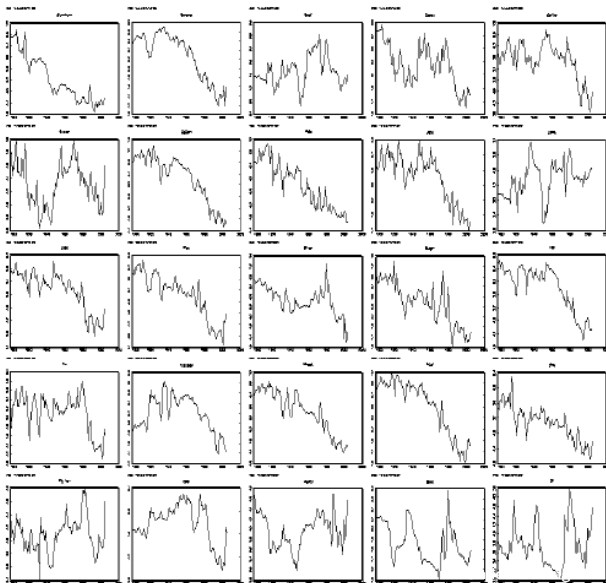
$$WD \max F_T(M, q) = \max_{1 \leq m \leq M} \frac{c(q, \alpha, 1)}{c(q, \alpha, m)} \times \sup_{(\lambda_1, \dots, \lambda_m) \in \Lambda_\epsilon} F_T(\lambda_1, \dots, \lambda_m; q)$$

We found that all the $UDmax$ and $WDmax$ tests are significant at 1% significance level. This clearly shows that at least one structural break is present in any of the relative primary commodity price.

- We employ **25 relative commodity prices** constructed by Harvey, Kellard Madsen and Wohar (2010)¹. 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 set1.
- 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. The set including all the commodity prices for which we have observations during the period 1872-2005 including set1 is called set2.
- Finally, the relative commodity prices of Banana and Jute cover the period 1900-2005. We call set3, the set including all the 25 relative commodity prices covering the period 1900-2005.

¹We thank David Harvey for providing the data.

Fig 1



Plot of relative commodity prices

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

Piecewise regressions

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)		

Analysis of the results of the Prebisch-Singer testing

- For **set 3**, on a total of **80 slopes**, **41 are negative and significant**, 11 are negative but insignificant, 21 are positive and significant, finally, 7 are positive and insignificant.
- In **set 1** there are **27 slopes**: **13 are negative and significant**, 13 other are positive and significant and one is positive but insignificant.
- Finally in **set2**, there are **71 slopes**: **forty four are negative and significant**, 7 are negative but insignificant, 11 are positive and significant and 9 are positive but insignificant.
- It is interesting to find the **possible drivers of these breaks**. Here are some potential ones: *declining shares of primary commodities in GDP overtime, rising productivity, increasing ability at creating substitutes, steady fall of transport costs, state intervention, technological breakthrough, wars, weather, financial crisis...*

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.
- primary commodity prices are relatively highly volatile and this volatility is time varying. Prices of manufactures have been found, generally, more tranquil.
- commodity price variability is big relatively to the secular trend.
- Cashin and McDermott (2002) describe primary commodity price volatilities as rapid, unexpected and often large.
- Since the breakdown of the Bretton Woods exchange regime, real commodity prices have exhibited increasing variability.
- Primary commodity cost represents only a tiny fraction of the final product price. therefore, an increase in the demand for finished products will cause a greater increase in the demand for the primary materials.

Volatility of relative commodity prices

- Fluctuations in supply will also contribute to price volatility.
- The weather is another factor for agricultural products.
- Important strikes or major technical accidents.
- Wars or expected wars.
- Since world II three commodity booms have occurred, 1950, 1973 and 2003 due to rapid macroeconomic expansion.
- During the more recent boom, prices increased sharply (food prices by more than 50% and fuel prices doubled) from 2003 until the first-half of 2008. Followed In the second-half of 2008 by a severe global contraction which stayed until the end of 2009. Then, commodity prices increased dramatically 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

Effects of high and changing volatility

Large and unexpected movements of commodity prices can have serious consequences for the terms of trade, real income, external and fiscal balances and poverty in commodity dependent countries and have serious implications for the achievement of macro-economic stabilization and social stability.

How to protect against these large and unexpected movements of prices

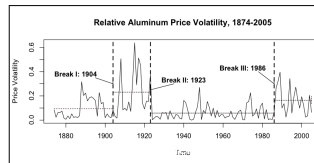
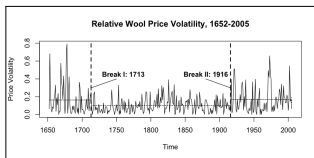
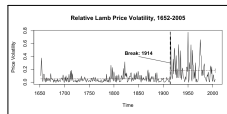
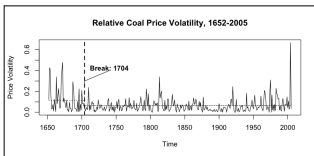
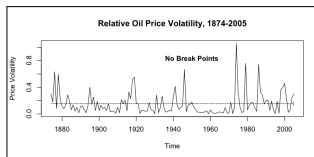
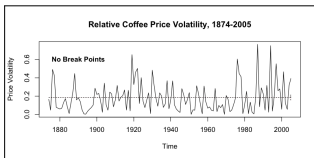
- Stabilization funds which often have been found inadequate.
- hedging using financial instruments like forward, futures and options.
- External finance facilities for credit rationed commodities exporting countries affected by negative temporary shocks. Not easy to access in this situation.
- On the 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 suffering of the poor and the young. These measures have to be finely targeted towards these groups.

Analysis of the volatility results

We test for multiple breaks in relative commodity price volatility employing the methods proposed by Bai and Perron (1998, 2003). Some of the results are reported graphically below.

- **Eleven price volatilities** are found **without breaks**. this include copper, pig iron, silver, tin, banana, tea, coffee, jute, tobacco, wheat, and oil.
- **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.
- **Four price volatilities** indicate **two breaks**. These are; nickel (1902 and 1985), zinc (1911 and 1938), hide (1917 and 1938), wool (1713 and 1966).
- **Two price volatilities** have **three breaks**: aluminium (1904, 1923 and 1986) and cotton (1913, 1934, 1970)
- In general, it seems that volatility has increased for most primary commodities in recent years.

Some volatility graphs



Conclusions

- We tested the **Prebisch-Singer hypothesis** employing 25 relative primary commodity prices observed over more than three-and-half centuries
- We found that all the series are stationary employing panel stationarity tests accounting for data driven structural breaks, cross sectional dependence and serial correlation.
- The results on the Prebisch-Singer hypothesis tests are mixed. The majority of the piecewise regressions have downward slopes.
- We also reviewed some potential causes of structural breaks.
- Possible **remedies** to the **secular decline** of relative primary commodity prices are: (1) **diversification** into manufactures and services for which the country concerned has comparative advantages. (2) Entering into **international commodity agreements** to keep relative prices of its resources at acceptable levels. (3) **Investing the rents** in worthwhile and competitive reproducible capital to ensure long-run sustainability including in well run sovereign wealth funds.

Conclusions

Analysing volatility

- We also investigated the volatility of primary commodity prices allowing for data driven structural breaks .
- We discovered that primary commodity prices are highly volatile with often time varying volatility.
- In general the volatility had the tendency to increase during the recent years.
- We examined 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: (1) to set-up **stabilizing funds** which often have been found inadequate, (2) finding **external finance facilities** which are difficult to access in these situations and (3) **hedging** using financial instruments.