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Trends and Cycles in Commodity Markets

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Abstract

The presence of trends and cycles in commodities is examined for the updated Grilli and Yang database from 1900 to 2010. We employ the Hamilton filter to obtain the trend and cycle for each commodity and the commodity indexes. The Prebisch-Singer Hypothesis, of a downward trend of the commodities, holds for the most period of our sample and for the majority of the data. The corresponding cycles from the Hamilton filter, have a shorter duration than the Super Cycles and have at least one additional cycle wave. The present analysis focuses also on the relationship among commodity prices, different levels of economic activity and interest rate. The empirical results provide evidence that commodity prices Granger-cause interest rate and mainly the Chile GDP, while interest rate Granger causes commodity prices and the economic activity of the US. Finally, there is a causality running from the economic activity of the world towards the commodity prices.

Keywords: Prebisch-Singer Hypothesis, Hamilton filter, Trends, Cycles, Granger Causality

Contents

1. Introduction

Commodity markets have been a roller coaster for several years. The recent global economic crisis was preceded by a boom in commodity prices that was unprecedented in its magnitude and duration. This peak in the commodity markets came to an end when the global economic activity slowed down, diminishing demand on the commodity markets with falling prices. However, commodity markets started to recover fast.

Understanding how commodity markets move and how the fluctuations of the prices affect the economic activity has been widely investigated in the literature even from the start of the 20th century. Kitchin and later Kondratiev and Schumpeter were among the first to outline the presence of commodity cycles and their connection to the prosperity and stagnation of the economic activity.

Why someone should focus on the trends and cycles in commodity markets? The presence of these two phenomena in commodity markets matters for obtaining the proper decision in many aspects of the markets such as the production of commodities, the stability of the financial sector and the consistent policy towards economic growth. A significant proportion of national income for many developing countries is often generated by a small number of primary commodities (see Harvey et al. 2010). The nature and causes of trends and cycles in commodity markets , therefore, have a significant implication for growth and poverty policies in developing countries. Production in many commodity markets is achieved through initial capital investments that take years to mature in revenue. Thus, firms must factor trends in the markets into their investment decisions. Commodity markets are considered recently by financial investors as a distinct asset class, that is widely used as a hedging tool in portfolio management. Moreover, this financialization fueled the speculation in commodity markets and this behavior can lead to the emerging of new cycles and trends in the markets. Subsequently, commodity price movements are connected to the financial sector and its crises (see Eberhardt and Presbitero. 2018).

The analysis of long-run commodity prices is dominated by the Prebisch-Singer Hypothesis (PSH) which implies a negative trend in commodity prices relative to manufactures. The majority of recent studies employ dataset form Grilli and Yang (1988), in order to obtain empirical evidence validating the PSH. Many studies find evidence supporting the PSH and the presence of a secular trend throughout the presence of structural breaks. Alongside the trend analysis of the commodity markets, there is also the analysis of the cyclical components of the commodities. The empirical analysis of this part of the literature is based on the use of different filters, that can separate the trend and the cycle portions of a series. From the analysis of the cycles in the commodity prices stems the Super Cycles theory (see Cuddington and Jerrett. 2007). Those long cycles have a duration of 35 years on average. Some studies have attempted to model the relationships between the long commodity series and macroeconomic variables (see Erten and Ocampo. 2012 and Harvey et al. 2017). They find evidence of a causal relationship between the commodity prices and historical macroeconomic data.

This paper attempts to examine the presence of trends and cycles in the commodity prices using a novel filtering technique, as it was proposed by Hamilton (2017). We use the extended Grilli and Yang database for the commodity prices and the commodity indexes from 1900 to 2011. In our analysis, furthermore, we are focusing on the causal relationship between the commodity prices, the economic activity and the interest rate, following the empirical approach of Harvey et al. (2017). In order to analyze the nexus of trends and cycles under this new approach, we are trying to answer the following questions: (i) Does the PSH holds in the commodity markets, in the trend obtained by the Hamilton filter? (ii) Does the cycle series of the commodities pay any resemblance to the Super Cycles? (iii) Is there a relationship among commodity prices, the economic activity , and interest rates? (iv) If yes, how different levels of economic activity shape the previous causal relations?

This study contributes to the existing literature in several ways. First of all, the present study uses a differentiated filtering approach, rather than previous researches, in order to alleviate the drawbacks of the Hordrick-Prescott Filter and the other filters. Our analysis is based on the extended dataset of Grilli and Yang that integrates the period of the recent economic crisis and we can obtain new empirical results regarding this period. Moreover, any significant relationship among our long series of macroeconomic variables and the commodity prices, contributes alongside previous researches to this less commonly addressed topic. Country-specific economic activity may have some important policy implications. If the results for commodity prices indicate a relationship with economic activity and interest rates, then policymakers would, therefore, need to pursue policies, that account for the monetary policy and promote growth.

The remainder of the paper is organized as follows: Section 2 presents a brief literature review of studies concerning the trends and cycles in commodity prices and Section 3 a more comprehensive literature review of studies focusing on the PSH and the Super Cycles. Section 4 describes the Hamilton filter and all the previous filters demonstrating their differences. There is also the specification of the stationary VAR, from which we obtain the Granger causality of our long-time variables. The data are presented in Section 5. Empirical results are discussed in Section 6 and concluding remarks are summarized in the final section. In Section 9, someone can find all the tables mentioned in the comments of our findings. Finally, Section 10 serves as the Appendix of the literature with the analytical review tables and in Section 11 someone can find all the Figures that present the trend and cycle result of different filters for each commodity and index.

2. The Cycles and Trends in Commodity Prices: A Brief Discussion of the Literature

The understanding of the movements of the basic economic factors was always a major discussion in the literature. Kitchin (1923) considers the wholesale prices of commodities as a significant factor, among bank clearings and interest rate, for his analysis of the cycles and trends of economic factors. He was able to identify, through a primal statistical analysis, evidence of a rising trend in the commodity prices and the other economic factors. Moreover, he illustrated the presences of small cycles that last for around three years and trade cycles that last about eight years. The debate about the effect of the prices of primary commodities on the economic factors continues. Barsky and Killian (2004) discuss the possible effect of oil prices on the macroeconomic factors, but they can not establish a significant link.

Commodity price fluctuations have always been of importance to the development of countries. Labys, Koubassi and Terraza (2000) employ the Structural Time Series (STS) to examine twenty-one primary commodity price series of export importance. Their result suggests the predominance of one short cycle with duration of less than a year and a second cycle that lasts around two years. Camacho and Perez-Quiros (2013) analyze the interactions between commodity prices and the GDP of seven Latin exporters. They conclude that commodity prices have nonlinear effects on the output and the state of the cycles of those two variables should be acknowledged in the economic policies.

The influence of the commodity price cycles is also important in investors' decision as Fernandez (2015) illustrates. The business cycles of commodities prices show strong co-movement and are highly significant for the whole period from 1968 to 2013.

Those co-movements are not only present on the short term but also on the long term as Chauduri (2001) finds evidence of cointegration on between real primary commodity prices and real oil prices. However, this trend is not single and varies in different periods as Ghoshray and Johnson (2010) and Ghoshray (2011) outline using different commodity prices and econometric methods for the trend and the unit root of the series.

The "financialization" of commodity markets can lead to new cycles to commodity prices. Those cycles originate not from endogenous cycles but from the speculators and the financial participants of the markets (Reitz and Westerhoff, 2007). Bastourre, Carrera and Ibarlucia (2010) find that small misalignments of the prices tend to persist when accounting for the "financialization" of the markets. In addition, they find real exchange rate, real international rate and real returns of stocks to be highly significant variables for the changes in commodity prices. The new relationship that emerges in the co-movements of the commodity prices is being investigated using different methods. They vary from GARCH to network analysis and causality testing. (Büyükşahin and Robe (2011); Nazlioglu, et al.(2013); Matesanz, et al.(2014); Bampinas and Panagiotidis (2015)). They all conclude that in the period after the financial crisis the spillovers have intensified and new relationships are emerging among the commodity prices. In this scope, there is a series of studies that try to identify the effect of global liquidity on the commodity prices (Belke et al. (2009); Belke et al. (2012); Belke et al. (2014)). They find evidence that global liquidity has a positive effect on the commodity prices and hence inflation. Moreover, they identify a negative relationship between the interest rate and commodity prices.

The importance of understating commodity price movements can be highlighted by the findings of Eberhardt and Presbitero (2018). They develop an empirical model to predict banking crises in a sample of 60 low-income countries (LICs) accounting for changes in primary commodity prices. They conclude that commodity price movements are a key driver of crisis episodes among other well-established drivers.

3. The Cycles and Trends in Commodity Prices: Prebisch–Singer Hypothesis

The early literature of cycles in real commodity prices was developed by Kondratiev and Schumpeter. Business Cycles (Schumpeter, 1939) was the first framework that analyzed the presence of long Kondratiev cycles and shorter Juglar and Kitchin cycles. Schumpeter argued that prices are driven down by innovation in the long run, but with a cyclical portion, that depends on the innovation's clusters that create growth or decay in the different sectors. These two phases will also affect the prices of primary commodities, that are at first increased their prices relative to manufactured goods. Following the accumulation of innovation in the different sectors their prices for primary commodities. tend to decrease relative to the ones of manufactured goods.

This deterioration in terms of trade between primary and manufactured goods was also observed in the terms of trade of developing countries. Singer (1950) and Prebisch (1950) studying both the case of economic development in Latin America faced a controversy. The increase of the gap between industrialized and developing countries alongside the deterioration of the terms of trade for exporters of primary commodities relative to Britain. They composed the Prebisch-Singer Hypothesis (PSH) claiming that the relative price of primary commodities in terms of manufactures shows a downward trend.

A huge part of the empirical studies is based on the comprehensive work and the dataset form Grilli and Yang (1988) (GY). They compiled a dataset of twenty-four non-fuel commodities that are aggregated in commodity price indexes that are deflated by the manufactures UN index and the United States Manufacturing Price Index. The dataset extends annually from 1900 to 1986. They confirm that there is a negative trend on the relative prices of all primary commodities, but the magnitude of the trend varies among the different subgroups of the primary commodities.

The following years different studies used that novel dataset to investigate the PSH using different methodological approaches. On strand employed models that focused on the analysis of deterministic and stochastic trend (Ardeni and Wright (1990); Kellard and Wohar (2002); Ocampo and Parra-Lancourt (2010)). Others focused on different methods (Bleaney and Greenaway (1993)) or tried alternative datasets (Reinhart and Wickham (1994)). Many of these studies find evidence supporting the PSH and the presence of a secular trend throughout the presence of structural breaks in the different variables. However, when the literature accounted for the structural breaks or advanced unit root testing (Kellard and Wohar (2005); Ghoshray and Johnson (2010); Nazlioglu (2014)) the PSH could not be validated to hold for all primary commodities and the cyclical part tends to be traced by the different studies.

Cuddington and Jerrett (2007) using a dataset of metals and applying the Christiano and Fitzgerald (CF) asymmetric band-pass filter established the method for examining the Super Cycles in commodity prices. They conclude that the evidence of three Super Cycles in the last a hundred and fifty years with phases spanning from ten to thirty-five years. Following the previous super cycle approach, Erten and Ocampo (2012) advanced their methodological approach. They examine an extended dataset that includes the oil and the GY aggregate indexes updated until 2010 alongside the output of OECD and world. They found evidence of four past Super Cycles ranging from thirty to forty years, with the mean of each super-cycle for non-oil commodities tending to be lower than that of the previous cycle. The innovation of using a VECM to assess the relationship among commodity prices and output cycles provided the evidence that Super Cycles in output can effectively predict Super Cycles in real non-fuel commodity prices.

They were the first that provided causal evidence of the relationship between commodity prices and output as it was first described in PSH. The literature before this novelty did not focus on prices directly but associated the output growth with the volatility in terms of trade of markets (Blattman, Hwang and Williamson (2004)) or accounted the increasing volatility of commodity prices as proxy of terms of trade deterioration (Jacks, Rourke and Williamson (2011)).

A most recent part of empirical studies is based on the new dataset from Harvey, Kellard, Madsen and Wohar (2010) (KHMW). The dataset is compiled by annual data from 1650 to 2005 for 25 commodities. They try to investigate the PSH using techniques to assess the trend function and the existence of any possible structural breaks. They find evidence of a long run secular, deteriorating trend phenomenon for a significant proportion of primary commodities. In a later study (Harvey, Kellard, Madsen and Wohar (2012)), they include the Super Cycle methodology and compare their results to the GY database (as updated by (Pfaffenzeller et al. (2007)). They show that relative commodity prices present a significant and downward global trend. In addition, there is evidence of Super-Cycles with a lifecycle of twenty-seven years and short-run cycles are lasting four years. Their most recent study Harvey, Kellard, Madsen and Wohar (2017) employs the trend and breaks techniques on a Stationary VAR similar to the model of Erten and Ocampo (2012). As variables for the VAR they account for the combinations of commodity prices, GDP and interest rates. The evidence of the VAR shows that commodity prices Granger-cause income and interest rates, while interest rates Granger cause commodity prices. On the scope of the PSH, they find a downward trend with breaks over the entire industrial age for commodity prices.

Using the KHMW dataset Bloch, Madsen, and Sapsford (2009) apply a Schumpeterian analysis to understand trend and cycle in the prices of primary commodities. They conclude showing that there is a downward trend in nominal commodity prices from the 17th through 19th Century and in the price of primary commodities relative to manufactures throughout our historical period, including the 20th Century. The find evidence of the PSH but it is not in the exact scope of their analysis. Arezki , Hadri, Loungani, and Rao (2014) perform advanced panel stationarity test on KHMW dataset. They find mixed results of the PSH, but with downward sloped regressions and possible structural breaks, evidence similar to previous studies with unit root methodology.

Yamada and Yoon (2014) use the updated GY database (Pfaffenzeller et al. (2007)) for investigating the PSH. They incorporate the L1 – trend filter method for retrieving the long-term trend. For the majority of primary commodities, they find that their piecewise linear trends are negatively sloped during some of the sample periods. They conclude that the Prebisch–Singer hypothesis holds sometimes, but not always, for many of the primary commodities in the Grilli–Yang data.

Winkelried (2015) extended the previous study with calibrating the L1 – trend filter for each specific series and investigated the presence of Super Cycles on the updated GY database (Pfaffenzeller et al. (2007)) and the KHMW dataset. The scope of the study is to revisit the trend and cyclical behavior of relative primary commodity prices. The findings regarding the PSH do not variate from the literature as the PSH holds in certain periods rather than universally. Super Cycles are present in every series in accordance with previous cycle literature.

There is also a part of the literature that is not directly connected to the PSH literature but overlaps with the selected scopes of our study.

Byrne, Fazio and Fiess (2010) apply PANIC and FAVAR in the updated GY database. They investigate the relationship of real commodity prices, real interest rate, and risk. There is evidence of co-movement of commodity prices, with a negative relationship between real interest rate and real commodity prices. These findings are similar to Harvey, Kellard, Madsen and Wohar (2017) where interest rate tends to Granger cause commodity prices.

Stuermer (2013) uses annual data from 1840 to 2010 to construct a Structural VAR with long term restriction between world primary production of each mineral, real commodity prices and World GDP. The selected commodities were copper, lead, tin, zinc, and crude oil. His findings suggest the partial support of PSH as the prices for copper show a significant negative linear trend. The trend is also negative but less significant for lead and zinc prices, but tin and crude oil do not present any trend. Similar to the VECM of Erten and Ocampo (2012), there are evidence of a relation between price fluctuations and the output demand rather than supply shocks.

Zapata, Detre and Hanabuchi (2012) using a Christiano and Fitzgerald (CF) band-pass filter finds evidence of cycles in S&P 500, PPI for all commodities and specific for farm and food products, fuels, and metals that have an average length of 31years.

Fernandez (2015) use the updated GY database (Pfaffenzeller et al. (2007)) trying to investigate the presence of short cycles and the possibility of co-movements of the commodity prices. There is evidence of short cyclical components on commodity prices and evidence of excess co-movement between the commodities.

Erdem and Ünalmıs (2016) use different datasets form oil prices to investigate the presence of Cycle in the prices of oil. They find evidence of short-term cycles, long-term cycle, super cycles and the long-term trend of the real oil price. Evidence of Super Cycles are also present in copper and agriculture prices. A more analytical review of the selected literature can be found on the corresponding tables in Appendix A.

4. Econometric Methodology

In this section, the econometric methodology used in this study is presented. The econometric approach to investigate the presence of trends and cycles in the prices of the commodities is based on the use of the Hamilton Filter. The first part involves the characteristics of the Hodrick-Prescott Filter and other frequency filters that are commonly implemented. The second part illustrates the innovative method of filtering as it is presented by Hamilton (2017). The third part investigates the implication of the findings of the Hamilton filter in a macroeconomic setting.

4.1 Hodrick-Prescott Filter and other filters

4.1.1 Hodrick-Prescott Filter

The Hodrick and Prescott (1997, HP) filter has been used to extract the trend and cycle components of economic time series data. The filter proposed for interpreting the trend component x_t by minimizing the objective function:

$$\sum_{t=1}^{T}(y_t - x_t)^2 + \lambda_{hp}\sum_{t=3}^{T}(\Delta^2 x_t)^2 \tag{1}$$

Where T is the sample size. The $y_t - x_t$ component measures the errors and the $\Delta^2 x_t$ measures the smoothness of the trend. The smoothing parameter that controls the trade-off between the size of the error and the smoothness of the trend is noted by λ_{hp}, which is a continuous function of time.

An alternative representation of (1) can be

$$\| y - x \|_2^2 + \lambda_{hp} \| Dx \|_2^2 , \tag{2}$$

Where $y = (y_1 ... y_t)' \in R^T$, $x = (x_1 ... x_t)' \in R^T$ and $\| u \|_2 = (\sum_i u_i^2)^{1/2}$ is the Euclidean or ℓ_2-norm vector of u. D represents the second-order matrix that $Dx = (\Delta^2 x_3 ... \Delta^2 x_t) \in R^{T-2}$ that has the following form:

$$D = \begin{pmatrix} 1 & -2 & 1 \\ \ddots & \ddots & \ddots \\ 1 & -2 & 1 \end{pmatrix} \in R^{(T-2)\times \mathrm{T}} \tag{3}$$

The solution to (1) is then given by

$$x^{hp} = (I_T + \lambda_{hp} D'D)^{-1} y = A^* y \qquad (4)$$

Where I_t is an identity matrix of size T. It is known that as $\lambda_{hp} \to 0, x^{hp}$ converges to the original series, whereas $\lambda_{hp} \to \infty, x^{hp}$ approaches the linear trend that fits the data best.

We can derive the cyclical component of the HP filter by

$$c_t = y_t - x^{hp} \qquad (5)$$

4.1.2 The Band- Pass filters

The band-pass filter proposed by Baxter and King (1999) takes the form of a two-sided moving average:

$$x^{bp} = \sum_{k=-K}^{K} a_k y_{t-k} = a(L) y_t \qquad (6)$$

The weight can be derived from the inverse Fourier transform of the frequency response function. Baxter and king adjust the filter with a constrain that the sum of coefficients must be zero. The $a(L)$ can be factored as

$$a(L) = (1-L)(1-L^{-1}) a^*(L) \qquad (7)$$

with $a^*(L)$ being a symmetric moving average with $K-1$ leads and lags.

Christiano and Fitzgerald (2003) proposed two variations to the band-pass filter. The first varies on the choice of the objective function used to select the moving average weights. The second introduced a time-varying filter with weights both depending on the data and changing for each observation.

In choosing between fixed length and full sample asymmetric methods, we should consider that the fixed length filters require that we use the same number of lead and lag terms for every weighted moving average. Thus, a filtered series computed using leads and lags observations will lose observations from both the beginning and end of the original sample. In contrast, the asymmetric filtered series do not have this requirement and can be computed to the ends of the original sample.

Acknowledging the advantages of the Asymmetric Christiano and Fitzgerald filter there is an empirical methodology introduced in Cuddington and Jerrett (2008) and also implemented by Erten and Ocampo (2012). This empirical methodology using the Asymmetric Christiano and Fitzgerald filter focuses on the detection of super cycles with long time span. The natural logarithms of real commodity price indices are decomposed into three components: the long-term trend (LP_T), the super-cycle component (LP_SC) and the other shorter cycle component (LP_O):

$$LP_t \equiv LP\_T_t + LP\_SC_t + LP\_O_t \qquad (8)$$

Considering how long a super cycle lasts Cuddington and Jerret, yielding a complete cycle of roughly 20–70 years. They extract the super-cycle component by applying the BP(20,70) filter to each price series:

$$LP\_SC \equiv LP\_BP(20,70) \tag{9}$$

The long-term trend is defined as all the cyclical components with a period in excess of 70 years:

$$LP\_T \equiv LP\_BP(70,\infty) \tag{10}$$

This approach allows the long-time trend to evolve over time. The remaining shorter cyclical components, that range with cycles of 2 through 20 years can be filtered:

$$LP\_O \equiv LP\_BP(2,20) \tag{11}$$

The total "non-trend" components are defined as the total deviation from the long-term trend, or the summation of the super cycles with the other shorter cycles :

$$LP\_NT \equiv LP\_BP(2,20) + LP\_BP(20,70) \tag{12}$$

Equivalently the cycle-trend decomposition in (8) can be written as follows:

$$\begin{aligned} LP_t &\equiv LP\_T_t + LP\_SC_t + LP\_O_t \\ LP_t &\equiv LP\_BP(70,\infty) + LP\_BP(20,70) + LP\_BP(2,20) \\ LP_t &\equiv LP\_T + LP\_NT \end{aligned} \tag{13}$$

4.1.3 The ℓ_1- filter

An interesting variation to HP filter was proposed by Kim et.al(2009) replacing the Euclidean or ℓ_2 -norm with an ℓ_1- norm, so the ℓ_1-trend is obtained by minimizing the following objective function :

$$\sum_{t=1}^{T}(y_t - x_t)^2 + \lambda_1 \sum_{t=3}^{T} |\Delta^2 x_t| \tag{14}$$

or, in matrix notation,

$$\| y - x \|_2^2 + \lambda_1 \| Dx \|_1 \tag{15}$$

where $\| u \|_1 = (\sum_i u_i)$ denotes the ℓ_1 - norm of the vector u.

Because of the appearance of ℓ_1 - norm in the objective function, Kim et.al (2009) term their approach ℓ_1 -trend filtering, which generally produces piecewise linear trends. The objective in (14) and (15) that is strictly convex and coercive in x and has a unique minimizer. The solution to (14) is :

$$x^{lt} = (x_1^{lt} \dots x_T^{lt}) \in R^T \tag{16}$$

where ‘lt’ stands for linear trend. The ℓ_1-trend is a piecewise function of time that connects $k+1$ linear segments, where k is the number of “structural breaks” in the series. The constant λ_1 is a smoothing parameter, and Kim et.al(2009) show that like λ_{hp} when $\lambda_1 \to 0$ the x^{lt} converges to the original data y_t, whereas as $\lambda_1 \to \infty$ it converges to the best affine fit to the data.

The cyclical component of the ℓ_1-trend filtering is:

$$c_{lt} = y_t - x^{lt} \tag{17}$$

The question of how to properly calibrate ℓ_1 still remains. The task is complicated and the adequate calibration needs to be data-dependent. Yamada and Yoon (2014) set the λ_1=20 when using the CVX package in MATLAB. Winkelried (2015) implement the same fitting error criterion that combines the λ_{hp} and the λ_1, calibrating the filters individually for each series conditional of the fitting for specified values of the smoothing parameters. For the

The drawbacks of using the above filters are being discussed among several studies. The HP filter is the one with the most shortcomings that are being outlined even in recent studies. Phillips and Jin (2015) concluded that the HP filter may not successfully de-trend even if the true series is only I (1). In addition, De Jong and Sakarya (2016) observed significant nonstationary stemming from observations near the end or the start of the sample, leading to the failure of the assumption of stationarity of the HP cycle. The BP filters tried to overcome some of the drawbacks with the Asymmetric Christiano and Fitzgerald filter achieving the most alleviation of the problems. Although, the use of weights still makes some underlying assumptions of the relationship of the filter with the selected data. Finally, the ℓ_1- filter seems to be the most adequate for the filtering process. However, the need for proper calibration and the deviations in the available methods in order to calculate the ℓ_1- norm, makes the use of it challenging.

Hamilton (2017) proposes an alternative to the HP filter, that might overcome the drawbacks of the other filters, due to its simplicity of calculation and the lack of use of an a priori transformation function for the series. He denotes the failure of the HP filter, as it introduces spurious dynamic relations that are an artifact of the filter and have no basis in the true data-generating process. His approach preserves the underlying dynamic relations and consistently estimates well-defined population characteristics for a broad class of possible data-generating processes.

4.2 The Hamilton Filter

If $(1-L)^d y_t$ is stationary for some $d \geq 1$, then for a finite $h \geq 1$,

$$y_{t+h} = k_h^{(1)} y_t + k_h^{(2)} \Delta y_t + \cdots + k_h^{(d)} \Delta^{d-1} y_t + w_t^{(h)} \tag{18}$$

with $\Delta^s = (1-L)^s$, $k_l^{(1)} = 1$ for $l = 1, 2, ..$ and $k_j^{(s)} = \sum_{l=1}^{j} k_l^{(s-1)}$ for $s = 2, 3, \ldots, d$ and $w_t^{(h)}$ is a stationary process.

Let $x_t = (y_t, y_{t-1}, \ldots, y_{t-p+1}, 1)'$ for some $p \geq d$ and consider an OLS estimation of $y_{t+h} = x_t'\beta + u_{t+h}$ for $t = 1, \ldots, T$ with estimated coefficient :

$$\hat{\beta} = \left(\sum_{j=1}^{T} x_t x_t' \right)^{-1} \left(\sum_{j=1}^{T} x_t y_{t+h} \right). \tag{19}$$

If $p = d$, the OLS residuals $y_{t+h} - x'\hat{\beta}$ converge to the variable $w_t^{(h)} - E\left(w_t^{(h)}\right)$ in (18).

If $p \geq d$, the OLS residuals converge to the residuals from a population linear projection of $w_t^{(h)}$ on $\left(\Delta^d y_t, \Delta^d y_{t-1}, \ldots, \Delta^d y_{t-p+d+1}, 1\right)'$.

The previous propositions establish that estimating an OLS regression of y_{t+h} on a constant and the $p = 4$ most recent values of y as of date t,

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + u_{t+h}, \tag{20}$$

the residuals

$$\hat{u}_{t+h} = y_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 y_{t-1} - \hat{\beta}_3 y_{t-2} - \hat{\beta}_4 y_{t-3} \tag{21}$$

offer a way to construct the stationary, or cyclical, component.

The advantages of the proposed procedure over the HP filter can be summarized as the following. First, a true ability of y to predict x is represented by and finding that $\hat{u}_{t+h}$ predicts some other variable x_{t+h+j}. Second, the value of $\hat{u}_{t+h}$ will be difficult to predict from variables dated t and earlier. Third, the value of $\hat{u}_{t+h}$ is model-free and essentially an assumption-free summary of the data. With Hamilton (2017) approach, that can isolate a stationary component from an $I(4)$ series, we can have consistently estimated population characteristics preserving at the same time the underlying dynamic relations. Hence, we get consistent estimations for the trend and the cycle characteristics of the underlying series.

For the identification of turning points and the measurement of cycle durations, we follow the approach of Winkelried (2015). We date cycles using the algorithm of Bry and Boschan (1971). We identify turning points in $\hat{u}_t$, that are the local maximum and minimum of the cycles. A local maximum is defined as peak and a local minimum as a trough, with peak and trough alternating. The window of the period to trace the turning points is calibrated for each cycle series, but we set values analogously to the super-cycle methods, as they described.

4.3 The Macroeconomic model

Erten and Ocampo (2013) investigated the possibility of cointegration between real commodity prices and income. Harvey et. All (2017) apply a stationary VAR to assess the relationship among commodity prices, economic activity and interest rate. To select among the two approaches, we have to test for a unit root. We apply the Zivot and Andrews unit root test with structural break both in constant and trend. This test is preferred to the usual ADF test, due to the findings and the characteristics of the selected macroeconomic variables that according to Harvey et. All (2017). Alongside with Harvey et. All (2017) there was evidence of stationarity with a broken trend, though we continue our approach using a stationary VAR, based on commodity prices, GDP series, and interest rates. A stationary VAR(p) is estimated:

$$z_t = u + \mathrm{A}_1 z_{t-1} + \cdots + \mathrm{A}_p z_{t-p} + u_t, t = 1, \ldots, T \qquad (22)$$

Where $z_t = (z_{1t}, \ldots, z_{kt})'$. The lag lengths are chosen by selecting the Schwartz from the selection criteria. An alteration to the original model comes from the inclusion to the VAR the commodity prices in the form of the cycle results of the Hamilton filter.

In order to validate our approach, we perform the Granger causality test and compare the results along with those from Harvey et. Al (2017).

5. The Dataset

The extended Grilli-Yang data series comprises twenty-four, internationally traded, non-fuel commodities, that comprises of three different categories: Food, nonfood, and metals. The commodities are Aluminum, Banana, Beef, Cocoa, Coffee, Copper, Cotton, Hide, Jute, Lamb, Lead, Maize, Palm Oil, Rice, Rubber, Silver, Sugar, Tea, Timber, Tin, Tobacco, Wheat, Wool, and Zinc. The commodity prices are deflated by the United Nations Manufacturers Unit Value (MUV) index, with the MUV series reflecting the unit values of manufacturing exports from a number of industrial countries.

The source of the data is http://www.stephan-pfaffenzeller.com/gycpi/, which is the latest revision maintained by Stephan Pfaffenzeller. Pfaffenzeller et al. (2007) extended the original Grilli-Yang data series until 2011. The sample period is from 1900 to 2011, with a total of 112 observations of annual data.

We also use the eight aggregate commodity price indexes that are available for the same period. They correspond to the whole group of commodities, as it was originally indexed by Grilli and Yang, alongside with the subgroups of metals, non-food agricultural commodities, and food commodities. They are also comprised of two groups, one with arithmetic weights and one with geometric weights. As weights are being used the 1977 to 1979 values of world export for each commodity. The commodity price indexes are also deflated by the MUV index.

For the historical macroeconomic data, we use datasets similarly to Harvey et. al (2017) and Erten and Ocampo (2013). In terms of economic activity, we source our data from Angus Maddison's data, covering from 1900 until 2010, by the Maddison Project available at https://www.rug.nl/ggdc/historicaldevelopment/maddison/. From the database there, we obtain the USA GDP, the UK GDP, the Chile GDP, and the World GDP. For the last annual series, there are available complete data from 1950 to 2010 and point estimates for 1900,1913 and 1940. Analogously to Erten and Ocampo (2013), we interpolate the missing world data using the note that the OECD GDP accounts for 52%,54% and 55% of world GDP, respectively for each point estimate.

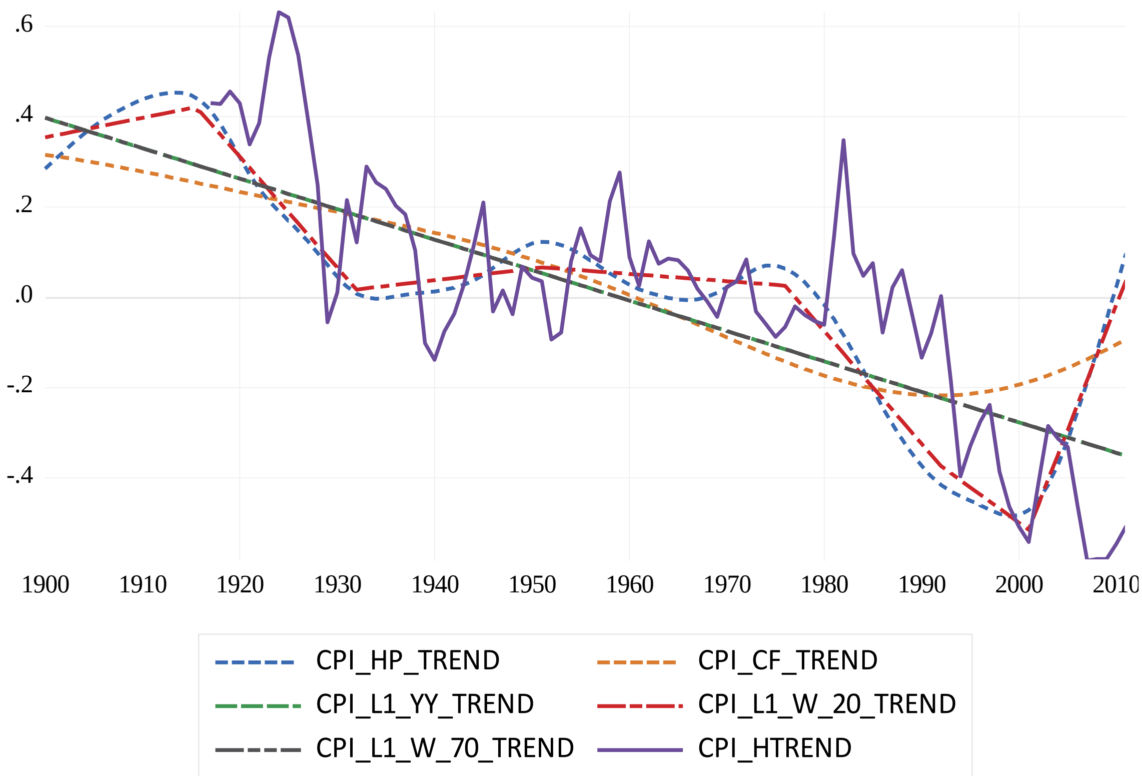
Finally, the source of the historical interest rate is from the Bank of England, that has available annual data on long-term government bonds from 1703 and was retrieved from the Federal Reserve Bank of St. Louis (FRED).

6. Empirical Analysis

In this section, we present the outcomes of the application of the Hamilton filter to the Grilli and Young dataset. For the beginning, we present the outcomes of the replication of all the previous filtering methods alongside the representation of the results of the Hamilton Filter. The first set of diagrams present the trends and cycles of the CPI for the sample period. In Figure 1, we observe similarities among the previous filtering methods, that tend to lead to the smoothed representation of the trend. On the contrary, the Hamilton filter leads to a more discrete trend that has many periods of an upward and downward trend. Moreover, the values of the Hamilton trend tend to be higher than the ones of the previous filters.

Those differences stem from the unique methodology of the Hamilton filter since the presented results are mostly data driven series. However, the presence of more upward trends in the results of the filter makes the support of the PSH hypothesis more challenging.

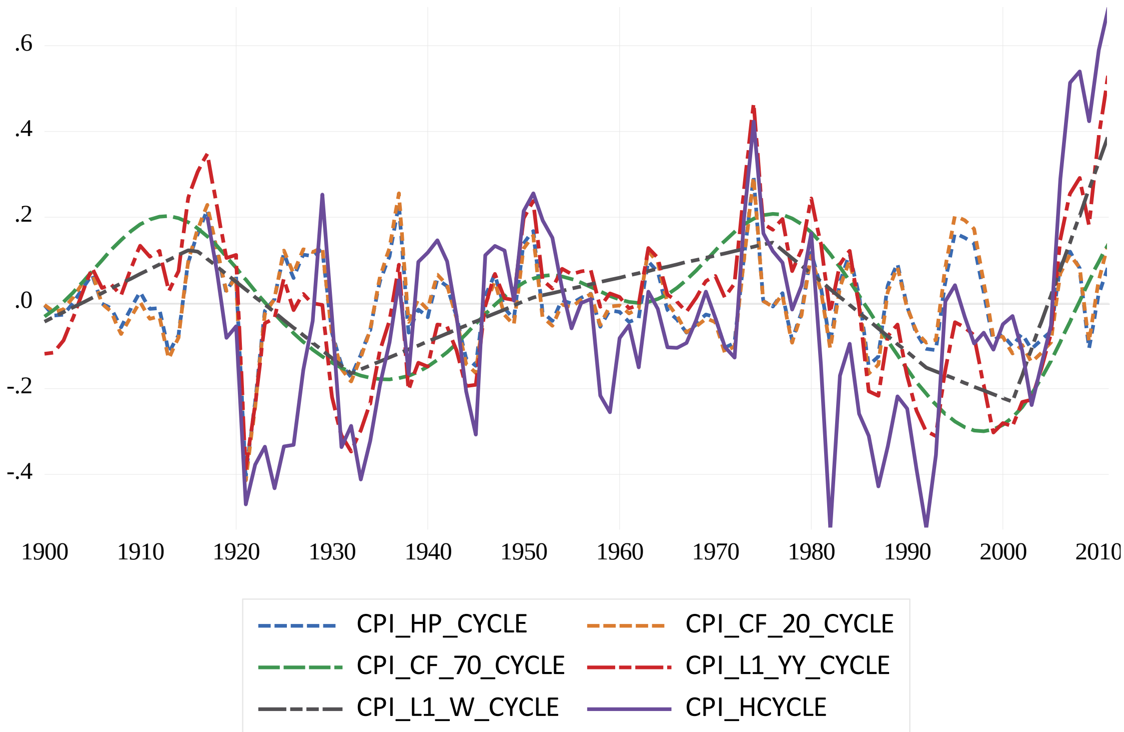
Figure 1: Trend representation of CPI



In Figure 2, we present the cycles of the different filters. The estimated Hamilton cycle differs also in this set. It follows the cyclical movements of the majority of the filters, with the main deviation of the larger scale of the reported values. Small variations in the Hamilton cycle of CPI can be observed especially in the 1920s era. The cycles appear to follow the super-cycle series as it is represented by the l_1-filter in Yamada and Yoon (2014).

Similar findings to those of the two previous diagrams are observed in the whole dataset, not only in the aggregate series but also in the specific commodity series that are available (Figures for the whole dataset, that present the trend and cycle representations, can be found in Appendix B).

Figure 2: Cycle representation of CPI



The Hamilton filter behaves differently from all the other filters. The estimated cycles have larger magnitude and the subsequent trends have more variation in their direction. Those preliminary results from the diagrams regarding the trend and cycles of the Hamilton filter are examined more thoroughly in the two following parts.

6.1. Trends and the PSH Hypothesis

We examine, the slope of the Hamilton trend for every commodity and the eight aggregate indexes. We are interested in the negative or downward trends that are present. Given their presence and adequate number, we can asses the longevity of the PSH hypothesis in the 20th century, under the scope of the Hamilton approach.

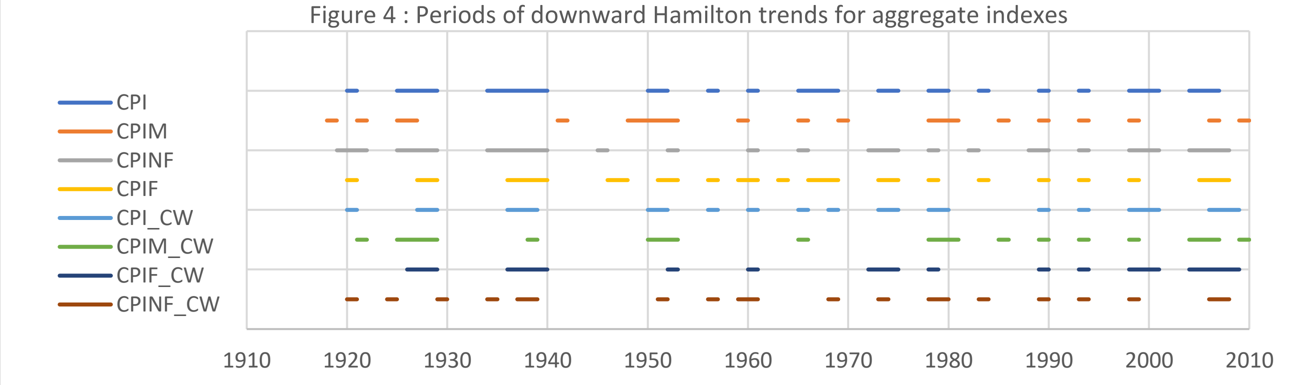
Figure 3 shows the negative trends for each commodity from the late 1910s to 2010. It is evident that each commodity has its unique trend characteristics. Some have small consecutive years of downward trend, in contrast with others that present long periods of a negative trend. Such groups of commodities can be identified in each of the three major commodity types. In the case of the metals, we have the zinc and lead, with many small periods of negative trend. On the contrary, silver, aluminum and copper exhibit some long periods of negative trend. From the group of non-foods commodities, we can distinguish as main representatives of this phenomenon the hide and jute. Finally, from the food commodities, the most representative groups are those of maize and lamb.

It is worth to point out that there are certain periods, in which the prices of different commodities lack a downward trend. Those periods are not common for every commodity, but we can distinguish the most prominent. The first one can be characterized as the period of the Great Depression in the early 1930s. The second on then one of the WWII in the 1940s. In the same manner, the commodities tend to uphold their downward trend of their prices in periods of economic depression.

The attempt to interpretate any relationship among the economic output and the price of commodities will be presented in the last part of the results.

We subsequently display the negative trends from the aggregate commodity indexes. Figure 4 illustrates the periods of downward trend for all the indexes. It is obvious that we can distingue certain periods with upward trend. Those periods can be identified as the periods of economic depression, similarly to the analysis above. When we compare the trends from the weighted indexes to the ones with geometric weights, we can observe that longer periods tend to shorten, resulting in some cases to lesser observations.

Figure 4 : Periods of downward Hamilton trends for aggregate indexes



Our figures vary from the ones reported from Yamada and Yoon (2014) and Winkelried (2015). This variation stems from the difference in our methodological approach. However, we can draw certain results regarding the PS Hypothesis. Most of the commodities exhibit slopes of their trends that are negative, for more than the half of the examined periods. Only three commodities, namely maize, beef and zinc, fail to hold the majority of their tredns’ slopes negative. Therefore, we find strong evidence that the Prebisch-Singer Hypothesis holds sometimes for these commodities.

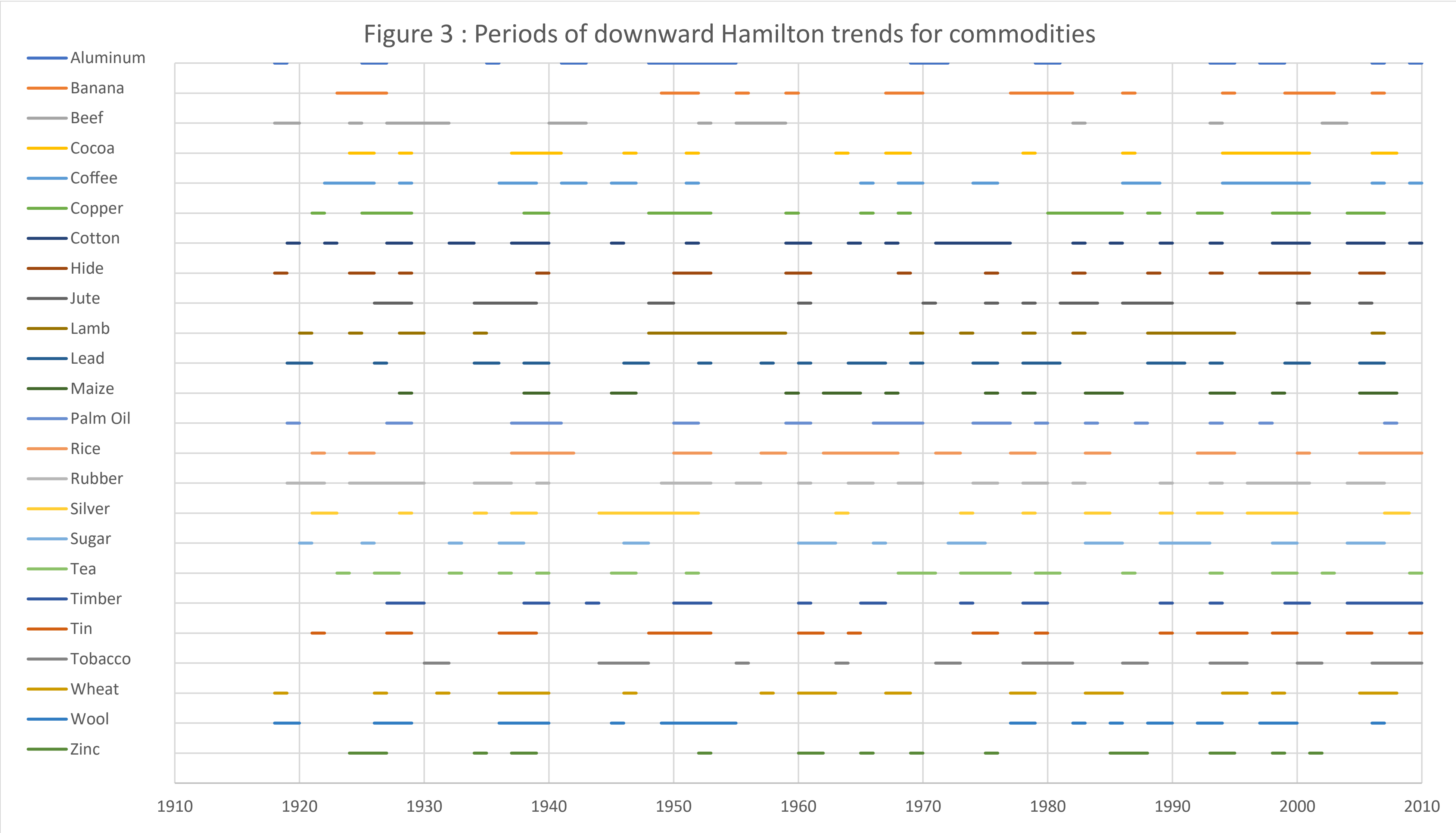


Figure 3 : Periods of downward Hamilton trends for commodities
Aluminum
Banana
Beef
Cocoa
Coffee
Copper
Cotton
Hide
Jute
Lamb
Lead
Maize
Palm Oil
Rice
Rubber
Silver
Sugar
Tea
Timber
Tin
Tobacco
Wheat
Wool
Zinc
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010

However, the strength of the hypothesis weakens during periods of economic depressions, where many commodity prices tend to increase. A similar picture emerges from the evaluation of the PS hypothesis on the aggregate commodity price indexes. Most indexes exhibit negatively sloped trends for most of the sample periods. The only index that fails to support the PSH is the metals one with geometric weights. Our findings are similar to the ones from Yamada and Yoon (2014) and Winkelried (2015). The Prebisch-Singer Hypothesis holds sometimes for the most periods in the data set.

6.2.Hamilton Cycles

From what we have seen in the first part of our analysis, we observed that the cycles that are extracted from the Hamilton filter pay many resemblances to the ones of the HP filter, the CF asymmetric filter and the two cycles of the variation of the l_1-filter in Winkelried (2015). However, we have noted that the cycles in Hamilton tend to have somewhat different periods and higher magnitude. The presence of cycles tends to have an effect on the price of the commodities as it variates the subsequent trend of each commodity. Following the approach of Winkelried (2015), we try to identify the periods that those discrepancies are apparent. Table 1 reports the turning points associated with the aggregate price indexes and Table 2 reports the turning points associated with each commodity price.

Our findings are mainly in agreement with the previously documented literature of Super Cycles (Cuddington and Jerrett, 2005; Erten and Ocampo,2013; Winkelried, 2015). The Hamilton cycles tend to have a resemblance to the Super Cycles but are in a degree shorter in length and suggest the presence of one or more cyclical waves.

From Table 1 we can identify that the median of peaks and troughs is three for the 20^{th} century. This suggests the presence of three cyclical waves during the sample period. The median duration of a contractionary phase, i.e. the transition from peak to trough is around 10 years and of an expansionary phase, i.e. the transition from through to peak is about 20 years, suggesting a cycle duration of 30 to 35 years. This is the main variation from the Supercycles evidence previous literature has identified.

We observe that the aggregate indexes of the food and non-food commodities have similar cyclical behavior to the one of the CPI. In contrast, the aggregate index of the metals has a shorter contractionary phase and greater expansionary phase. When we examine the geometrically weighted indexes, we do not observe variations in the previous results for the CPI_CW and CPIM_CW. The differences are evident on the geometrical indexes of food and non-food, with additional peaks and troughs identified, leading to shorter cycles of around 20 years with the contractionary phase of 9 years and of expansionary phase of 12 years.

In Table 2 we present the associated turning points for each commodity price along with the number of peaks and troughs. There we can identify some distinctive patterns among groups of commodities. Food prices have in median three cycle waves, with duration from 24 to 35 years. The expansionary phase and contractionary phase vary among the different food prices. Metals have in median more than four peak and troughs, with shorter duration (25 years). The expansionary phase is shorter than the contractionary phase for most metals. The remaining commodities have in median around three cycle waves, with duration from 25 to 51 years. The expansionary phase and contractionary phase vary among the different non-food prices.

Table 1: Turning points and duration of Hamilton Cycles for aggregate indexes

	N_P	Peaks (P) Dates	N_T	Troughs (T) Dates	Mean Duration in Years $P \rightarrow P$	$T \rightarrow T$	$T \rightarrow P$	$P \rightarrow T$
CPI	3	1929,1974 ,2008	3	1921,1933,1982,	39	30.5	25	6
CPIM	3	1929,1955,2007	3	1924,1945,1993	39	34.5	9.6	27
CPINF	3	1940,1979,2007	4	1921,1959,1986,2009	33.5	29.3	20	9.3
CPIF	3	1947,1974,2008	3	1933,1958,1982	30.5	24.5	18.6	9.5
CPI_CW	3	1929,1974,2008	3	1921,1933,1992	39.5	35.5	21.6	11
CPIM_CW	3	1929,1955,2007	3	1924,1945,1993	39	34.5	9.6	27
CPINF_CW	4	1940,1951,1979,2007	4	1931,1949,1967,1986	22.3	18.3	12.5	8.6
CPIF_CW	4	1929,1947,1974,2008	5	1921,1933,1962,1992,2009	26.3	22	12.5	9.5

Moreover, most prices produce a peak and a trough surrounding 1920 (the end of the American industrialization momentum), a peak or a trough during the 1950s (the reconstruction of Europe) or 1970s and 1980s (the recession in US and Japan) and a trough in late 1990s (early recession in western world). Notably, most prices produce a peak in the late 2000s (the recent recession of 2008), which in some cases are followed by a trough in the subsequent following years.

It is evident that the Hamilton Cycles are somewhat shorter than the previously documented literature of Super Cycles and have at least one cycle wave. In addition to this, the expansion of the sample date until 2010 allows for the incorporation of the effects of the recent recession of 2008. The cyclical behavior is apparent for the commodities and their indexes and the analysis of the interactions with macroeconomic data is evident from the recent literature. (Erten and Ocampo,2013; Harvey et al., 2017)

We can still observe the presence of values of high correlation among the cycle series of the commodities, as it is presented in Table 3. In order to evaluate which cyclical component is leading, we imply the Granger Causality test in the VAR of the commodity cycles. From Table 4 we can observe that certain commodities tend to cause other commodities more often than others. The main leading components are those of Aluminum, Copper, Cotton, Lamb, Lead, Maize, Timber and Wool. There are also bidirectional causalities showing that certain commodities tend to co-move during the cycle period. These findings are similar to those of Fernandez (2015) that validate the presence of co-movements among the commodities. In analogy, we perform the same test for VAR with the groups of Food, Metals and Non-food commodities (Tables 5 to7). We are able to identify also, in this case, certain commodities that are leading the cycle of the other commodities for every different group.

Table 2: Turning points and duration of Hamilton Cycles for commodity prices

		Peaks (P)		Troughs (T)	Mean Duration in Years			
	N_P	Dates	N_T	Dates	$P \to P$	$T \to T$	$T \to P$	$P \to T$
Banana	3	1932,1982,2008	3	1919,1974,1999	38	40	10	29.5
Beef	4	1931,1960,1983,2004	4	1923,1951,1975,1996	24.3	24.3	8.25	16
Cocoa	3	1954,1973,2008	3	1923,1962,1993	27	35	19	14
Coffee	3	1929,1954,1977	4	1921,1940,1962,1992	24	23.6	12.3	11.3
Lamb	4	1935,1960,1983,2003	4	1923,1950,1975,1995	22.6	24	9.5	14
Maize	3	1929,1974,2008	3	1921,1955,1992	39.5	35.5	14.3	22
Palm Oil	3	1941,1998,2008	3	1926,1986,2005	33.5	39.5	10	26
Rice	3	1926,1974,2008	3	1920,1936,1982	41	31	23.3	9
Sugar	3	1920,1974,1993	3	1931,1982,2004	36.5	36.5	27	46
Tea	3	1928,1954,1984	4	1921,1946,1973,1992	28	23.6	35.5	15
Wheat	3	1947,1974,2008	3	1923,1954,1982	30.5	29.5	23.3	7.5
Cotton	4	1923,1946,1976,1994	3	1931,1970,1992	23.6	30.5	7.6	46.5
Hide	3	1930,1979,2001	4	1923,1958,1981,2009	35.5	28.6	16	12.6
Jute	3	1951 ,1984,2006	4	1933,1959,1993,2007	27.5	24.6	18.6	6
Rubber	3	1940,1980,2007	4	1933,1971,1992,2009	33.5	25.3	10.3	21.5
Timber	4	1918,1941,1974,2007	3	1926,1949,1986	29.6	30	20.3	38
Tobacco	4	1920,1935,1983,2002	4	1929,1942,1993,2005	27.3	25.3	18.6	34
Wool	2	1951,2007	2	1932,1981	56	49	22.5	30
Aluminum	4	1931,1955,1981,2006	4	1924,1947,1973,1993	25	23	9	15.3
Copper	4	1929,1953,1989,2007	4	1924,1945,1978,1998	26	24.6	8.25	16.6
Lead	3	1952,1979,2007	3	1933,1962,1987	27.5	27	18.6	9
Silver	3	1919,1935,1980	3	1921,1943,1991	30.5	35	25.5	40
Tin	5	1925,1939,1965,1980,2008	5	1921,1943,1959,1973,1991	20.75	17.5	6	14.5
Zinc	4	1929,1975,1989,2006	5	1923,1958,1982,1998,2008	25.6	21.25	9.5	15

Since our next step is to evaluate the composite commodity prices indexes, we also perform the previous test to the prices of the commodities alongside with the index. From Table 8 we can observe nine commodities leading the CPI, namely Copper, Cotton, Lamb, Silver, Timber, Tobacco, Wheat, Wool and Zinc. Causal bidirectional relation with the CPI is found for four of them. We perform these tests for the leading components for all the indexes and the corresponding commodities (Tables 9 to 14). We notice certain commodities to maintain their lead regardless of the index, showing evidence of being the leading elements for the prices. Although aggregation for the cyclical components may lead to wrong results, the most noticeable cases of commodities are those of Maize, Rice, Aluminum, Silver, Cotton and Wool.

6.3 Stationary VAR analysis with macroeconomic variables

To assess whether the approach is appropriate for the relationship among the commodity prices, the economic activity and the interest rate we test each series for unit root. Table 15 presents results from Zivot and Andrews unit root test with structural break both in constant and trend.

The selection of the Zivot and Andrews unit root test is due to the findings and the characteristics of the selected macroeconomic variables that according to Harvey et. All (2017). We find evidence of stationarity of all the series and we proceed in analogy to Harvey et. All (2017) with the estimation of a stationary VAR. Analyzing the relationships among the Hamilton cycle series of the commodities, the GDP series, and the interest rate, we show in the following tables the results of the Granger causality tests, within different VAR frameworks.

Table 15: Unit root tests

	ZA
CPI	0.000828***
CPI_CW	0.000473***
CPIF	0.000936***
CPIF_CW	0.001106***
CPIM	0.051954*
CPIM_CW	0.005318***
CPINF	0.040362**
CPINF_CW	-6.293131^
GDP World	0.003964 ***
GDP US	0.000637***
GDP UK	0.001925***
GDP Chile	0.001270 ***
Interest Rate	0.007634***

Note: *, **, *** denote the 10%,5%,1% significance level respectively. ^ notes the Lee Strazicich LM t-stat at a 5% significance level with two structural breaks.

Table 16 shows the results of different Granger causality tests in the Framework of the CPI cycle component as a proxy for the commodity prices. We detect causality running from the cycle of commodity prices to the GDP of Chile when we refer to a VAR of CPI and a joint GDP series of Chile. There is also evidence of one-way causality running from CPI to the interest rate in the corresponding VAR. We, therefore, apply a VAR framework corresponding to different GPD series, with the CPI and Interest rate. We find bidirectional causality between the interest rate and the CPI and one-way causality, running from the World GDP to CPI, in the subsequent VAR. When we account for the US GDP in the VAR, we find also a bidirectional causality between interest rate and the CPI. Similarly, there is bidirectional causality between the CPI and the interest rate in the VAR that accounts for the UK GDP as an alternative for the GDP. Finally, the VAR, that examines the relationship of the GDP of Chile with the CPI and the interest rate, finds evidence of bidirectional causality between the GDP of Chile and the CPI and between the interest rate and the CPI.

In Table 17 we present the results of the causality test in the framework that accounts for the CPIF (CPI of food commodities). There is a causality running from the CPIF to the GDP of Chile and a causality running from CPIF to interest rate, in the corresponding VAR frameworks. In the VAR frameworks, that have as endogenous all three variables, we find a bidirectional causality running between the CPIF and interest rate. In the case of the UK GDP, the causality runs only from the CPIF to the interest rate. Surprisingly, there is one-way causality running from the interest rate to the US GDP in the specific VAR framework. For the remaining framework, that integrates the Chile GDP, we find two bidirectional causalities, one between the CPIF and interest rate and one among causality the CPIF and the Chile GDP.

In Table 18 we have some differences in the results of the Granger Causality tests. For the first five VAR frameworks, we can only find evidence of causality running from the Chile GDP to the CPIM (CPI of metal commodities). A bidirectional causality is evident among the World GDP and the interest rate, with the World GDP Granger causing the CPIM, in the subsequent VAR. For the VAR, that integrate three variables and the proxy of Chile GDP, we find that GDP series of the Chile GDP Granger causes the CPIM, with the interest rate Granger causing the CPIM. In the framework with the US GDP, a Granger causality is running from the interest rate to the US GDP. The framework with the UK GDP fails to identify any causality.

When we account for the CPI of non-food commodities (CPINF) the identified causal relationships are fewer (Table 19). We find a causality funning from CPINF to the interest rate. In the VAR frameworks with three variables, there are significant findings only when we account for the World GDP and the US GDP. We find evidence of causality running from World GDP to the CPINF and a causality running from the interest rate to the CPINF. For the VAR with the US GDP, we find causality running from interest rate to the US GDP and causality running from CPINF to the interest rate. No causal relationship was evident in the VAR framework with the UK GDP.

To account for the validity of our causality results and to explore possible relationships that arise from the different aggregation of the indexes we incorporate in the previous VAR frameworks the geometrically aggregated indexes of the commodity prices (CPI_CW, CPIF_CW, CPIM_CW, and CPINF_CW).

Regarding the findings of the Granger causality test for the CPI_CW, we observe some differences from the previous iteration of the CPI. There are three new causal relationships that arise, two in the VAR frameworks with two variables and one in the framework with three variables and the US GDP (Table 20). The first is the one-way Granger causality running from the CPI_CW to the UK GDP. The second one is the bidirectional causality between Chile GDP and CPI_CW. The last Granger causality runs from the interest rate to the US GDP. In Table 21, no new findings rise, but the same causal relations are evident for each of the different VAR frameworks, in analogy to the findings of CPIF.

There are two VAR frameworks with the CPIM_CW, that exhibit new findings, regarding the Granger causality (Table 22). There is bidirectional causality between CPIM_CW and the Chile GDP, in the subsequent VAR. We also identify for the first time a Granger causality running from the US GDP to the CPIM_CW, the sole evidence of causality among US GDP and a commodity index.

Finally, in the VAR frameworks with the CPINF_CW (Table 23) some new causalities are evident and only two remain significant in comparison to the findings regarding the CPINF. There is evidence of causality running from the CPINF_CW to the UK GDP and also from the CPINF_CW to the Chile GDP, in the VARs that integrate these iterations of GDP. Moreover, we find evidence of a Granger causality between the CPINF_CW and the World GDP and a Granger causality from the CPINF_CW to the UK GDP. Finally, the two causal relations that are still significant are those of the interest rate towards the US GDP and the CPINF_CW towards the interest rate, in the corresponding VAR iteration.

Taken as a whole the results in the following tables we can confirm that commodity prices tend to Granger cause mainly the economic activity of the Chile and interest rates, while the interest rate tends to Granger cause prices and the GDP of US. We also observe that the World GDP Granger causes the CPI, CPIM, and CPIM_CW in the specific VAR frameworks. Interestingly, these implications pay resemblance to the findings of Harvey et al. (2017), even though our analysis is based on a smaller dataset and with alternative approximations for the commodity prices.

7. Concluding Remarks

This study examines the presence of trends and cycles in the commodity prices, by introducing an alternative filtering method in order to obtain the trend and cycle of the underlying commodities. We utilize the Hamilton filter, using the extended Grilli and Yang dataset from 1900 to 2011. The empirical analysis focuses on three different paths. First, we examine the validation of the PSH in the findings of the trend series, acquired by the Hamilton filter. Then we evaluate the characteristics of the cycle series. Finally, we focus on the relationship between the commodity prices, the interest rate, and the economic activity.

Considering the replication of previous studies that utilize different filters, we compare our findings from the Hamilton filter to them. We observe that the series obtained from the new filtering method have different characteristics. The trends tend to have higher variation than before. The cycles tend to have higher magnitude compared to those of the other filters.

The results from the trend analysis, validate the presence of a downward trend for most of the commodities and the aggregate indexes. This suggests that the Prebisch-Singer Hypothesis holds sometimes, but not in periods of economic depressions.

Furthermore, we try to identify the turning points and the length of the cycles of commodity prices. Our findings indicate the presence of cycles that are marginally shorter than the previously documented Super Cycles. Moreover, we show that the resent economic depression of 2009 produces an additional cycle wave to the ones previously identified during periods of economic downturns. Results from the Granger causality of the cycles show that certain prices of commodities are leading the cyclical components of the prices of the remaining commodities and the underlying indexes.

Following the recent work that suggested the presence of relations among economic activity, interest rates, and commodity prices, we adopt a stationary VAR approach that assesses different ranges of economic activities with the different composite price indexes. The causality analysis confirms the existence of certain relationships. There is evidence that commodity prices Granger-cause interest rate and mainly the GDP Chile, while interest rate Granger causes commodity prices and the economic activity of the US. Moreover, there is a causality running from the economic activity of the world towards the commodity prices. The results pay resemblance to the findings of Harvey et al. (2017). From an economic policy perspective, our results indicate that any changes in the monetary policy have a significant effect on the commodity prices and the economic activity of large economies like the US. Moreover, any change in commodity prices has a significant effect on the exporting countries that have smaller economic activity and are not that diverse, in respect of terms of trade. Finally, the global economic activity has a direct effect on the prices of most of the commodities except for the ones related to food consumption. Since commodity prices have a significant role in the advancement of the economic activity of the exporting countries, any variations of them must be taken into consideration before policymakers implement any policy that can affect the economic activity.

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9. Tables of Results

Table 3: Correlation Matrix of Commodities

	Aluminum	Banana	Beef	Cocoa	Coffee	Copper	Cotton	Hide	Jute	Lamb	Lead	Maize	Palm Oil	Rice	Rubber	Silver	Sugar	Tea	Timber	Tin	Tobacco	Wheat	Wool	Zinc
Aluminum	1.00																							
Banana	0.56	1.00																						
Beef	0.25	-0.07	1.00																					
Cocoa	0.07	0.12	-0.25	1.00																				
Coffee	0.12	0.27	-0.44	0.70	1.00																			
Copper	0.40	0.29	0.07	0.35	0.22	1.00																		
Cotton	-0.39	-0.26	-0.30	0.31	0.46	0.09	1.00																	
Hide	0.02	-0.16	0.11	0.20	-0.01	0.05	0.10	1.00																
Jute	0.04	0.18	-0.03	0.29	0.32	0.42	0.40	0.23	1.00															
Lamb	0.32	-0.03	0.79	-0.34	-0.46	-0.08	-0.29	0.00	-0.22	1.00														
Lead	0.08	0.34	-0.25	0.55	0.49	0.68	0.38	-0.08	0.51	-0.26	1.00													
Maize	-0.02	0.06	0.01	0.34	0.22	0.40	0.46	0.24	0.44	0.03	0.48	1.00												
Palm Oil	0.12	-0.04	0.08	0.43	0.27	0.39	0.43	0.20	0.43	0.16	0.46	0.66	1.00											
Rice	-0.23	0.10	-0.23	0.50	0.42	0.38	0.31	-0.20	0.35	-0.25	0.62	0.31	0.28	1.00										
Rubber	0.14	0.16	-0.15	0.38	0.30	0.57	0.23	0.13	0.38	-0.05	0.53	0.28	0.32	0.51	1.00									
Silver	0.35	0.09	0.09	0.47	0.35	0.33	0.24	-0.13	0.13	0.19	0.46	0.37	0.48	0.33	0.35	1.00								
Sugar	-0.34	-0.42	-0.16	0.29	0.08	0.22	0.53	0.06	0.07	-0.14	0.28	0.40	0.26	0.35	0.25	0.24	1.00							
Tea	0.26	0.44	-0.17	0.30	0.52	0.21	0.27	-0.14	0.35	-0.03	0.35	0.05	0.24	0.34	0.40	0.13	-0.22	1.00						
Timber	-0.17	-0.42	0.15	0.17	-0.03	0.24	0.45	0.29	0.11	0.08	0.16	0.39	0.52	-0.02	0.17	0.13	0.46	-0.11	1.00					
Tin	0.41	0.29	0.05	0.52	0.44	0.47	0.28	-0.04	0.36	0.16	0.62	0.49	0.60	0.43	0.47	0.81	0.14	0.39	0.14	1.00				
Tobacco	-0.02	0.00	-0.01	-0.19	0.07	-0.33	0.23	-0.41	0.07	0.15	-0.12	-0.03	0.00	-0.17	-0.35	0.10	-0.12	0.14	-0.13	0.03	1.00			
Wheat	-0.11	-0.11	-0.09	0.48	0.21	0.36	0.39	0.17	0.42	-0.14	0.54	0.71	0.52	0.45	0.25	0.43	0.54	-0.12	0.27	0.42	-0.03	1.00		
Wool	0.06	0.17	-0.21	0.29	0.23	0.38	0.42	0.00	0.40	-0.12	0.54	0.47	0.43	0.26	0.32	0.31	0.24	0.26	0.30	0.42	0.21	0.43	1.00	
Zinc	0.24	0.22	-0.05	0.39	0.21	0.71	0.11	0.33	0.45	-0.20	0.56	0.40	0.27	0.36	0.63	0.22	0.29	0.11	0.21	0.43	-0.49	0.42	0.29	1.00

Table 4: VAR Granger Causality test for all Commodities

Beef → Aluminum 0.0245	Lamb → Aluminum 0.0423	Lead → Aluminum 0.0357	Maize → Aluminum 0.0342	Silver → Aluminum 0.0000	Tea → Aluminum 0.0347
Copper → Banana 0.0345	Cotton → Cocoa 0.0419	Tea → Cocoa 0.0282	Timber → Cocoa 0.0296	Coffee → Cotton 0.0101	Cocoa → Copper 0.0384
Coffee → Copper 0.0468	Hides → Copper 0.0077	Maize → Copper 0.0194	Timber → Copper 0.0005	Tobacco → Copper 0.0319	Maize → Cotton 0.0008
Wheat → Cotton 0.0078	Aluminum → Hides 0.0447	Beef → Hides 0.0002	Jute → Hides 0.0048	Lamb → Hides 0.0008	Lead → Hides 0.0010
Rubber → Hides 0.0447	Wool → Hides 0.0001	Zinc → Hides 0.0010	Aluminum → Jute 0.0064	Copper → Jute 0.0313	Wheat → Jute 0.0018
Aluminum → Lamb 0.0433	Coffee → Lamb 0.0482	Tin → Lamb 0.0476	Wheat → Lamb 0.0156	Zinc → Lamb 0.0411	Aluminum → Lead 0.0034
Beef → Lead 0.0374	Copper → Lead 0.0081	Cotton → Lead 0.0059	Hides → Lead 0.0102	Lamb → Lead 0.0012	Timber → Lead 0.0001
Tobacco → Lead 0.0080	Wool → Lead 0.0002	Zinc → Lead 0.0005	Banana → Maize 0.0127	Copper → Maize 0.0013	Cotton → Maize 0.0003
Lead → Maize 0.0026	Rubber → Maize 0.0095	Tobacco → Maize 0.0425	Zinc → Maize 0.0243	Copper → Palm Oil 0.0174	Lamb → Palm Oil 0.0122
Aluminum→ Rice 0.0343	Copper → Rice 0.0344	Rubber → Rice 0.0418	Timber → Rice 0.0041	Wool → Rice 0.0024	Aluminum → Rubber 0.0044
Beef → Rubber 0.0097	Copper → Rubber 0.0002	Lamb → Rubber 0.0419	Maize → Rubber 0.0419	Rice → Rubber 0.0437	Timber → Rubber 0.0000
Banana → Silver 0.0403	Tea → Silver 0.0416	Timber → Silver 0.0112	Tin → Silver 0.0030	Wool → Silver 0.0279	Aluminum → Sugar 0.0138
Copper → Sugar 0.0000	Lamb → Sugar 0.0433	Lead → Sugar 0.0024	Maize → Sugar 0.0900	Tea → Sugar 0.0216	Wool → Sugar 0.0115
Copper → Timber 0.0076	Lamb → Timber 0.0309	Lead →Timber 0.0413	Wool →Timber 0.0038	Cocoa → Tin 0.0487	Cotton → Tin 0.0047
Hides → Tin 0.0289	Lamb → Tin 0.0016	Maize → Tin 0.0045	Tea → Tin 0.0236	Timber → Tin 0.0000	Tobacco → Tin 0.0280
Wool → Tin 0.0012	Aluminum → Tobacco 0.0417	Rubber → Tobacco 0.0481	Zinc → Tobacco 0.0320	Timber → Wheat 0.0010	Coffee → Wool 0.0234
Cotton → Wool 0.0066	Timber→ Wool 0.0108	Aluminum → Zinc 0.0047	Copper → Zinc 0.0315	Jute → Zinc 0.0367	Lead → Zinc 0.0017
Timber → Zinc 0.0062	Tobacco → Zinc 0.0199				

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of all the Hamilton Cycles for each commodity

Table 5: VAR Granger Causality test for Food Commodities

Wheat → Beef 0.0084	Coffee → Cocoa 0.0394	Maize → Cocoa 0.0039	Rice → Coffee 0.0043	Wheat → Lamb 0.0063	Palm Oil → Maize 0.0338
Lamb → Palm Oil 0.0244	Banana → Sugar 0.0109	Rice → Sugar 0.0166	Banana → Tea 0.0242	Beef → Tea 0.0015	Lamb → Tea 0.0081
Maize → Tea 0.0332					

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 6: VAR Granger Causality test for Metal Commodities

Silver → Aluminum 0.0077	Aluminum → Lead 0.0074	Tin → Silver 0.0498	Lead → Tin 0.0095

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 7 : VAR Granger Causality test for Non-Food Commodities

Hides → Cotton 0.0369	Wool → Hides 0.0001	Cotton → Jute 0.0053	Timber → Jute 0.0141	Cotton → Rubber 0.0290	Jute → Rubber 0.0277
Timber → Rubber 0.0000	Wool → Rubber 0.0495	Hides → Timber 0.0092	Wool → Timber 0.0059	Cotton → Tobacco 0.0458	Rubber → Tobacco 0.0004
Timber → Tobacco 0.0377	Timber → Wool 0.0274				

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 8: VAR Granger Causality test for Food Commodities and CPI

Copper → CPI 0.0000	Cotton → CPI 0.0002	Lamb → CPI 0.0010	Silver → CPI 0.0159	Timber → CPI 0.0019	Tobacco → CPI 0.0122
Wheat → CPI 0.0231	Wool → CPI 0.0015	Zinc → CPI 0.0059			
CPI → Cotton 0.0076	CPI → Lamb 0.0473	CPI → Tea 0.0039	CPI → Timber 0.0002	CPI → Tobacco 0.0011	

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 9: VAR Granger Causality test for Food Commodities and CPI_CW

Copper → CPI_CW	Cotton → CPI_CW	Lamb → CPI_CW	Wheat → CPI_CW	Wool → CPI_CW	CPI_CW → Timber
0.0000	0.0011	0.0039	0.0449	0.0332	0.0299

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 10: VAR Granger Causality test for Food Commodities and CPIF

Maize → CPIF	Rice → CPIF	Sugar → CPIF	Wheat → CPIF	CPIF → Lamb
0.0027	0.0267	0.0088	0.0148	0.0174

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 11: VAR Granger Causality test for Food Commodities and CPIF_CW

Coffee → CPIF_CW	Maize → CPIF_CW	Rice → CPIF_CW
0.0337	0.0311	0.0028

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 12: VAR Granger Causality test for Food Commodities and CPIM_CW

Aluminum → CPIM_CW	Copper → CPIM_CW	Lead → CPIM_CW	Silver → CPIM_CW
0.0166	0.0174	0.0209	0.0012

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 13: VAR Granger Causality test for Food Commodities and CPINF

Cotton → CPINF	Jute → CPINF	Timber → CPINF	CPINF → Tobacco	CPINF → Wool
0.0147	0.0256	0.0128	0.0046	0.0145

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 14: VAR Granger Causality test for Food Commodities and CPINF_CW

Cotton → CPINF_CW	Wool → CPINF_CW
0.0363	0.0278

Note: Tabulated numbers are p -values. All reported values are the statistically significant ones from VAR of the Hamilton Cycles for each commodity

Table 16: VAR Granger Causality test for CPI

World GDP →CPI	CPI→ World GDP	US GDP →CPI	CPI→ US GDP	UK GDP →CPI	CPI→ UK GDP
0.1682	0.3561	0.4385	0.9184	0.2930	0.0595
Underlying VAR (CPI and World GDP)		Underlying VAR (CPI and US GDP)		Underlying VAR (CPI and UK GDP)	
Chile GDP →CPI	CPI→ Chile GDP	Interest Rate →CPI	CPI→ Interest Rate		
0.0556	0.0288*	0.0567	0.0037*		
Underlying VAR (CPI and Chile GDP)		Underlying VAR (CPI and Interest Rate)			

World GDP →CPI	Interest Rate →CPI	CPI→ World GDP	Interest Rate → World GDP	CPI→ Interest Rate	World GDP → Interest Rate
0.0037*	0.0037*	0.3335	0.7372	0.0048*	0.2553

Underlying VAR (CPI, World GDP and Interest Rate)

US GDP →CPI	Interest Rate →CPI	CPI→ US GDP	Interest Rate → US GDP	CPI→ Interest Rate	US GDP → Interest Rate
0.1078	0.0037*	0.3335	0.7372	0.0046*	0.7394

Underlying VAR (CPI, US GDP and Interest Rate)

UK GDP →CPI	Interest Rate →CPI	CPI→ UK GDP	Interest Rate → UK GDP	CPI→ Interest Rate	UK GDP → Interest Rate
0.1025	0.0198*	0.2092	0.7806	0.0092*	0.5648

Underlying VAR (CPI, UK GDP and Interest Rate)

Chile GDP →CPI	Interest Rate →CPI	CPI→ Chile GDP	Interest Rate → Chile GDP	CPI→ Interest Rate	Chile GDP → Interest Rate
0.0053*	0.0146*	0.0205*	0.3637	0.0048*	0.2906

Underlying VAR (CPI, Chile GDP and Interest Rate)

Note: Tabulated numbers are p-values. * denotes the potential of a Granger causality

Table 17: VAR Granger Causality test for CPIF

World GDP →CPIF	CPIF→ World GDP	US GDP →CPIF	CPIF→ US GDP	UK GDP →CPIF	CPIF→ UK GDP
0.5426	0.6650	0.8112	0.9175	0.7489	0.0816
Underlying VAR (CPIF and World GDP)		Underlying VAR (CPIF and US GDP)		Underlying VAR (CPIF and UK GDP)	
Chile GDP →CPIF	CPIF→ Chile GDP	Interest Rate →CPIF	CPIF→ Interest Rate		
0.2119	0.0165*	0.1454	0.0073*		
Underlying VAR (CPIF and Chile GDP)		Underlying VAR (CPIF and Interest Rate)			

World GDP →CPIF	Interest Rate →CPIF	CPIF→ World GDP	Interest Rate → World GDP	CPIF→ Interest Rate	World GDP → Interest Rate
0.0545	0.0160*	0.6478	0.8349	0.0120*	0.5358
Underlying VAR (CPIF, World GDP and Interest Rate)					
US GDP →CPIF	Interest Rate →CPIF	CPIF→ US GDP	Interest Rate → US GDP	CPIF→ Interest Rate	US GDP → Interest Rate
0.2608	0.0465*	0.5176	0.0102*	0.0078*	0.6555
Underlying VAR (CPIF, US GDP and Interest Rate)					
UK GDP →CPIF	Interest Rate →CPIF	CPIF→ UK GDP	Interest Rate → UK GDP	CPIF→ Interest Rate	UK GDP → Interest Rate
0.2862	0.0556	0.2525	0.6997	0.0149*	0.4794
Underlying VAR (CPIF, UK GDP and Interest Rate)					
Chile GDP →CPIF	Interest Rate →CPIF	CPIF→ Chile GDP	Interest Rate → Chile GDP	CPIF→ Interest Rate	Chile GDP → Interest Rate
0.0397*	0.0238*	0.0113*	0.3402	0.0109*	0.5512
Underlying VAR (CPIF, Chile GDP and Interest Rate)					

Note: Tabulated numbers are p-values. * denotes the potential of a Granger causality

Table 18: VAR Granger Causality test for CPIM

World GDP →CPIM	CPIM → World GDP	US GDP →CPIM	CPIM → US GDP	UK GDP →CPIM	CPIM → UK GDP
0.0529	0.8499	0.2231	0.8543	0.3400	0.4799
Underlying VAR (CPIM and World GDP)		Underlying VAR (CPIM and US GDP)		Underlying VAR (CPIM and UK GDP)	

Chile GDP →CPIM	CPIM → Chile GDP	Interest Rate →CPIM	CPIM → Interest Rate
0.0140*	0.2551	0.4045	0.0912
Underlying VAR (CPIM and Chile GDP)		Underlying VAR (CPIM and Interest Rate)	

World GDP →CPIM	Interest Rate →CPIM	CPIM → World GDP	Interest Rate → World GDP	CPIM → Interest Rate	World GDP → Interest Rate
0.0015*	0.0086*	0.8275	0.8573	0.0493*	0.2621

Underlying VAR (CPIM, World GDP and Interest Rate)

US GDP →CPIM	Interest Rate →CPIM	CPIM → US GDP	Interest Rate → US GDP	CPIM → Interest Rate	US GDP → Interest Rate
0.0630	0.1131	0.8833	0.0196*	0.2652	0.6144

Underlying VAR (CPIM, US GDP and Interest Rate)

UK GDP →CPIM	Interest Rate →CPIM	CPIM → UK GDP	Interest Rate → UK GDP	CPIM → Interest Rate	UK GDP → Interest Rate
0.1301	0.1526	0.5352	0.2698	0.3736	0.3482

Underlying VAR (CPIM, UK GDP and Interest Rate)

Chile GDP →CPIM	Interest Rate →CPIM	CPIM → Chile GDP	Interest Rate → Chile GDP	CPIM → Interest Rate	Chile GDP → Interest Rate
0.0022*	0.0476*	0.2364	0.5658	0.0651	0.4326

Underlying VAR (CPIM, Chile GDP and Interest Rate)

Note: Tabulated numbers are p-values. * denotes the potential of a Granger causality

Table 19: VAR Granger Causality test for CPINF

World GDP →CPINF	CPINF → World GDP	US GDP →CPINF	CPINF → US GDP	UK GDP →CPINF	CPINF → UK GDP
0.2307	0.0688	0.5127	0.8826	0.1008	0.1410
Underlying VAR (CPINF and World GDP)		Underlying VAR (CPINF and US GDP)		Underlying VAR (CPINF and UK GDP)	

Chile GDP →CPINF	CPINF → Chile GDP	Interest Rate →CPINF	CPINF → Interest Rate
0.1981	0.4847	0.0964	0.0243*
Underlying VAR (CPINF and Chile GDP)		Underlying VAR (CPINF and Interest Rate)	

World GDP →CPINF	Interest Rate →CPINF	CPINF → World GDP	Interest Rate → World GDP	CPINF → Interest Rate	World GDP → Interest Rate
0.0295*	0.0469*	0.0605	0.6104	0.0543	0.3186

Underlying VAR (CPINF, World GDP and Interest Rate)

US GDP →CPINF	Interest Rate →CPINF	CPINF → US GDP	Interest Rate → US GDP	CPINF → Interest Rate	US GDP → Interest Rate
0.2944	0.0563	0.5726	0.0118*	0.0368*	0.9310

Underlying VAR (CPINF, US GDP and Interest Rate)

UK GDP →CPINF	Interest Rate →CPINF	CPINF → UK GDP	Interest Rate → UK GDP	CPINF → Interest Rate	UK GDP → Interest Rate
0.0972	0.0930	0.3189	0.5265	0.0744	0.7369

Underlying VAR (CPINF, UK GDP and Interest Rate)

Chile GDP →CPINF	Interest Rate →CPINF	CPINF → Chile GDP	Interest Rate → Chile GDP	CPINF → Interest Rate	Chile GDP → Interest Rate
0.0760	0.1420	0.4354	0.5628	0.0602	0.4240

Underlying VAR (CPINF, Chile GDP and Interest Rate)

Note: Tabulated numbers are p -values. * denotes the potential of a Granger causality

Table 20: VAR Granger Causality test for CPI_CW

World GDP →CPI_CW	CPI_CW→ World GDP	US GDP →CPI_CW	CPI_CW→ US GDP	UK GDP →CPI_CW	CPI_CW→ UK GDP
0.2890	0.3363	0.6158	0.7981	0.4730	0.0367*
Underlying VAR (CPI_CW and World GDP)		Underlying VAR (CPI_CW and US GDP)		Underlying VAR (CPI_CW and UK GDP)	

Chile GDP →CPI_CW	CPI_CW→ Chile GDP	Interest Rate →CPI_CW	CPI_CW→ Interest Rate
0.0364*	0.0058*	0.0864	0.0139*
Underlying VAR (CPI_CW and Chile GDP)		Underlying VAR (CPI_CW and Interest Rate)	

World GDP →CPI_CW	Interest Rate →CPI_CW	CPI_CW→ World GDP	Interest Rate → World GDP	CPI_CW→ Interest Rate	World GDP → Interest Rate
0.0106	0.0110*	0.3169	0.7435	0.0091*	0.4453

Underlying VAR (CPI_CW, World GDP and Interest Rate)

US GDP →CPI_CW	Interest Rate →CPI_CW	CPI_CW→ US GDP	Interest Rate → US GDP	CPI_CW→ Interest Rate	US GDP → Interest Rate
0.1878	0.0037*	0.6532	0.0152*	0.0075*	0.7677

Underlying VAR (CPI_CW, US GDP and Interest Rate)

UK GDP →CPI_CW	Interest Rate →CPI_CW	CPI_CW→ UK GDP	Interest Rate → UK GDP	CPI_CW→ Interest Rate	UK GDP → Interest Rate
0.1979	0.0153*	0.1325	0.7828	0.0153*	0.5995

Underlying VAR (CPI_CW, UK GDP and Interest Rate)

Chile GDP →CPI_CW	Interest Rate →CPI_CW	CPI_CW→ Chile GDP	Interest Rate → Chile GDP	CPI_CW→ Interest Rate	Chile GDP → Interest Rate
0.0087*	0.0117*	0.0086*	0.3005	0.0085*	0.4730

Underlying VAR (CPI_CW, Chile GDP and Interest Rate)

Note: Tabulated numbers are p -values. * denotes the potential of a Granger causality

Table 21: VAR Granger Causality test for CPIF_CW

World GDP →CPIF_CW	CPIF_CW→ World GDP	US GDP →CPIF_CW	CPIF_CW→ US GDP	UK GDP →CPIF_CW	CPIF_CW→ UK GDP
0.5870	0.7805	0.8104	0.8480	0.6794	0.0627
Underlying VAR (CPIF_CW and World GDP)		Underlying VAR (CPIF_CW and US GDP)		Underlying VAR (CPIF_CW and UK GDP)	

Chile GDP →CPIF_CW	CPIF_CW→ Chile GDP	Interest Rate →CPIF_CW	CPIF_CW→ Interest Rate
0.1639	0.0102*	0.0796	0.0060*
Underlying VAR (CPIF_CW and Chile GDP)		Underlying VAR (CPIF_CW and World GDP)	

World GDP →CPIF_CW	Interest Rate →CPIF_CW	CPIF_CW→ World GDP	Interest Rate → World GDP	CPIF_CW→ Interest Rate	World GDP → Interest Rate
0.0623	0.0161*	0.7601	0.8481	0.0083*	0.5343

Underlying VAR (CPIF_CW, World GDP and Interest Rate)

US GDP →CPIF_CW	Interest Rate →CPIF_CW	CPIF_CW→ US GDP	Interest Rate → US GDP	CPIF_CW→ Interest Rate	US GDP → Interest Rate
0.2893	0.0284*	0.7498	0.0165*	0.0070*	0.7003

Underlying VAR (CPIF_CW, US GDP and Interest Rate)

UK GDP →CPIF_CW	Interest Rate →CPIF_CW	CPIF_CW→ UK GDP	Interest Rate → UK GDP	CPIF_CW→ Interest Rate	UK GDP → Interest Rate
0.3287	0.0390*	0.1826	0.6525	0.0122*	0.4734

Underlying VAR (CPIF_CW, UK GDP and Interest Rate)

Chile GDP →CPIF_CW	Interest Rate →CPIF_CW	CPIF_CW→ Chile GDP	Interest Rate → Chile GDP	CPIF_CW→ Interest Rate	Chile GDP → Interest Rate
0.0250*	0.0174*	0.0062*	0.2944	0.0076*	0.5547

Underlying VAR (CPIF_CW, Chile GDP and Interest Rate)

Note: Tabulated numbers are p -values. * denotes the potential of a Granger causality

Table 22: VAR Granger Causality test for CPIM_CW

World GDP →CPIM_CW	CPIM_CW→ World GDP	US GDP →CPIM_CW	CPIM_CW→ US GDP	UK GDP →CPIM_CW	CPIM_CW→ UK GDP
0.0591	0.5833	0.2033	0.8156	0.3444	0.1947
Underlying VAR (CPIM_CW and World GDP)		Underlying VAR (CPIM_CW and US GDP)		Underlying VAR (CPIM_CW and UK GDP)	

Chile GDP →CPIM_CW	CPIM_CW→ Chile GDP	Interest Rate →CPIM_CW	CPIM_CW→ Interest Rate
0.0182*	0.1300	0.2990	0.0594
Underlying VAR (CPIM_CW and Chile GDP)		Underlying VAR (CPIM_CW and Interest Rate)	

World GDP →CPIM_CW	Interest Rate →CPIM_CW	CPIM_CW→ World GDP	Interest Rate → World GDP	CPIM_CW→ Interest Rate	World GDP → Interest Rate
0.0008*	0.0034*	0.5529	0.7846	0.0297*	0.2348

Underlying VAR (CPIM_CW, World GDP and Interest Rate)

US GDP →CPIM_CW	Interest Rate →CPIM_CW	CPIM_CW→ US GDP	Interest Rate → US GDP	CPIM_CW→ Interest Rate	US GDP → Interest Rate
0.0436*	0.0660	0.8198	0.0190*	0.4124	0.6784

Underlying VAR (CPIM_CW, US GDP and Interest Rate)

UK GDP →CPIM_CW	Interest Rate →CPIM_CW	CPIM_CW→ UK GDP	Interest Rate → UK GDP	CPIM_CW→ Interest Rate	UK GDP → Interest Rate
0.1007	0.0894	0.2213	0.2688	0.5036	0.3345

Underlying VAR (CPIM_CW, UK GDP and Interest Rate)

Chile GDP →CPIM_CW	Interest Rate →CPIM_CW	CPIM_CW→ Chile GDP	Interest Rate → Chile GDP	CPIM_CW→ Interest Rate	Chile GDP → Interest Rate
0.0019*	0.0249*	0.1086	0.4750	0.0382*	0.3691

Underlying VAR (CPIM_CW, Chile GDP and Interest Rate)

Note: Tabulated numbers are p -values. * denotes the potential of a Granger causality

Table 23: VAR Granger Causality test for CPINF_CW

World GDP →CPINF_CW	CPINF_CW→ World GDP	US GDP →CPINF_CW	CPINF_CW→ US GDP	UK GDP →CPINF_CW	CPINF_CW→ UK GDP
0.5822	0.0220	0.8167	0.6909	0.7918	0.0009*
Underlying VAR (CPINF_CW and World GDP)		Underlying VAR (CPINF_CW and US GDP)		Underlying VAR (CPINF_CW and UK GDP)	

Chile GDP →CPINF_CW	CPINF_CW→ Chile GDP	Interest Rate →CPINF_CW	CPINF_CW→ Interest Rate
0.1423	0.0322*	0.4832	0.1271
Underlying VAR (CPINF_CW and Chile GDP)		Underlying VAR (CPINF_CW and Interest Rate)	

World GDP →CPINF_CW	Interest Rate →CPINF_CW	CPINF_CW→ World GDP	Interest Rate → World GDP	CPINF_CW→ Interest Rate	World GDP → Interest Rate
0.1394	0.0783	0.0208*	0.6882	0.1807	0.6429

Underlying VAR (CPINF_CW, World GDP and Interest Rate)

US GDP →CPINF_CW	Interest Rate →CPINF_CW	CPINF_CW→ US GDP	Interest Rate → US GDP	CPINF_CW→ Interest Rate	US GDP → Interest Rate
0.5088	0.0906	0.6534	0.0177*	0.0475*	0.9153

Underlying VAR (CPINF_CW, US GDP and Interest Rate)

UK GDP →CPINF_CW	Interest Rate →CPINF_CW	CPINF_CW→ UK GDP	Interest Rate → UK GDP	CPINF_CW→ Interest Rate	UK GDP → Interest Rate
0.5073	0.0932	0.0030*	0.6264	0.1057	0.7974

Underlying VAR (CPINF_CW, UK GDP and Interest Rate)

Chile GDP →CPINF_CW	Interest Rate →CPINF_CW	CPINF_CW→ Chile GDP	Interest Rate → Chile GDP	CPINF_CW→ Interest Rate	Chile GDP → Interest Rate
0.2247	0.1388	0.1046	0.4647	0.1710	0.7435

Underlying VAR (CPINF_CW, Chile GDP and Interest Rate)

Note: Tabulated numbers are p -values. * denotes the potential of a Granger causality

10. Appendix A - Literature Tables

Table A1: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Kitchin (1923)	Wholesale prices of commodities	1890-1922 (selected dates)	Graphical analysis of cycles and minimum and maximum analysis	US and UK bank clearings, Wholesale prices of commodities and interest rate	Evidence of rising trend in prices. Small cycles last 3.3 years and trade cycles about 8 years.
Grilli and Yang (1988)	Grilli and Yang Commodity Price Index	1900-1986 (annual data)	OLS estimation of model with time trend and dummy variables	6 aggregate commodity price indexes (of 24 commodities) for nonfuel, nonfuel with alternative weights, all commodities, food ,metals ,nonfood agricultural raw materials and the manufactures UN index and the United States Manufacturing Price Index	Relative prices of all primary commodities fell on trend by 0.5 percent a year and those of nonfuel primary commodities by 0.6 percent a year. They confirm the sign, but not the magnitude, of the trend (Support of PSH) Possibility of changing trends of relative primary commodity prices over time.
Ardeni and Wright (1990)	Grilli and Yang Commodity Price Index	1865-1986 (annual data)	ARIMA models with deterministic and stochastic trend with structural breaks	Total commodities, Total metals, Mainly tropical agriculture and Mainly non-tropical agriculture	The evidence of a secular deterioration in the permanent component of commodity prices is confirmed over all samples. PSH seems validated. Evidence of structural breaks that may show cyclical behavior is trace with dummies for each commodity variable.

Table A2: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Bleaney and Greenaway (1993)	Grilli and Yang (1988) dataset, aggregate ad component series	1990-1991 (annual data)	OLS with error correction towards trend	aggregate series and component series of food, non-food agricultural commodities and metal	Statistically significant long-run downward trend in the prices of primary products, but a slow one. The magnitude and statistical significance of the trend varies according to the time span of data used. (Evidence of PSH)
Reinhart and Wickham (1994)	All non-oil commodities, beverages, food , metals	1957:I- 1993:II (quarterly data)	ARMA with disentangling trend from cycle and Kalman Filter	prices of All non-oil commodities, beverages, food, metals	Trends for all series from both methods are negative. Evidence of cycles in series is presented. (Evidence of PSH) Real commodity prices have been declining, with this decline being mostly secular.
Kellard and Wohar (2002)	Grilli and Yang (1988) dataset, 24 commodities price indexes	1990-1998 (annual data)	ARMA model with trend tracing for unit root and structural breaks	Commodity prices and traced structural breaks	23 out of the 24 commodities can be classified as trend-stationary. No examination of the presence of negative trend. No Cycle tracing. (Weak support of PSH)

Table A3: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Blattman,Hwang and Williamson(2004)	42 commodities on world markets	1870–1939 (annual data)	Panel analysis of empirical model of Trade and Capital with Hodrick-Prescott (HP) filter	Average GDP per capita growth rates, on average trend growth and volatility in the terms of trade and Level of capital flows on terms of trade growth and volatility	No PSH with trends but investigation through volatility and HP filter calibration. Volatility was more important for accumulation and growth than secular change and both effects were asymmetric between Core and Periphery. Support of PSH trivial through, Terms of Trade which are important determinant of growth.
Kellard and Wohar (2005)	Grilli and Yang (1988) dataset, 24 commodities price indexes	1990-1998 (annual data)	ARMA model with trend tracing and structural breaks	Commodity prices and traced structural breaks	Although 15 commodity prices exhibit at least one negative trend, a measure of the prevalence of a negative trend reveals that in only 8 cases does the deterioration exists for at least 70% of the sample period. (Weak support of PSH)
Cuddington and Jerrett (2007)	Aluminum, copper, lead, nickel, tin, and zinc (Heap Dataset (2005))	1850–2005 (annual data)	Hodrick-Prescott (HP) filter , Christiano and Fitzgerald (CF) asymmetric band-pass filter	real and nominal prices of aluminum, copper, lead, nickel, tin, and zinc	Evidence of super cycles in metal prices with phases from 10 to 35 years. The super cycle is more clearly defined when one looks at nominal rather than real prices. PSH holds for some commodities and some periods in others.

Table A4: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Bloch, Madsen , and Sapsford (2009)	Harvey, Kellard, Madsen and Wohar (HKMW 2010) dataset	1650-2005 (annual data)	Schumpeterian analysis to understanding trend and cycle in the prices of primary commodities	Real price of primary commodities, Price index for primary commodities and Price index for manufactured goods.	A downward trend in nominal commodity prices from the 17th through 19th Century and in the price of primary commodities relative to manufactures throughout our historical period, including the 20th Century. Cyclical movements not accounted (Support PSH)
Ocampo and Parra-Lancourt (2010)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007)	1865-2009 (annual data)	ARMA with deterministic and stochastic trend with structural breaks	Total commodities, Total metals, Mainly tropical agriculture and Mainly non-tropical agriculture	Negative trend experienced by the commodity prices in the 20th century. PSH seems validated. Evidence of structural breaks that may show cyclical behavior is traced for each commodity variable.
Erten and Ocampo (2010)	Grilli and Yang Commodity Price Index updated by Ocampo and Para(2010) and Oil	1865-2010 (annual data))	VECM and Christiano and Fitzgerald (CF) band-pass filter for variables	Total prices, metals, Total agriculture. Tropical agriculture, Non-tropical agriculture, Oil and OECD output, World output	Four past Super Cycles are traced ranging from 30 to 40 years. The mean of each super cycle for non-oil commodities tends to be lower than that of the previous cycle, suggesting a step-wise deterioration over the entire period. Long term trends are mostly negative. (Partial Support PSH). VECM results support super cycles in world output level predict the super cycles in real non-fuel commodity prices, both for the total index and sub-indices.

Table A5: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Ghoshray and Johnson (2010)	crude oil, natural gas and coal prices	Jan1975- Dec 2007 (monthly data)	Advanced unit root testing and ARMA model with trend tracing and structural breaks	crude oil, natural gas and coal prices	Oil is mostly negatively trended in time periods, coal is trendless, and gas is mainly positive and less trendless. (Partial Support PSH). No cycle analysis All series exhibit multiple breaks in trend and level.
Byrne, Fazio and Fiess (2010)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007)	1900-2008 (annual data) and	PANIC and Factor Augmented VAR	real commodity prices, real interest rate and risk	Analysis does not provide evidence on cycles or PSH. Evidence of co-movement of commodity prices, with negative relationship between real interest rate and real commodity prices and between risk and commodity prices.
Harvey, Kellard, Madsen and Wohar (2010)	Beef, Coal, Cotton, Gold, Lamb, Lead, Rice, Silver, Sugar, Tea, Wheat, Wool, Coffee, Tobacco, Pig Iron, Aluminum, Cocoa, Copper, Hide Banana and Jute, Nickel, Oil, Tin, Zinc, Banana and Jute	1650-2005 (annual data)	Harvey et al. (2007, 2008) techniques to assess the trend function and the existence of any possible structural breaks.	25 commodities (composing Harvey, Kellard, Madsen and Wohar (HKMW 2010) dataset)	Results show that eleven price series present a significant and downward trend over all or some fraction of the sample period. In the long run a secular, deteriorating trend is a relevant phenomenon for a significant proportion of primary commodities. (Support of PSH).

Table A6: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Jacks, Rourke and Williamson (2011)	Different commodities based on different datasets	1700-1950 (annual data) 1720-2008 (monthly data)	Volatility analysis and GARCH Conditional Variance	Prices for all food, agricultural raw materials, minerals, ores, and metals , manufactures or final goods and aggregates	Analysis does not provide evidence on cycles or PSH. Volatility has not increased over time, with primary commodities being more volatile than manufactures. Globalization and world market integration lead to lower commodity price volatility. Volatility is associated with growth.
Zapata, Detre and Hanabuchi (2012)	PPI for farm and food products, fuels, and metals.	1871–2010 (annual data)	Christiano and Fitzgerald band-pass filter and MOTAD	S&P 500, PPI for all commodities and specific for farm and food products, fuels, and metals.	Cycles have average length of 31 years. (no evidence of PSH) Relative price strength is dominated by commodities with rational investors focusing more on agricultural commodities.
Harvey, Kellard, Madsen and Wohar (2012)	Harvey, Kellard, Madsen and Wohar (HKMW 2010) dataset	1650-2010 (annual data)	Trend tests with structural breaks and Christiano and Fitzgerald (CF) asymmetric band-pass filter for cycle decomposition.	Commodity Composite Price Index(CPI), a non-oil version of the Commodity Composite Price Index (CCPI') and GY non-fuel weighted aggregate real index (GYCPI)	Relative commodity prices present a significant and downward global trend. (Sypport of PSH). Super-Cycles evidence suggest a lifecycle of 27 years and short-run cycles are lasting four years.

Table A7: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Stuermer(2013)	copper, lead, tin, zinc, and crude oil	1840-2010 (annual data)	Structural vector autoregressive (VAR) model with long term restictions to each of the five markets.	World primary production of each mineral, real commodity prices, World GDP.	Prices for copper show significant negative linear trend. The trend is also negative but less significant for lead and zinc prices. Tin and crude oil present no trend.(Partial evidence of PSH) Results of VAR suggest that price fluctuations are primarily driven by output demand rather than supply shocks.
Nazlioglu (2014)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007)	1865-2003 (annual data)	Panel KPSS test and trend stationary model with structural breaks	24 commodities from Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007))	International commodity prices are trend stationary and shows that the commodity prices have different trend dynamics. PSH does not hold in all significant estimated trends. (Partial Support PSH)
Arezki, Hadri, Loungani,and Rao (2014)	Harvey, Kellard, Madsen and Wohar (HKMW 2010) dataset	1650-2005 (annual data)	Panel stationarity tests with multiple structural breaks and Piecewise regressions	25 relative commodity prices	All series are found to be stationary. PSH test results are mixed, however most of the regression slopes are downward. Primary commodity prices are found highly volatile, possible evidence of cycles due to presence of structural breaks.

Table A8: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Yammada and Yoon (2014)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007)	1900-2010 (annual data)	Hodrick and Prescott filter and L1 – trend filter with structural breaks	24 commodities and 8 aggregate commodity price indexes from Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007))	Prebisch–Singer hypothesis(PSH) holds sometimes, but not always, for many of the primary commodities in the Grilli–Yang data. (Partial support of PSH) For most primary commodities, we find that their piecewise linear trends are negatively sloped during some of the sample periods.
Winkelried (2015)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007) & Harvey, Kellard, Madsen and Wohar (HKMW) data	1900–2010 (annual data) And 1650-2005 (annual data)	Hodrick and Prescott filter, L1 – trend filter, Bry and Boschan Cycle	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007)) for all the commodities & Harvey, Kellard, Madsen and Wohar (HKMW) data for all commodities	PSH holds in specific commodities. Evidence of super cycles in all series
Fernandez (2015)	Updated Grilli and Yang Commodity Price Index (Pfaffenzeller et al. (2007) and oil	1900-2010 (annual data)	OLS and 2SLS for co-movement analysis (use of HP Filter), Business Cycles with Bry and Boschan algorithm, CVaR	Commodity prices, apparent consumption and macroeconomic indicators	Evidence of short cyclical components on commodity prices. (no evidence of PSH) Evidence of excess co-movement between the commodities.

Table A9: Literature review of studies in commodity cycles and PSH

Authors	Commodities	Period	Method	Variables	Empirical Results
Erdem and Ünalmıs (2016)	Oil, Copper and Agriculture Prices	1861-2014 (annual data) And 1946:1 to 2014:4 (quarterly data)	Hodrick-Prescott (HP) filter , Christiano and Fitzgerald (CF) band-pass filter and Bry and Boschan (BB) Cycle	Oil, Copper and Agriculture Prices filtered by HP, CF and BB Cycle	Evidence of short-term cycles, long-term cycle, super cycles and the long-term trend of the real oil price. Evidence of Super Cycles in Copper and Agriculture Prices. PSH does not seem to hold from HP filter
Harvey, Kellard, Madsen and Wohar (2017)	Harvey, Kellard, Madsen and Wohar (HKMW 2010) dataset	1650-2014 (annual data)	Techniques to assess the trend function and the existence of any possible structural breaks and Stationary VAR	Commodity price series and GDP and combinations of commodity prices, GDP, and interest rates	Commodity prices present a downward trend with breaks over the entire industrial age (Support of PSH). Evidence of VAR show that commodity prices Granger cause income and interest rates, while interest rates Granger cause commodity prices. Commodity price movements have an asymmetric country effect on economic activity

11. Appendix B- Figures of commodities and indexes

Figure B1 : Trend representation of Aluminum

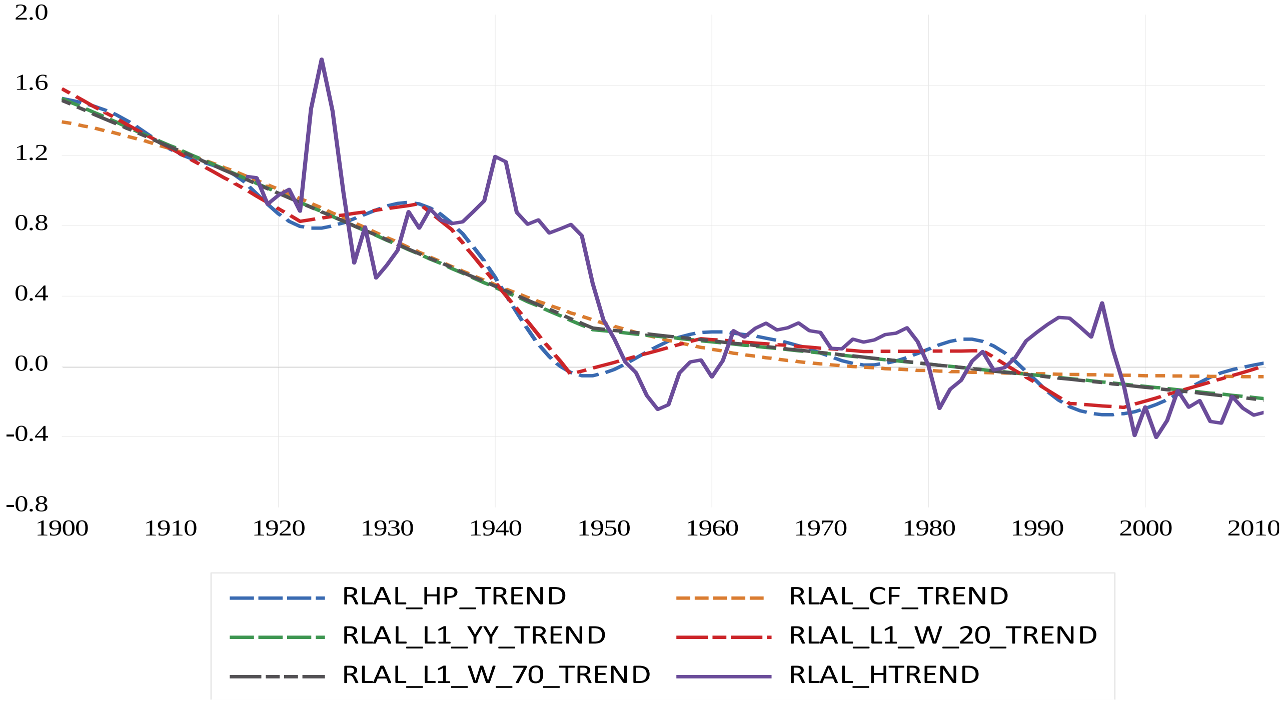

Figure B2 : Cycle representation of Aluminum

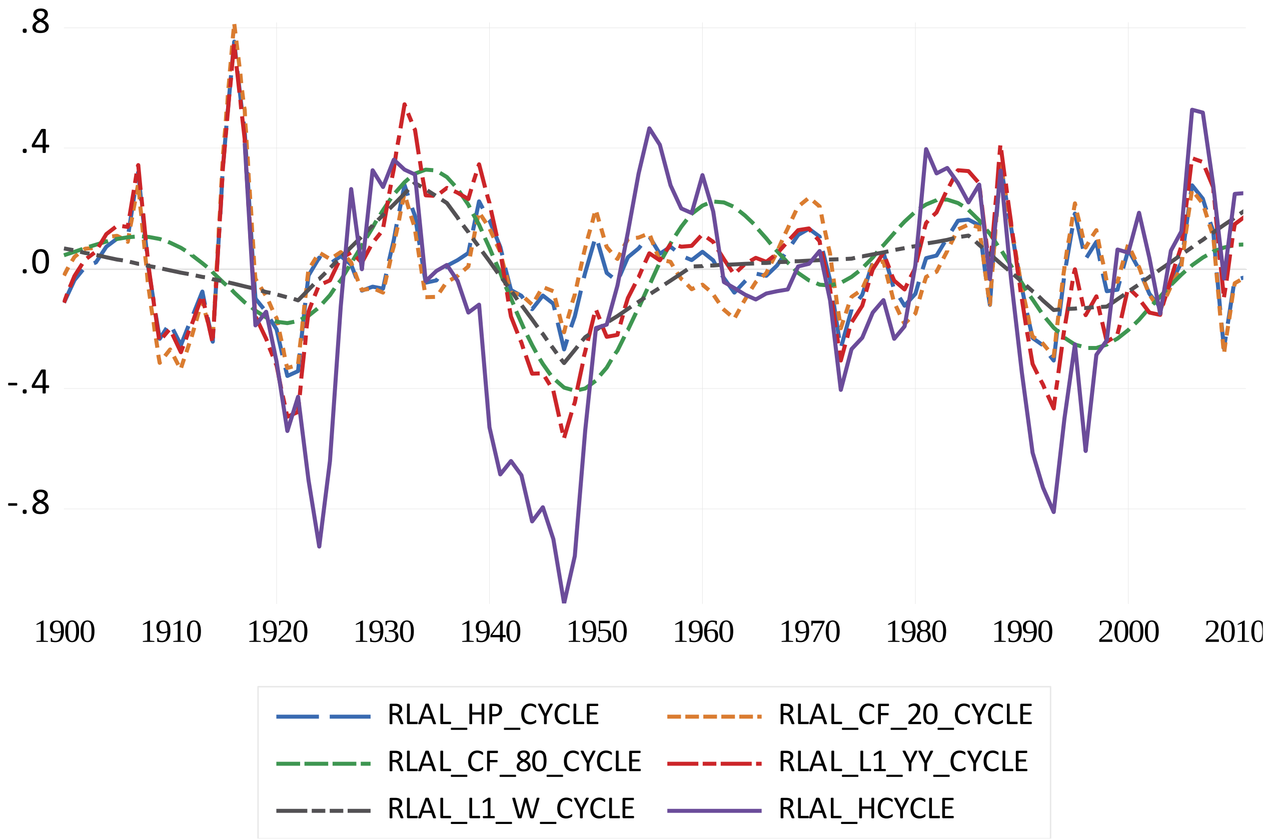

Figure B3 : Trend representation of Banana

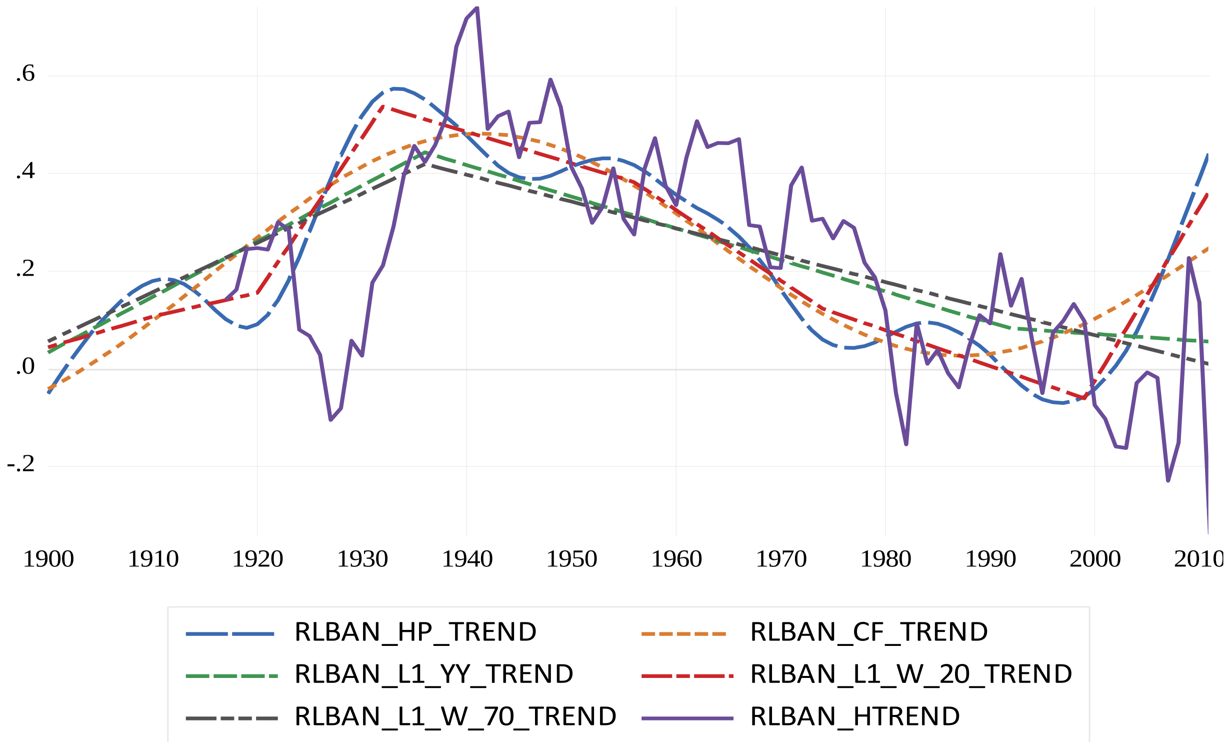

Figure B4 : Cycle representation of Banana

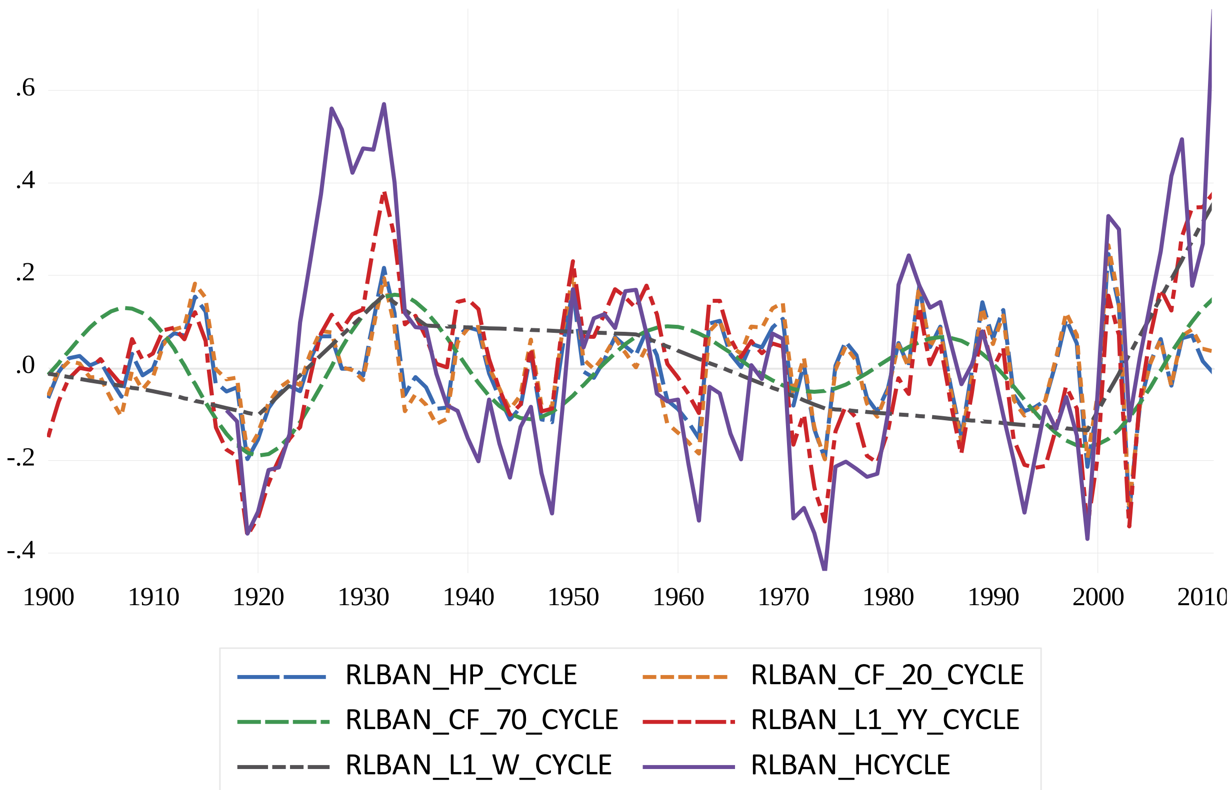

Figure B5 : Trend representation of Beef

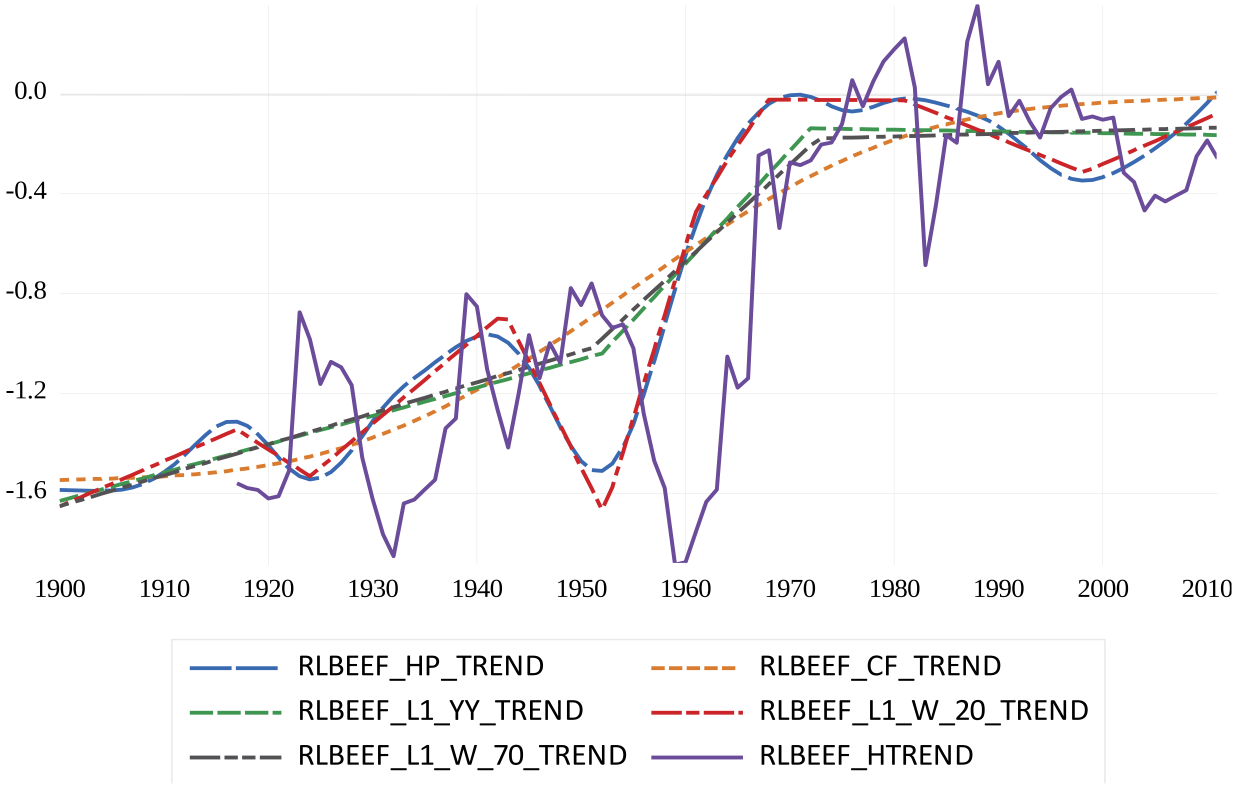

Figure B6 : Cycle representation of Beef

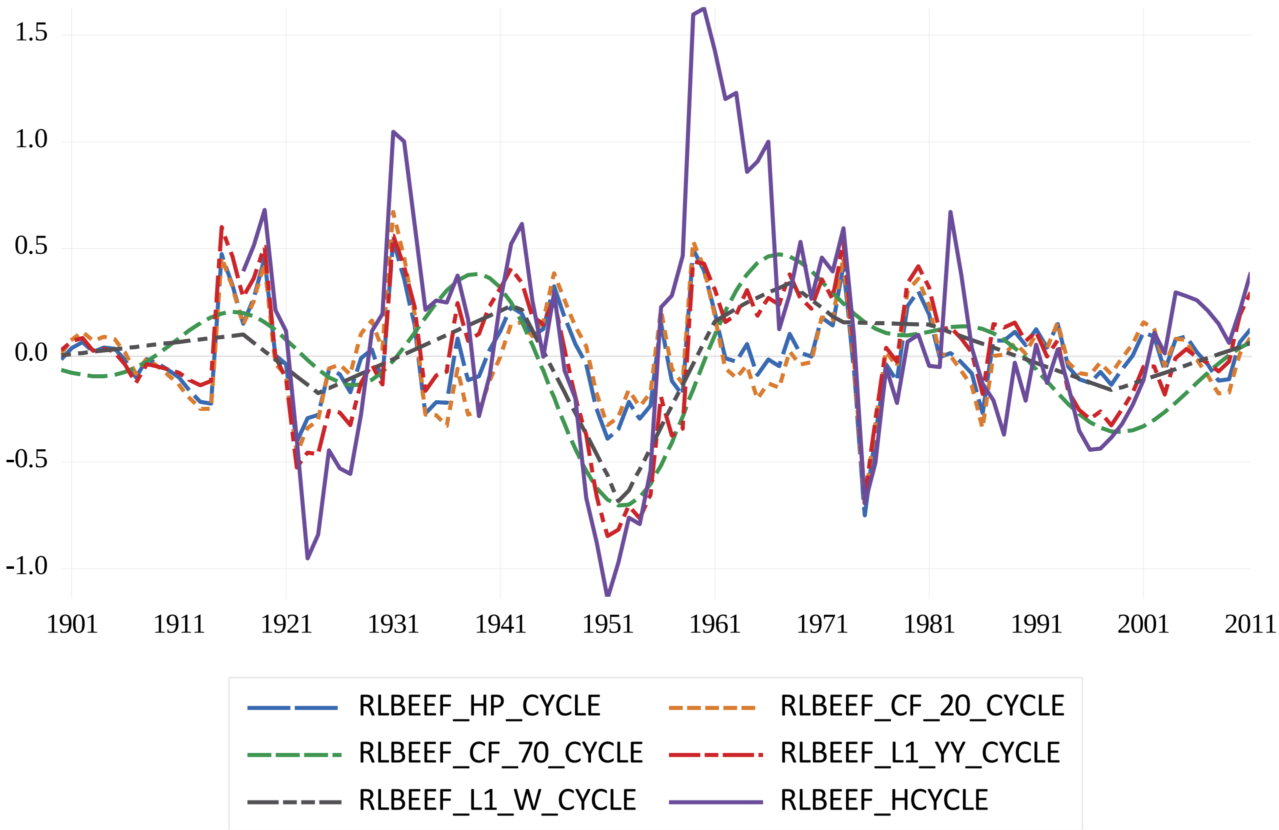

Figure B7 : Trend representation of Cocoa

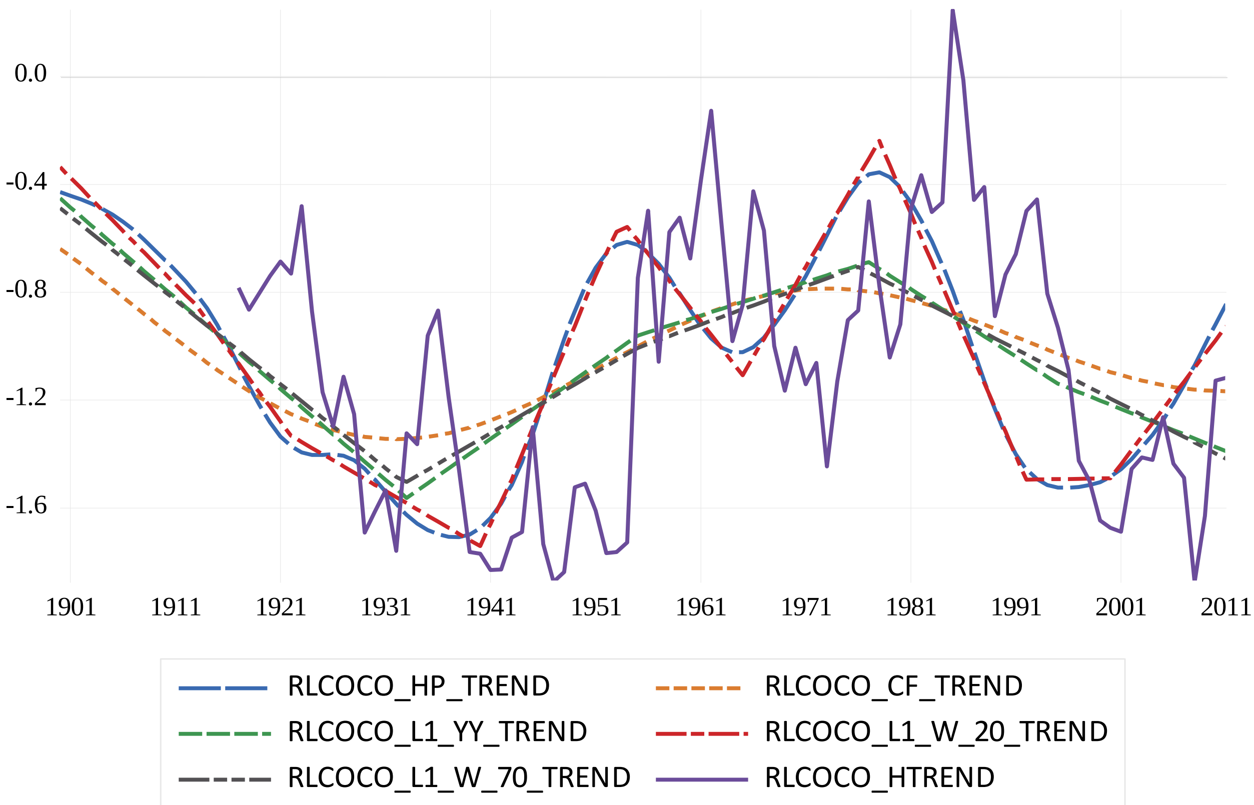

Figure B8 : Cycle representation of Cocoa

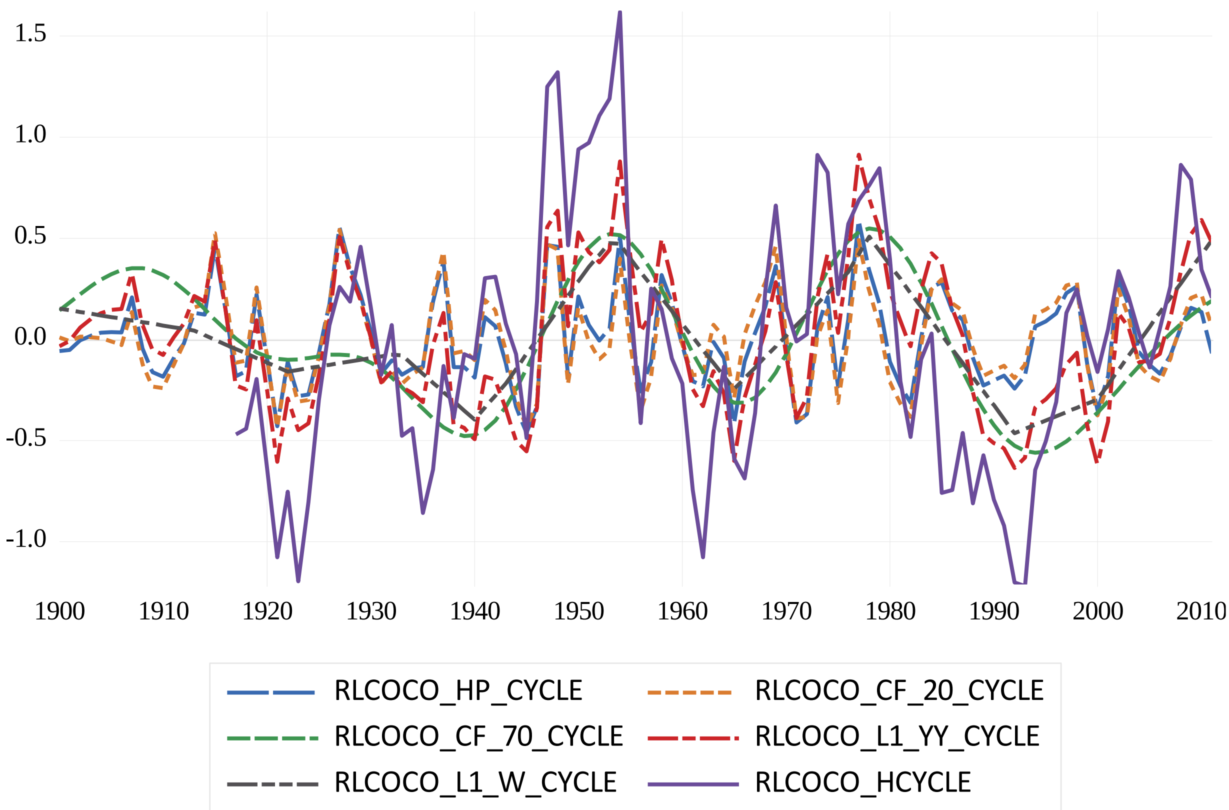

Figure B9 : Trend representation of Coffee

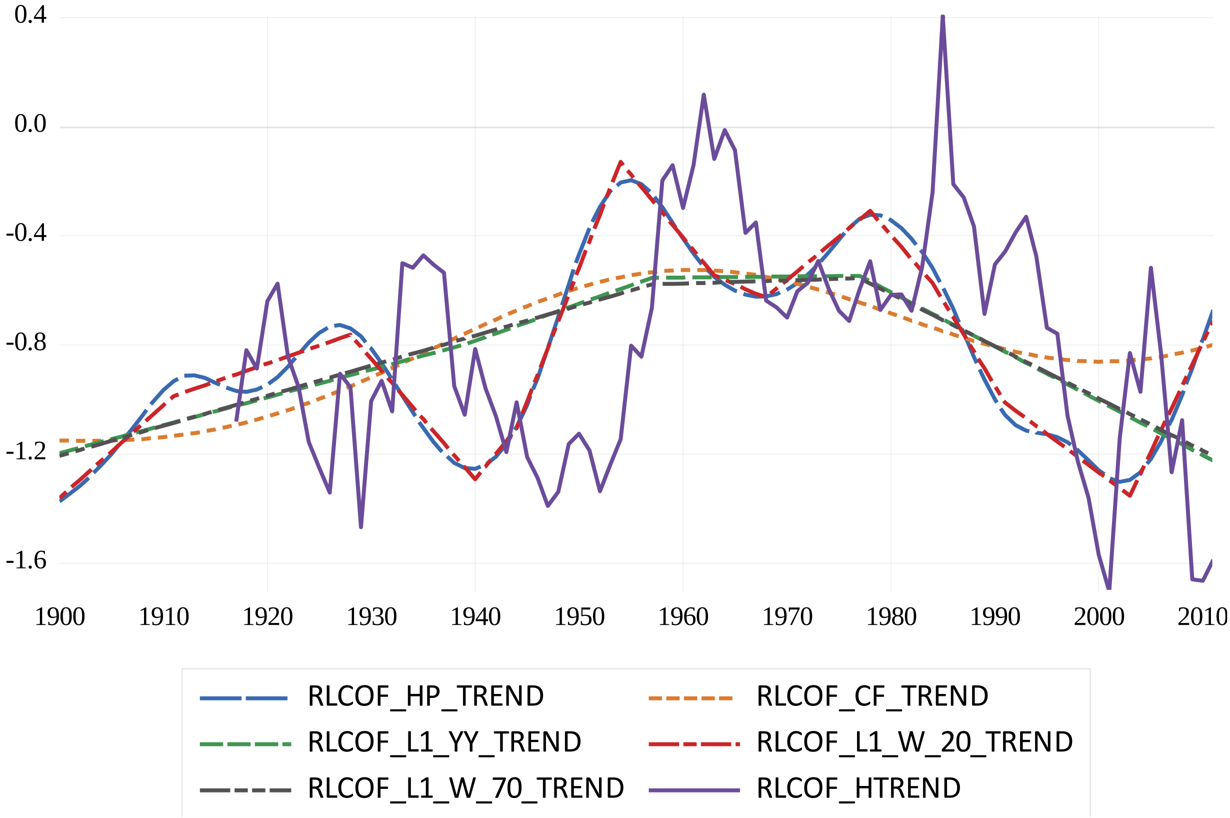

Figure B10 : Cycle representation of Coffee

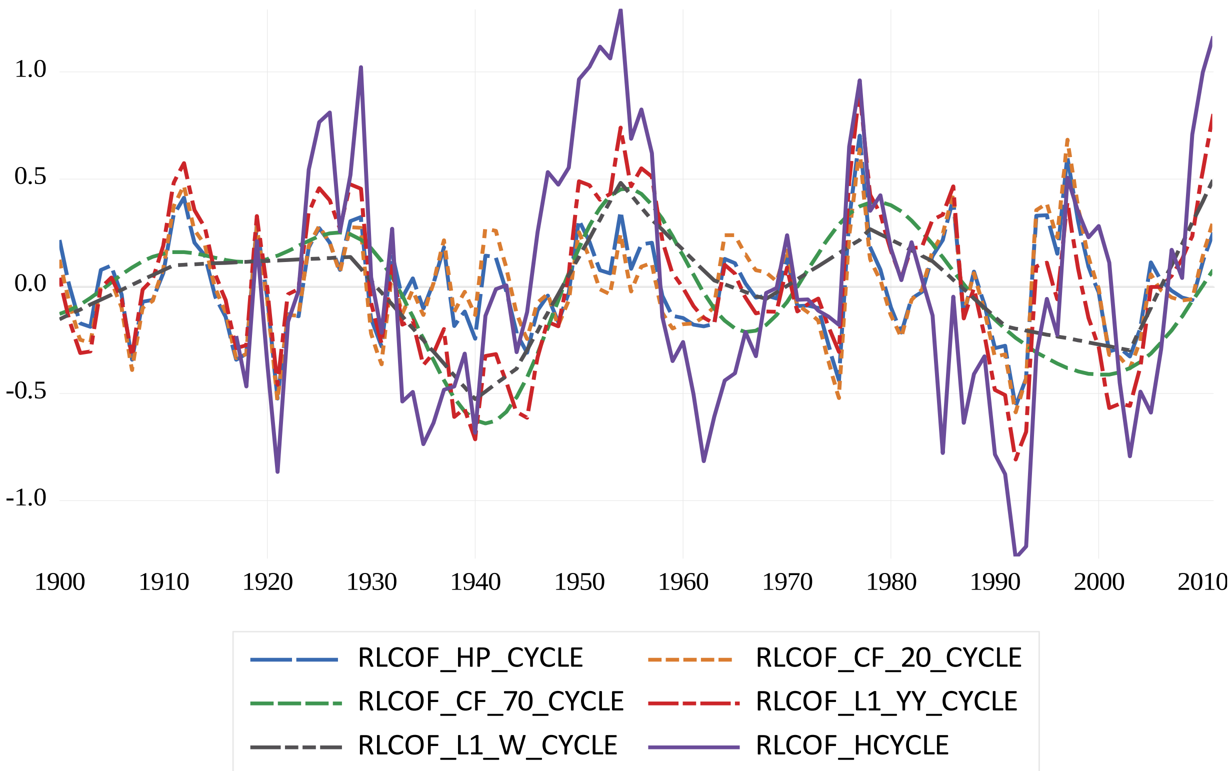

Figure B11 : Trend representation of Copper

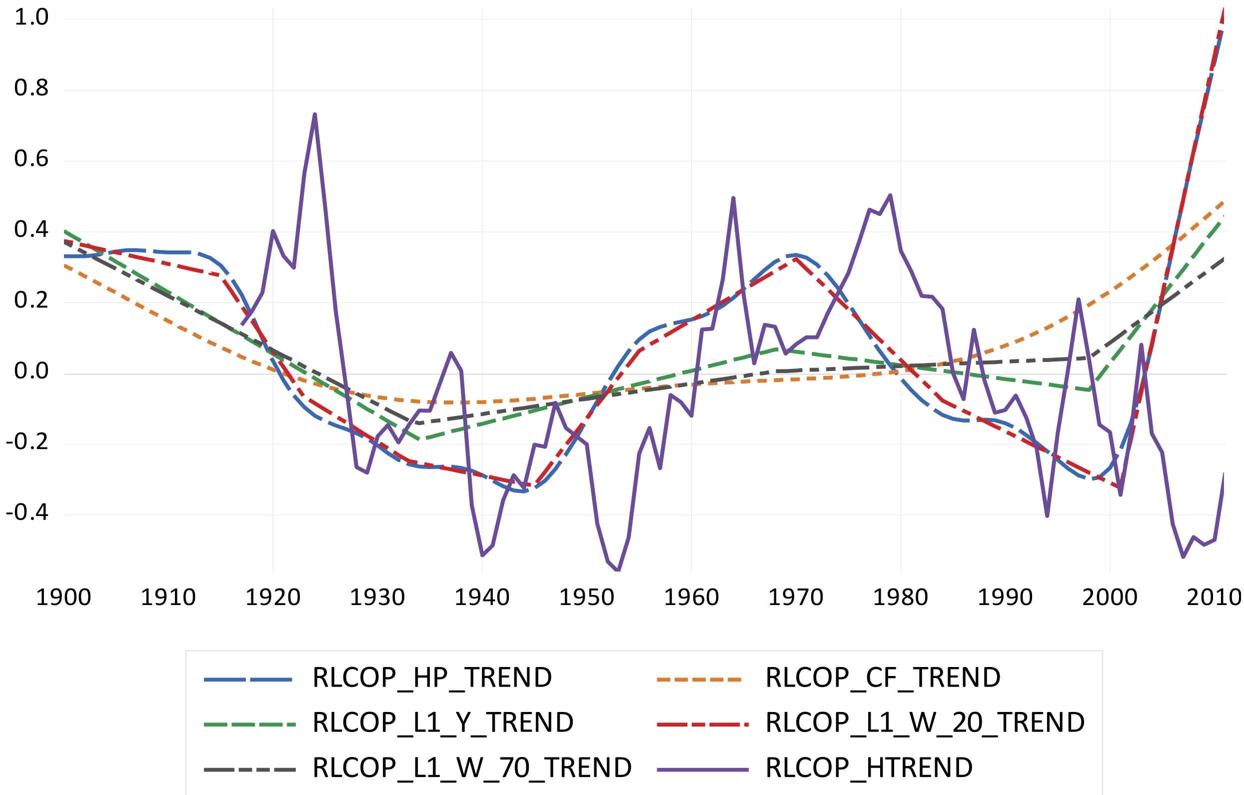

Figure B12 : Cycle representation of Copper

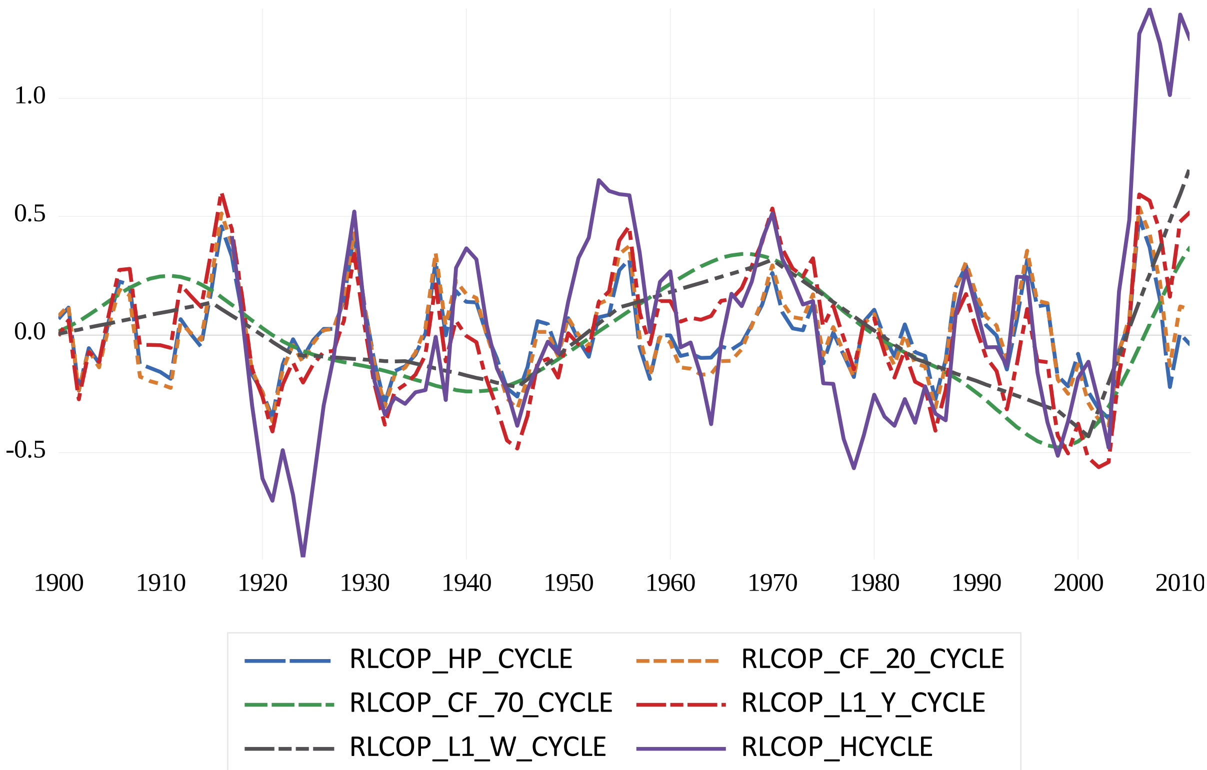

Figure B13: Trend representation of Cotton

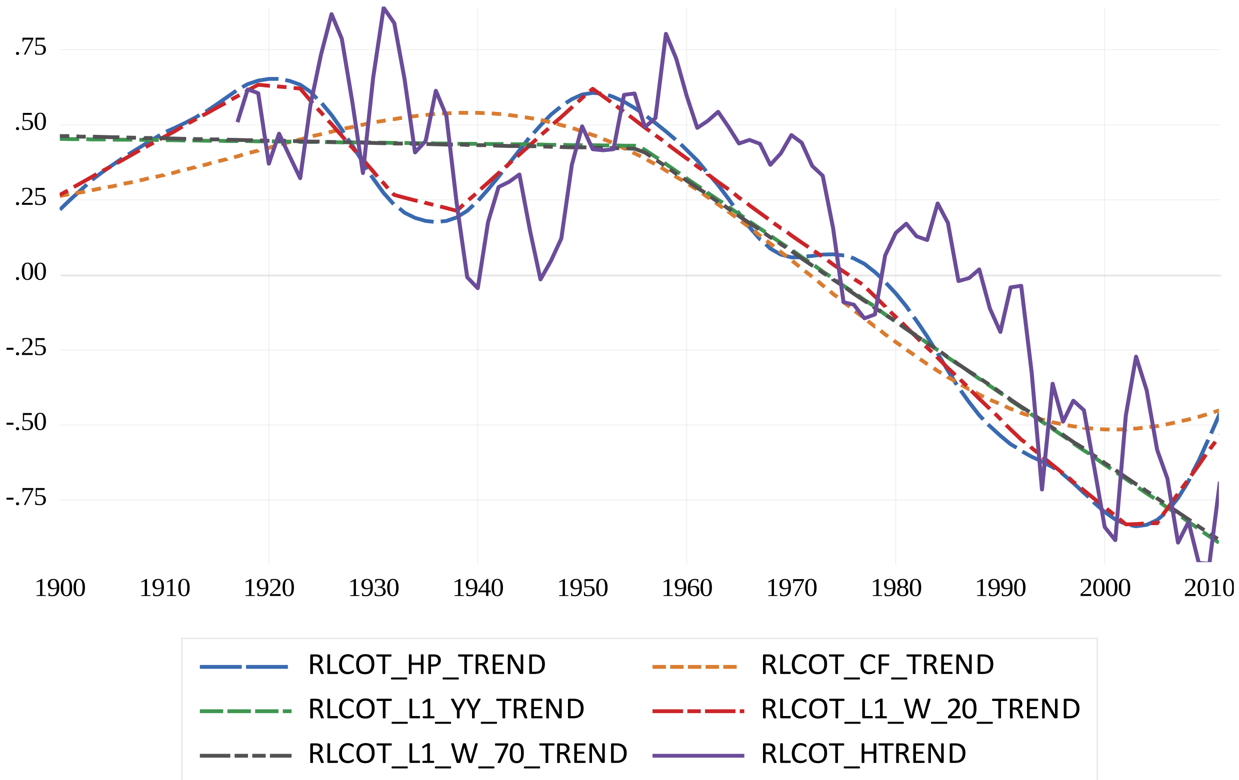

Figure B14 : Cycle representation of Cotton

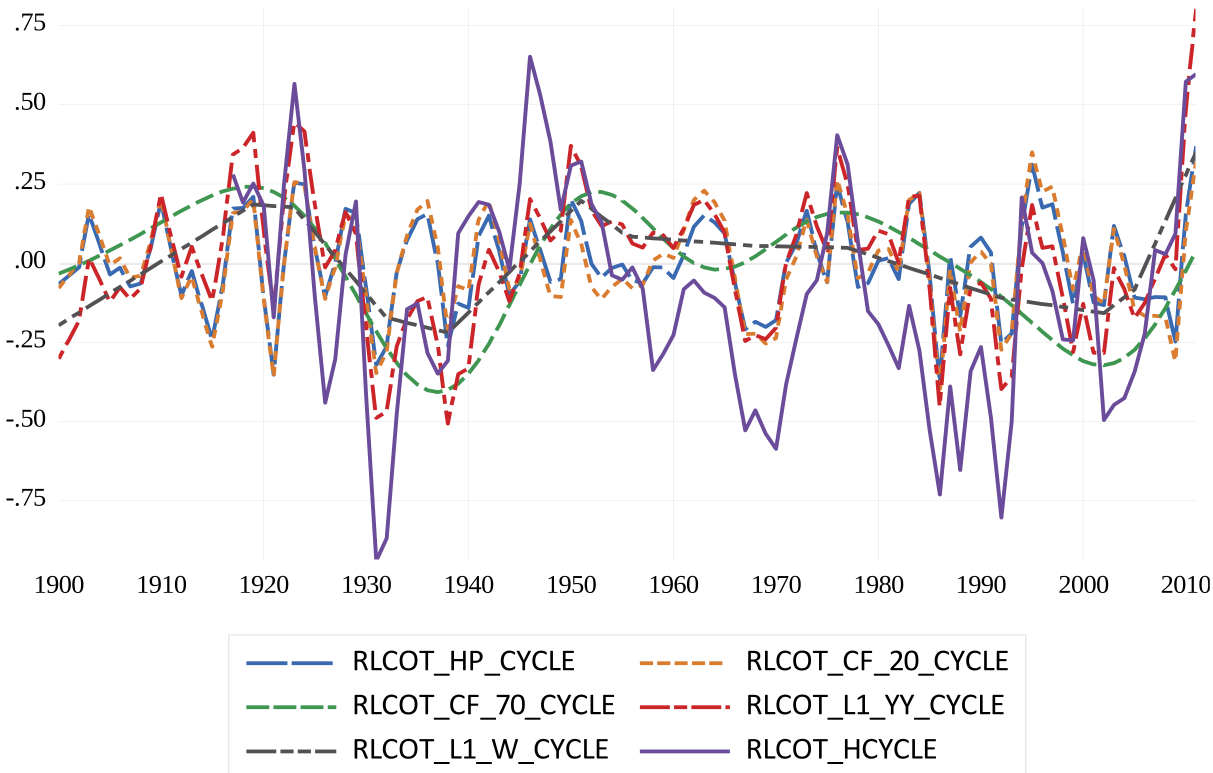

Figure B15 : Trend representation of CPI

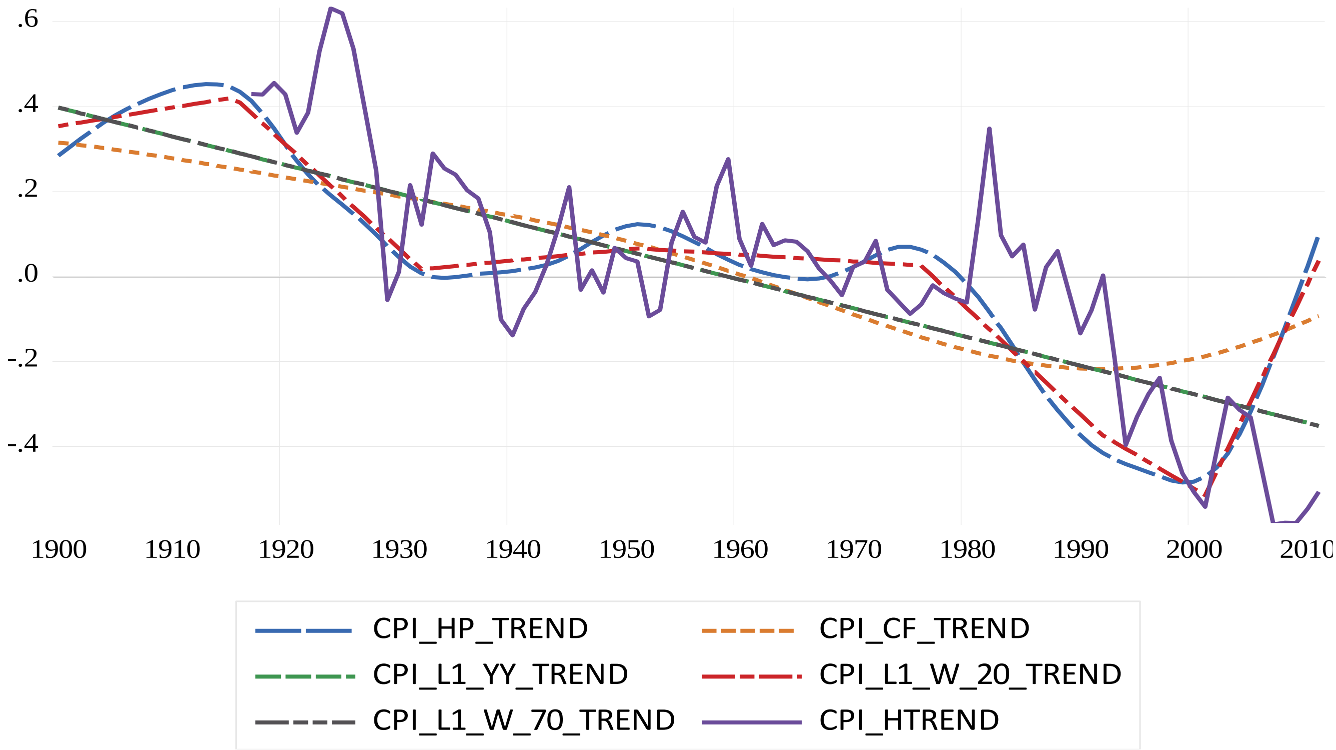

Figure B16 : Cycle representation of CPI

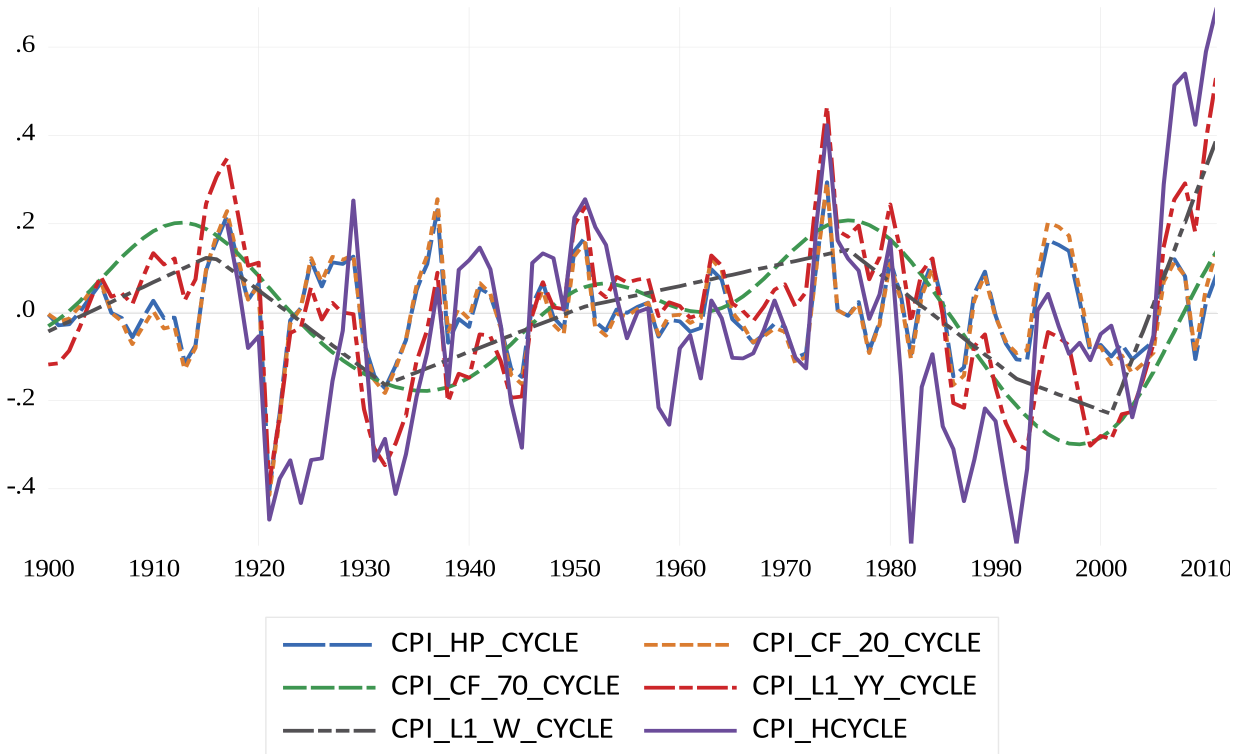

Figure B17 : Trend representation of CPIF

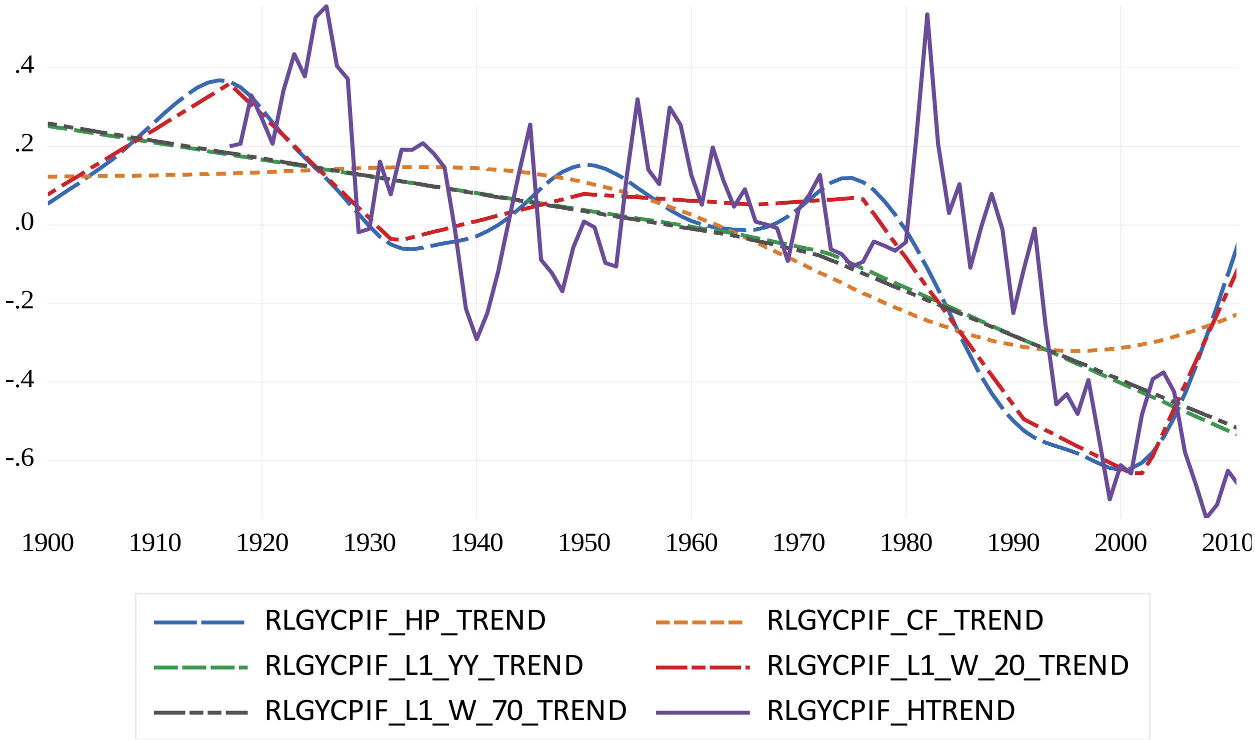

Figure B18 : Cycle representation of CPIF

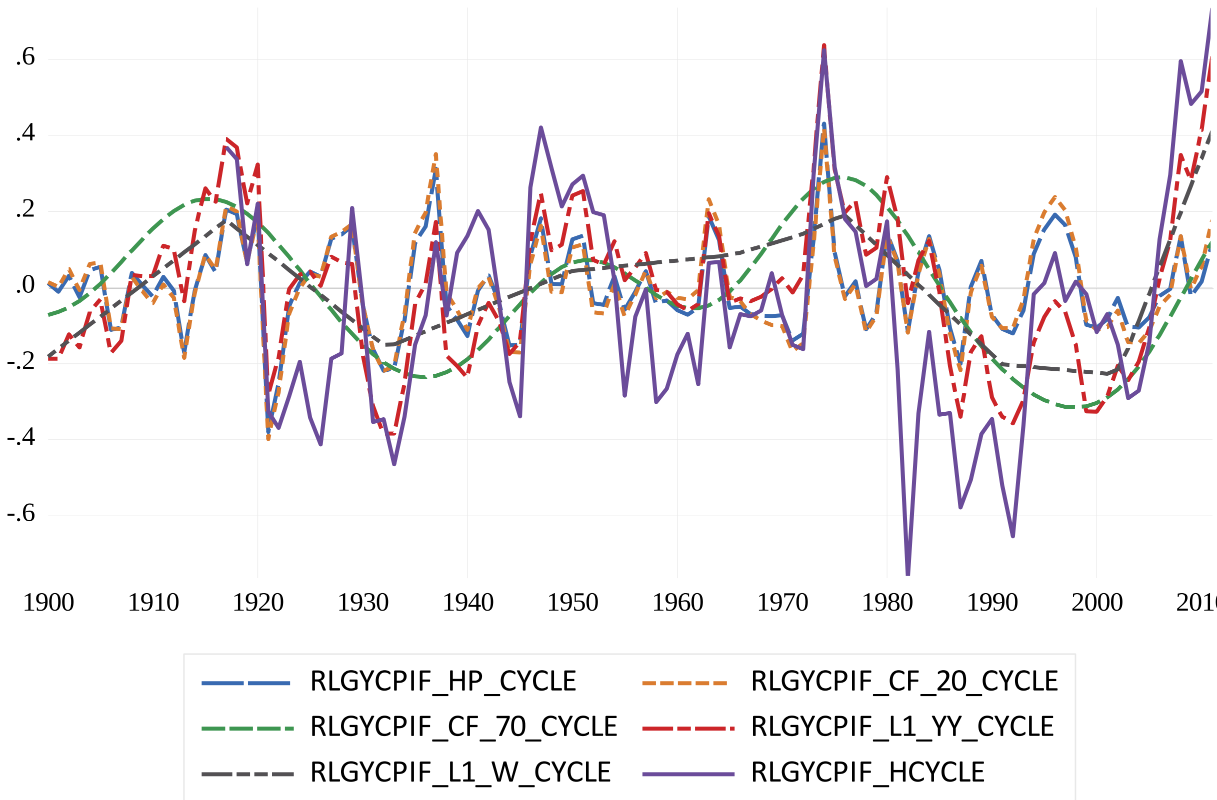

Figure B19 : Trend representation of CPIM

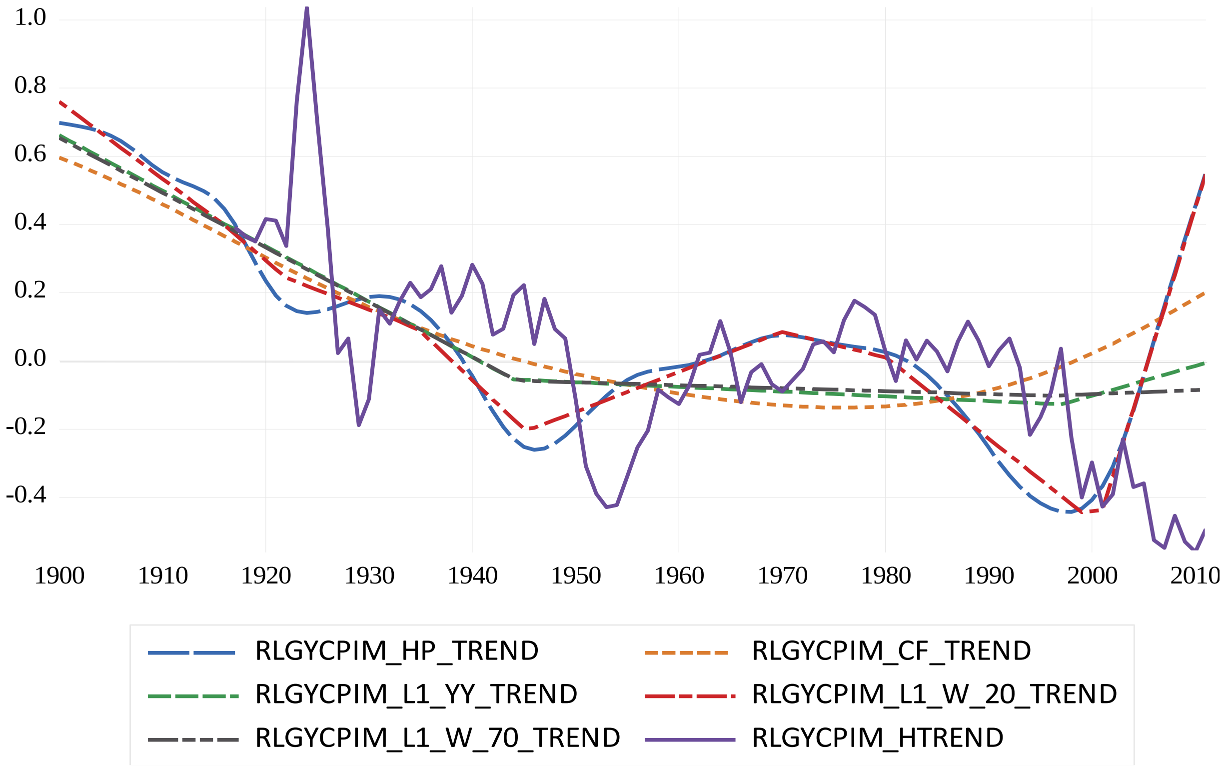

Figure B20 : Cycle representation of CPIM

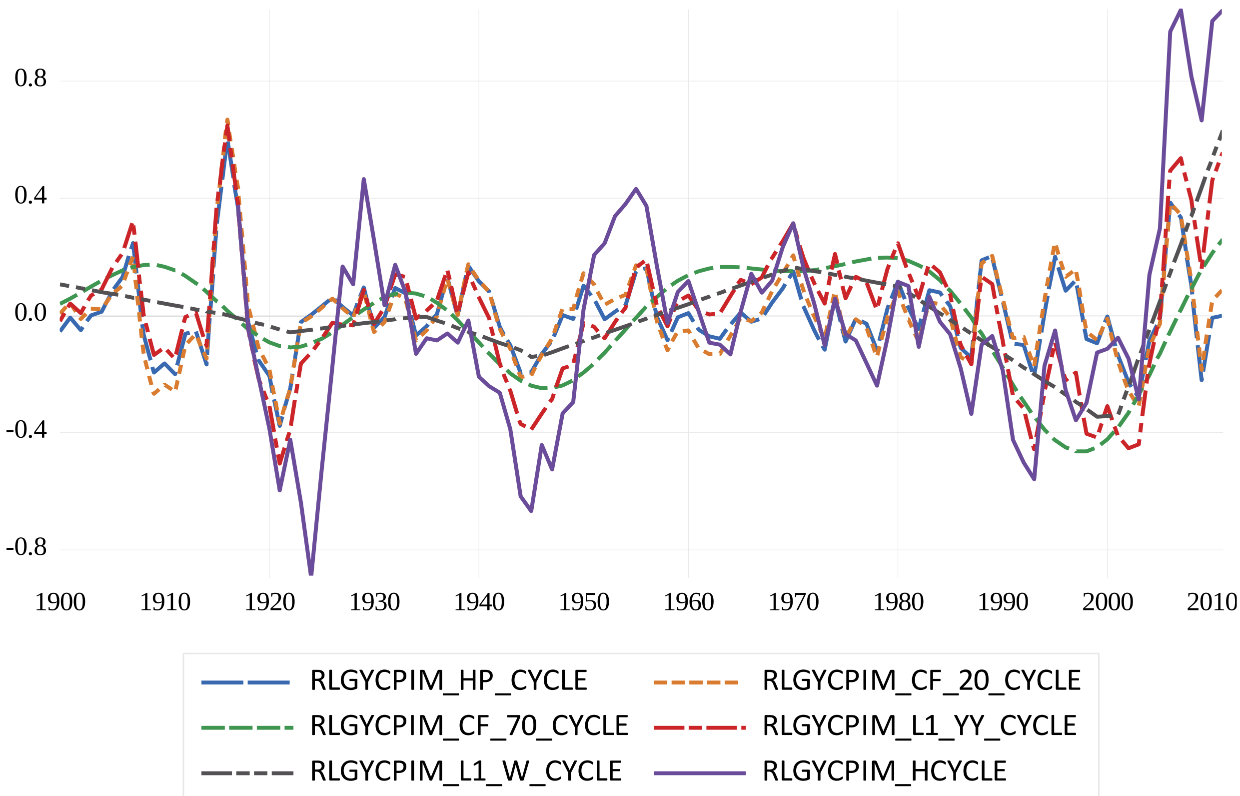

Figure B21 : Trend representation of CPINF

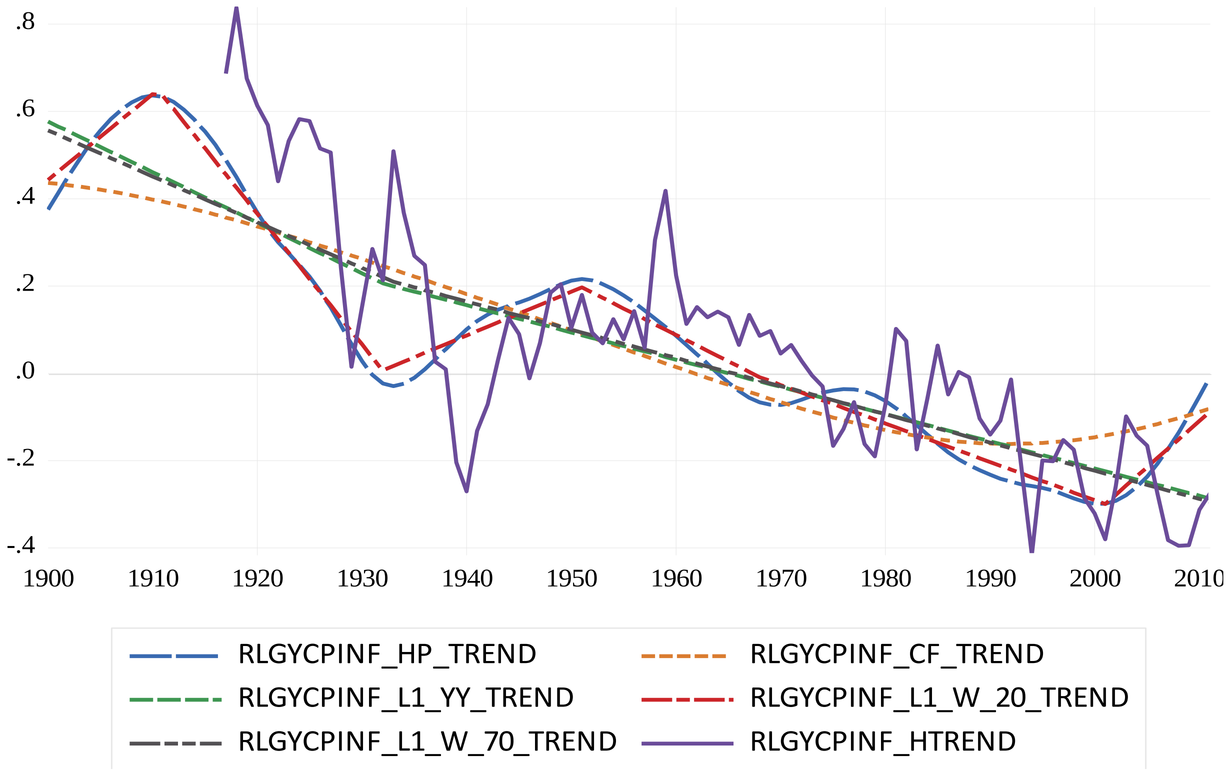

Figure B22 : Cycle representation of CPINF

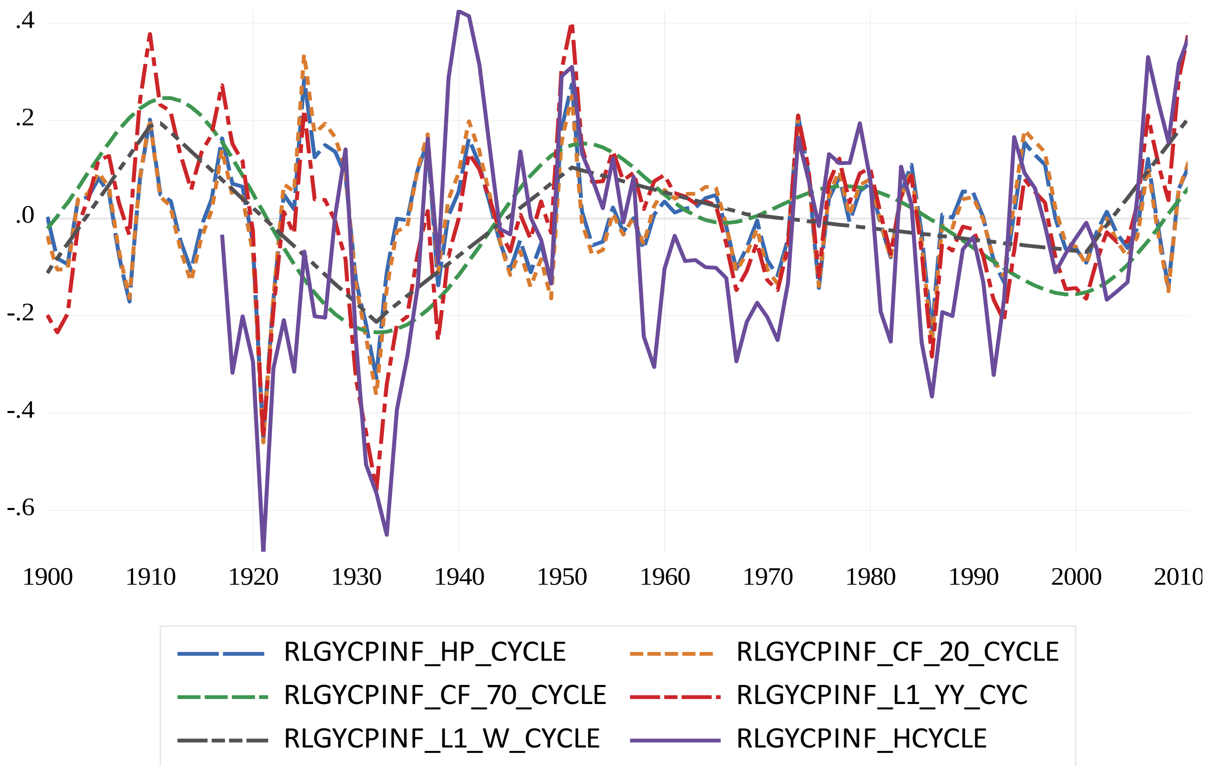

Figure B23 : Trend representation of CPI CW

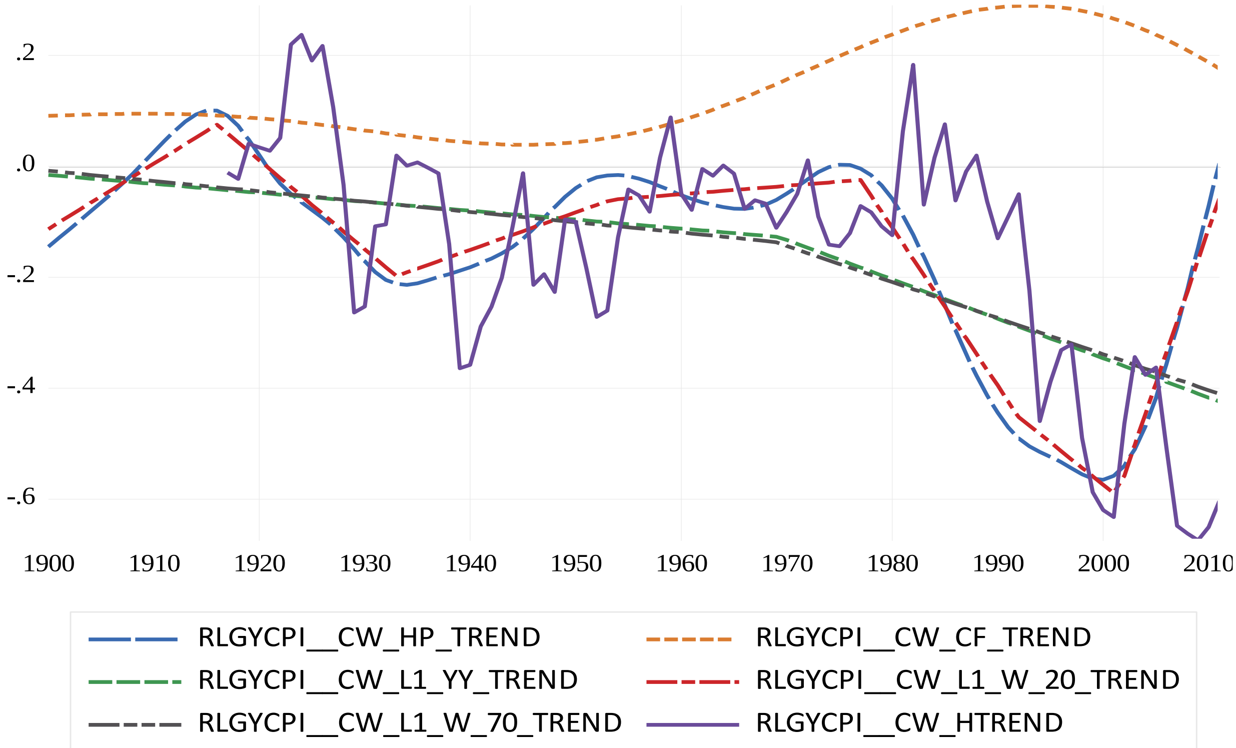

Figure B24 : Cycle representation of CPI CW

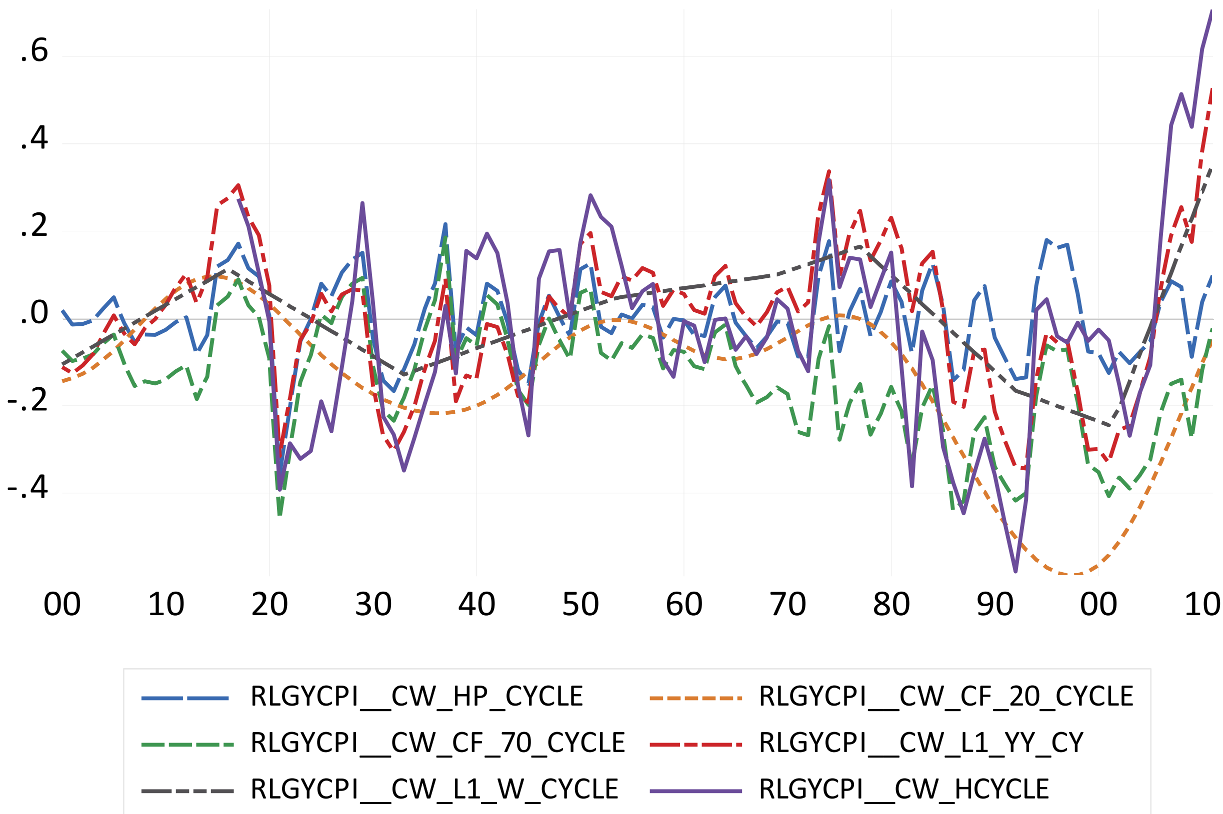

Figure B25 : Trend representation of CPIF CW

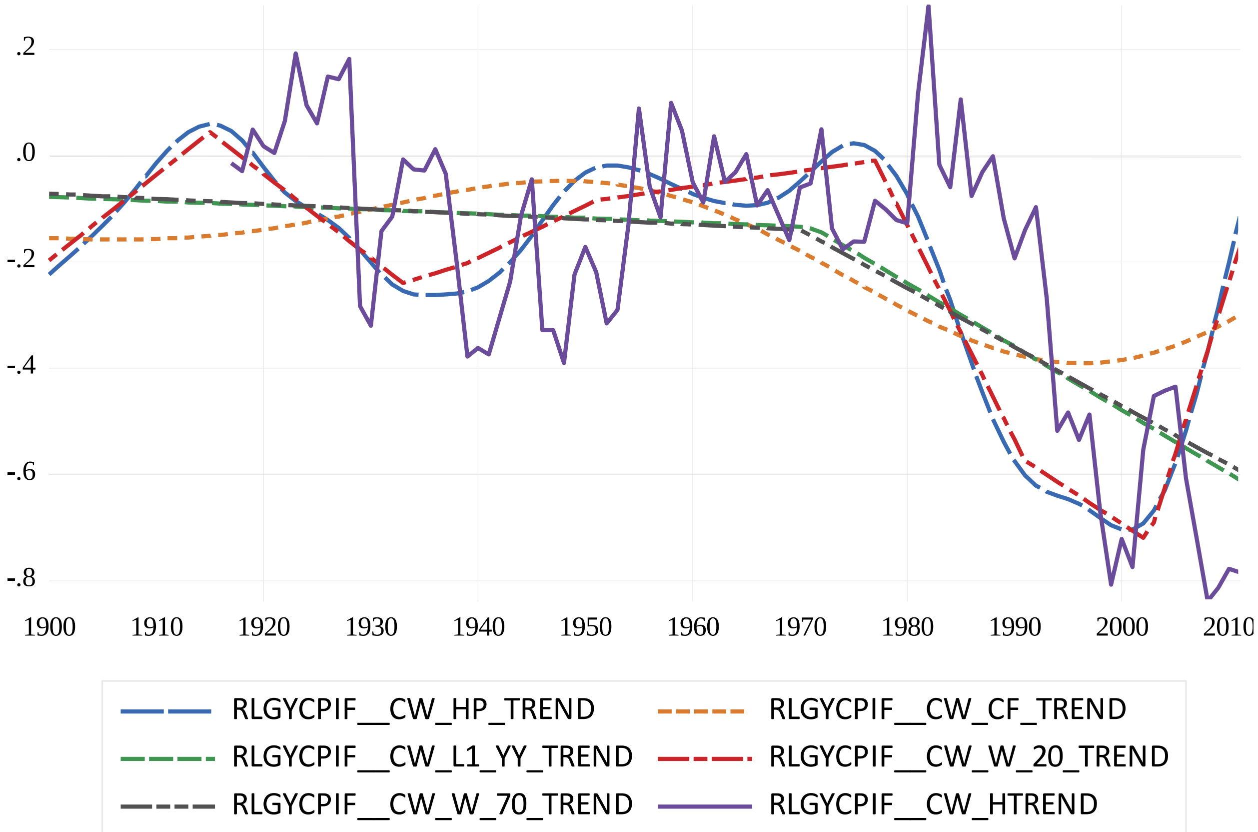

Figure B26 : Cycle representation of CPIF CW

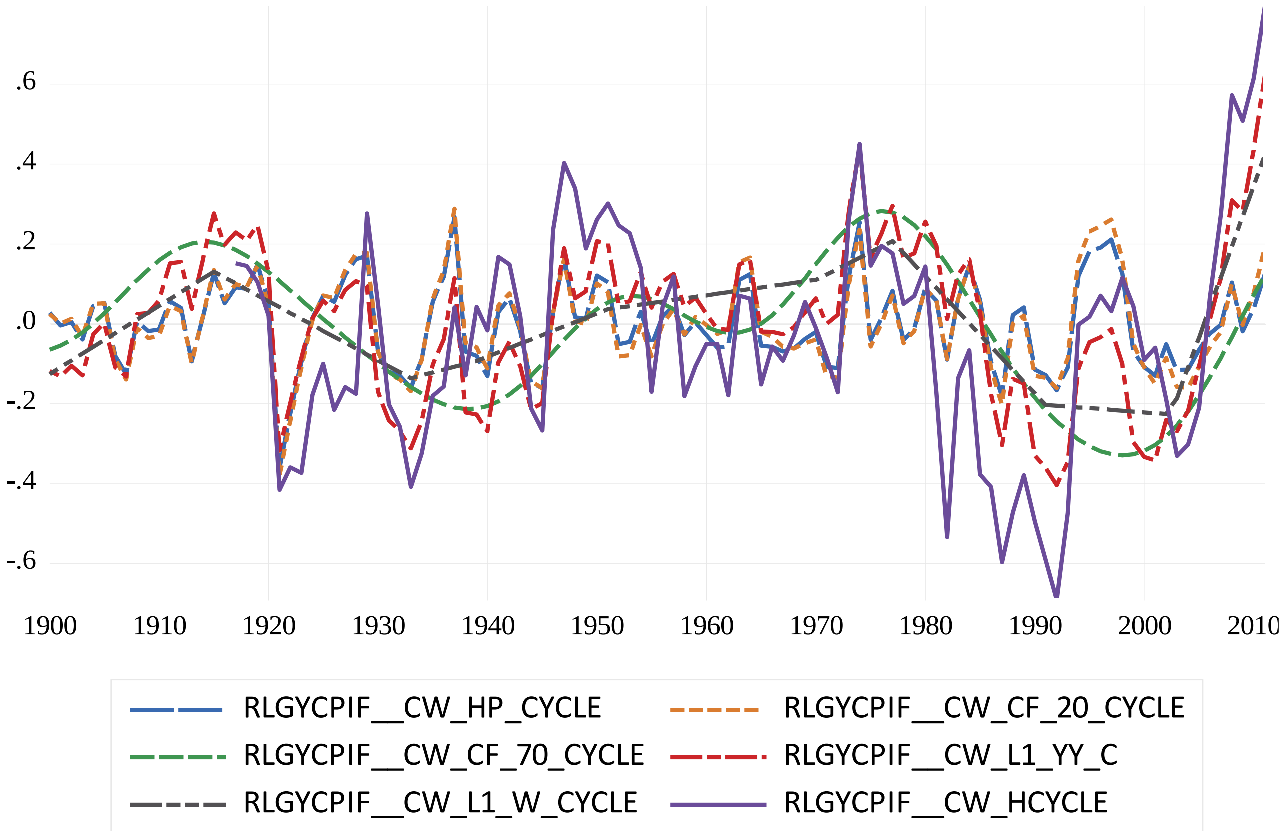

Figure B27 : Trend representation of CPIM CW

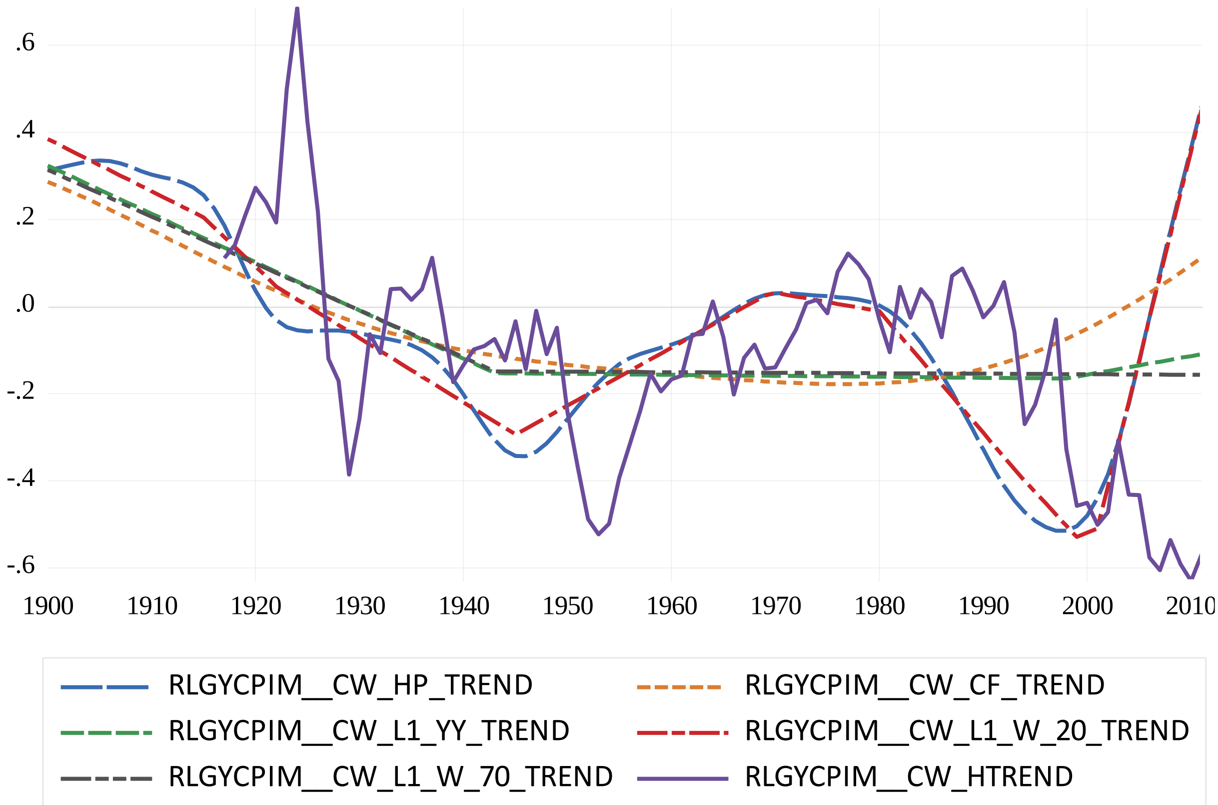

Figure B28 : Cycle representation of CPIM CW

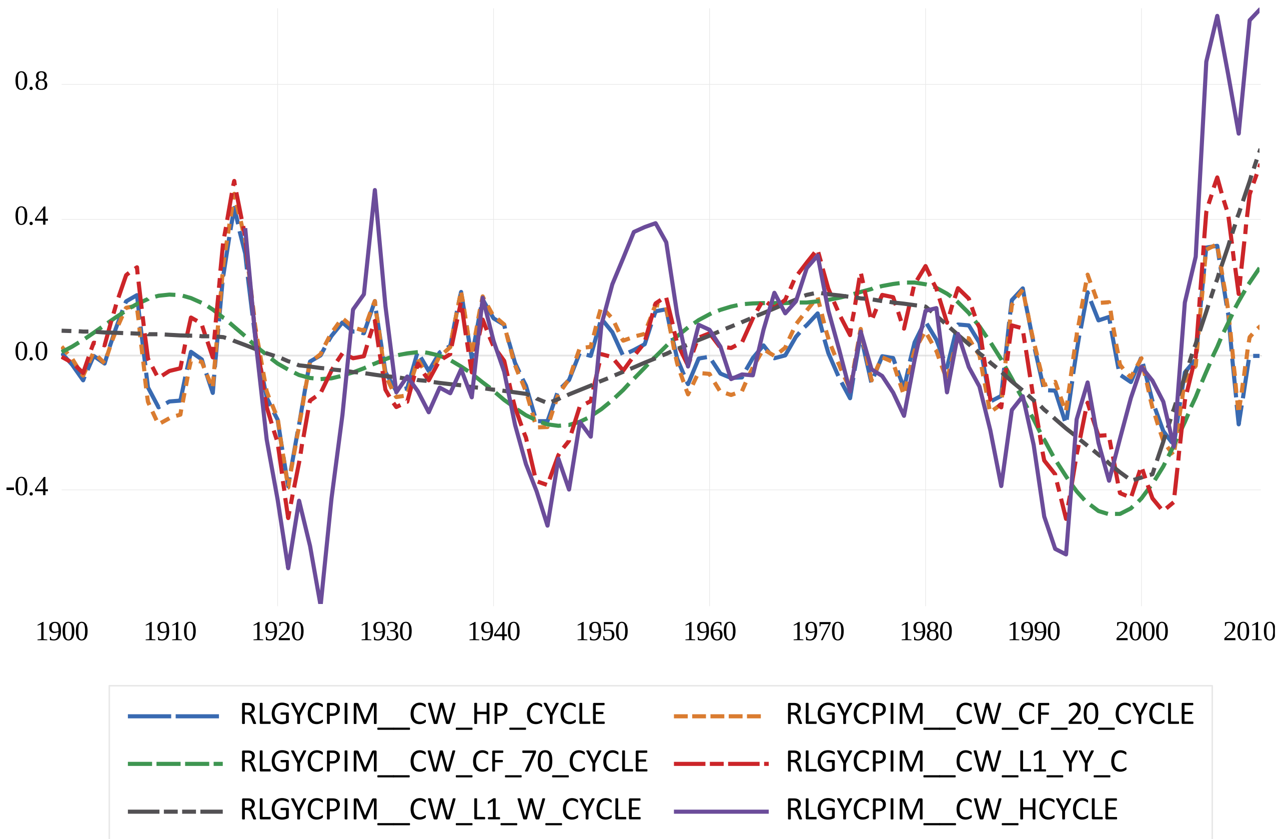

Figure B29 : Trend representation of CPINF CW

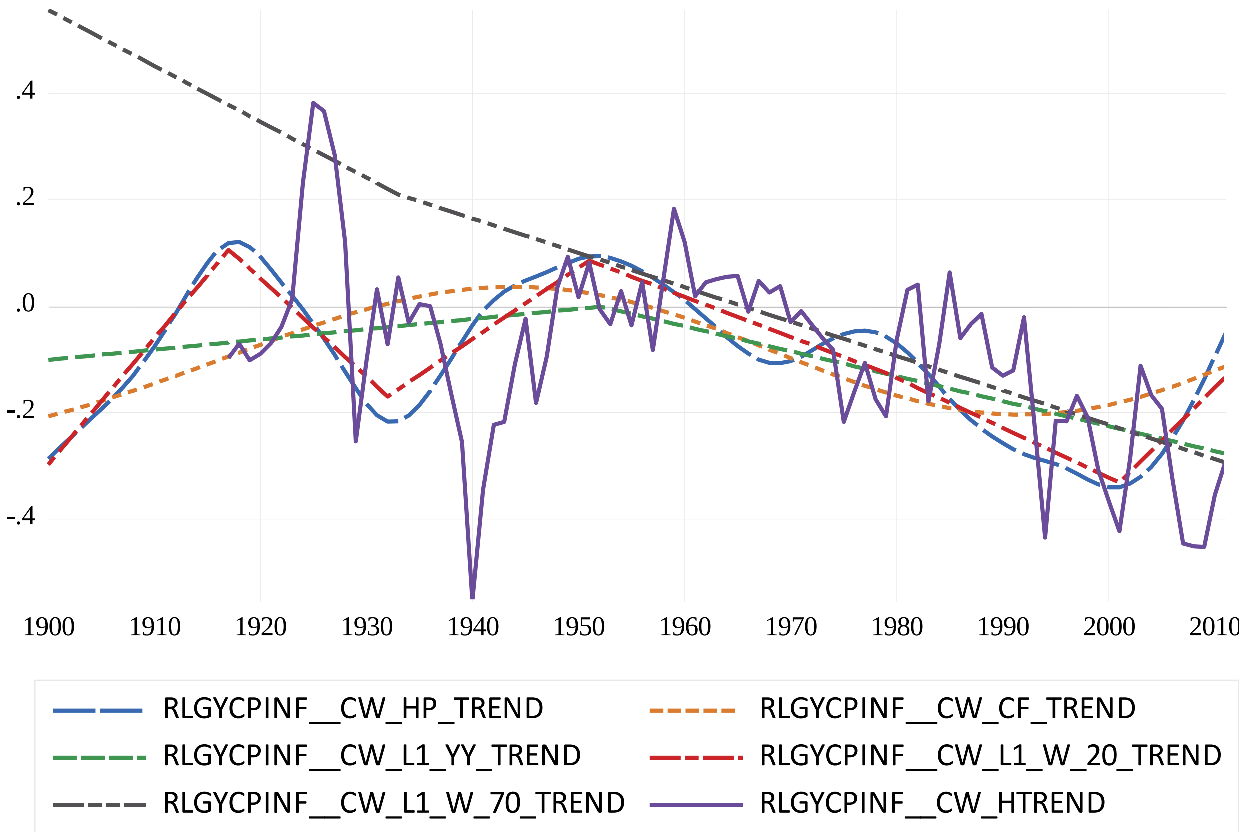

Figure B30 : Cycle representation of CPINF CW

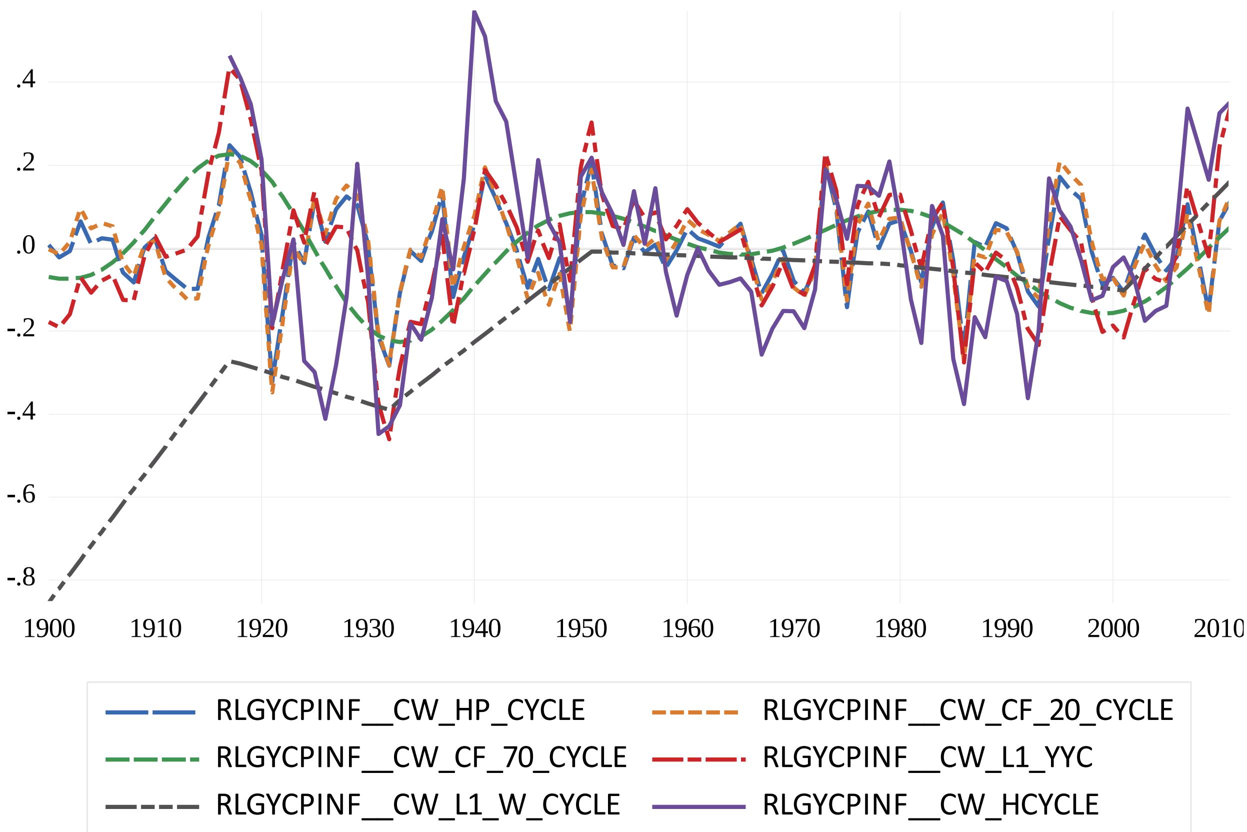

Figure B31 : Trend representation of Hides

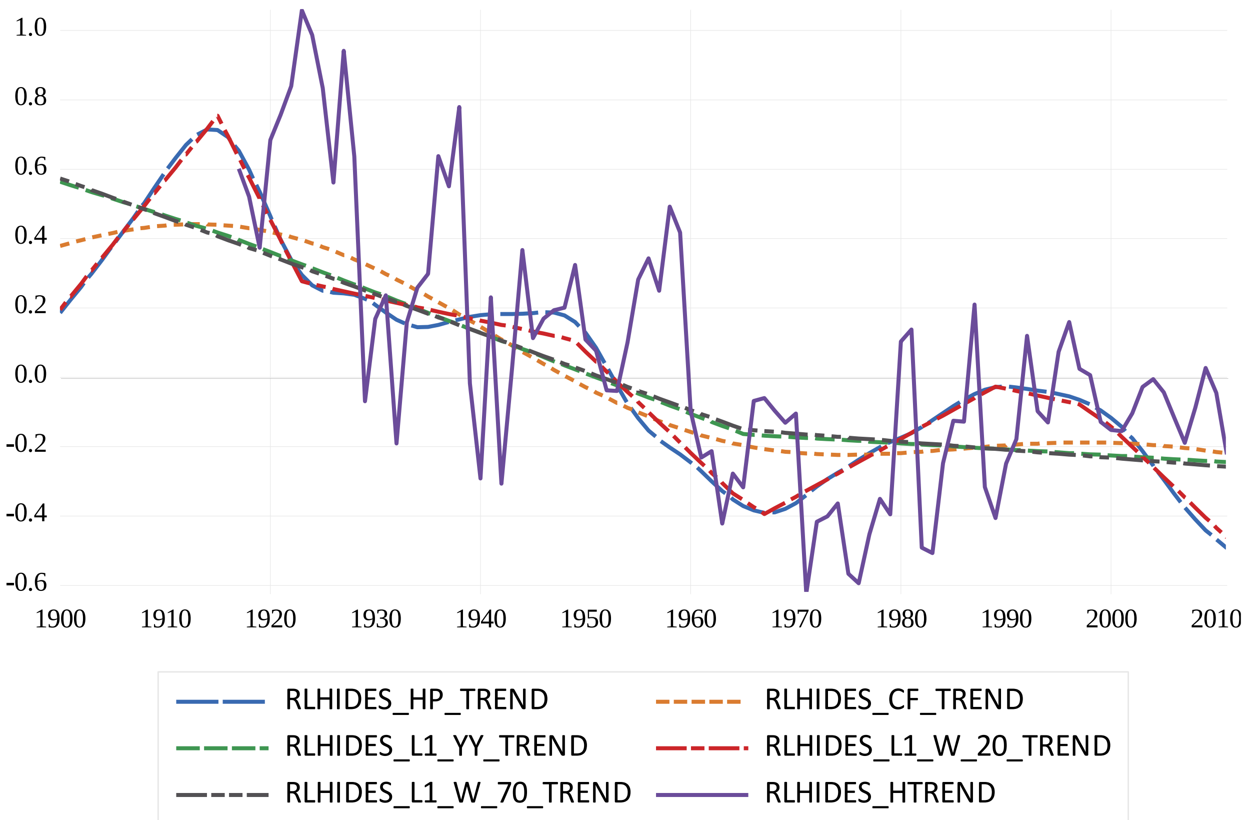

Figure B32 : Cycle representation of Hides

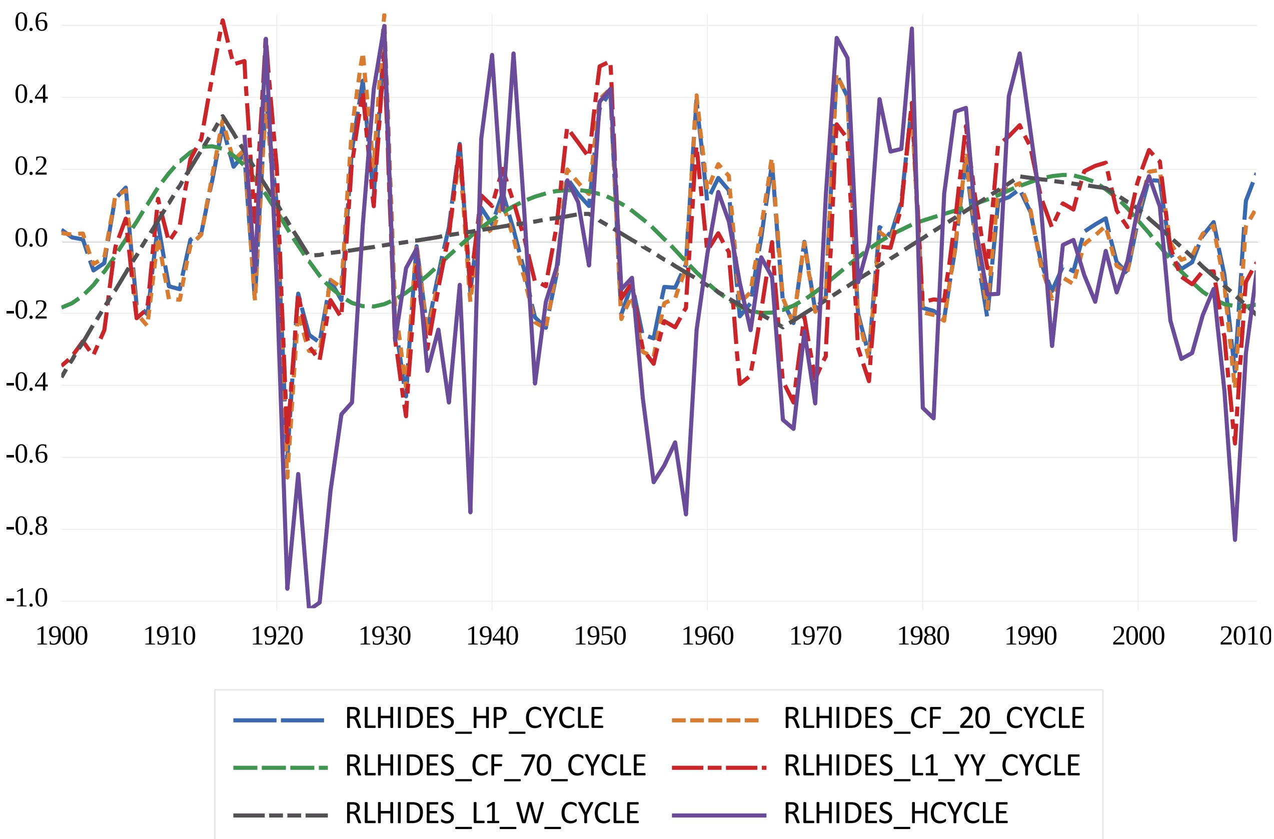

Figure B33 : Trend representation of Jute

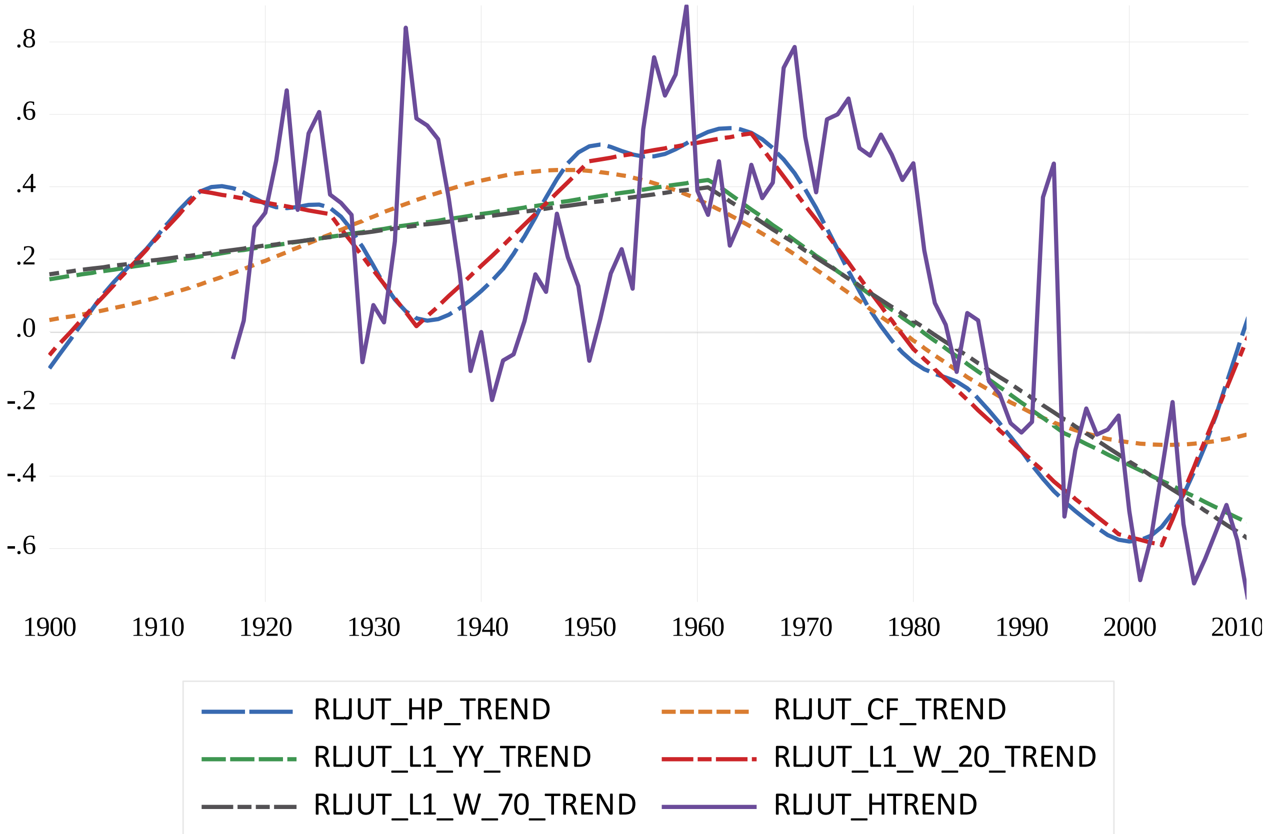

Figure B34 : Cycle representation of Jute

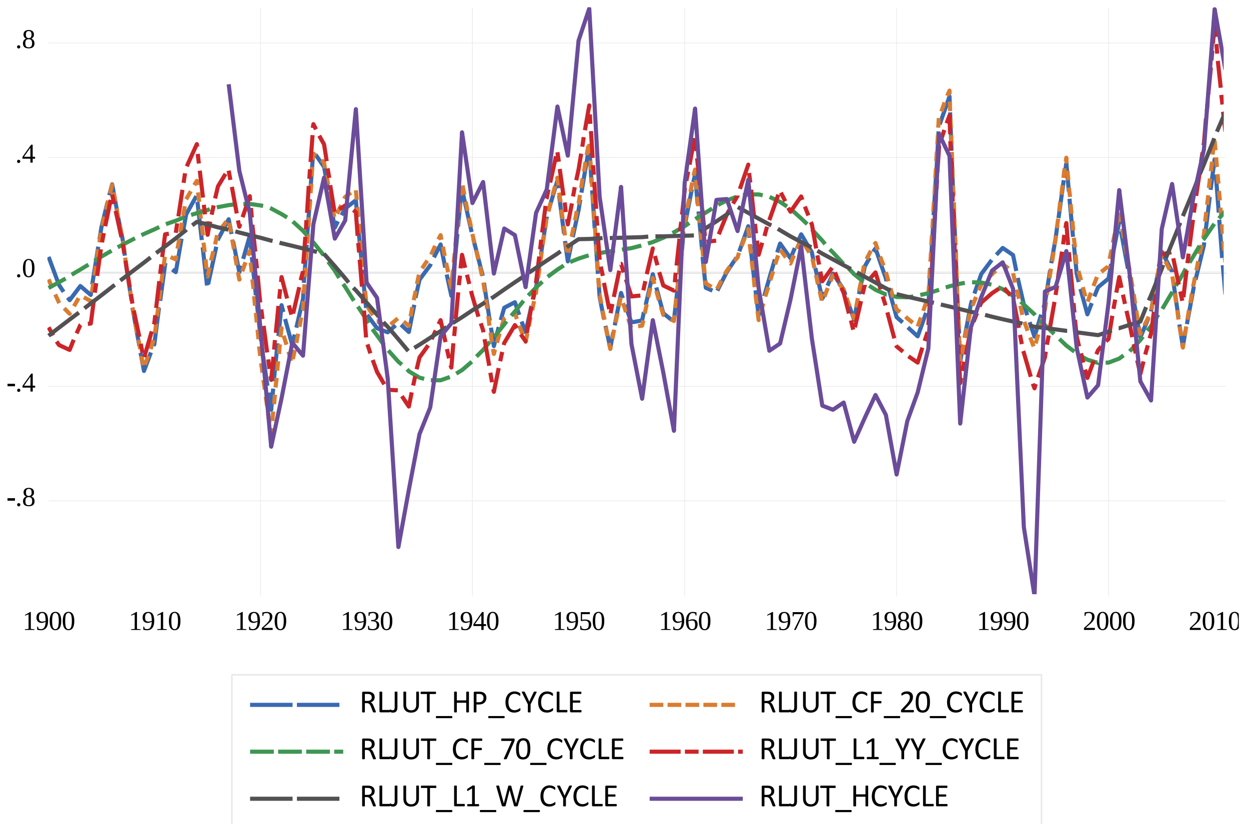

Figure B35 : Trend representation of Lamb

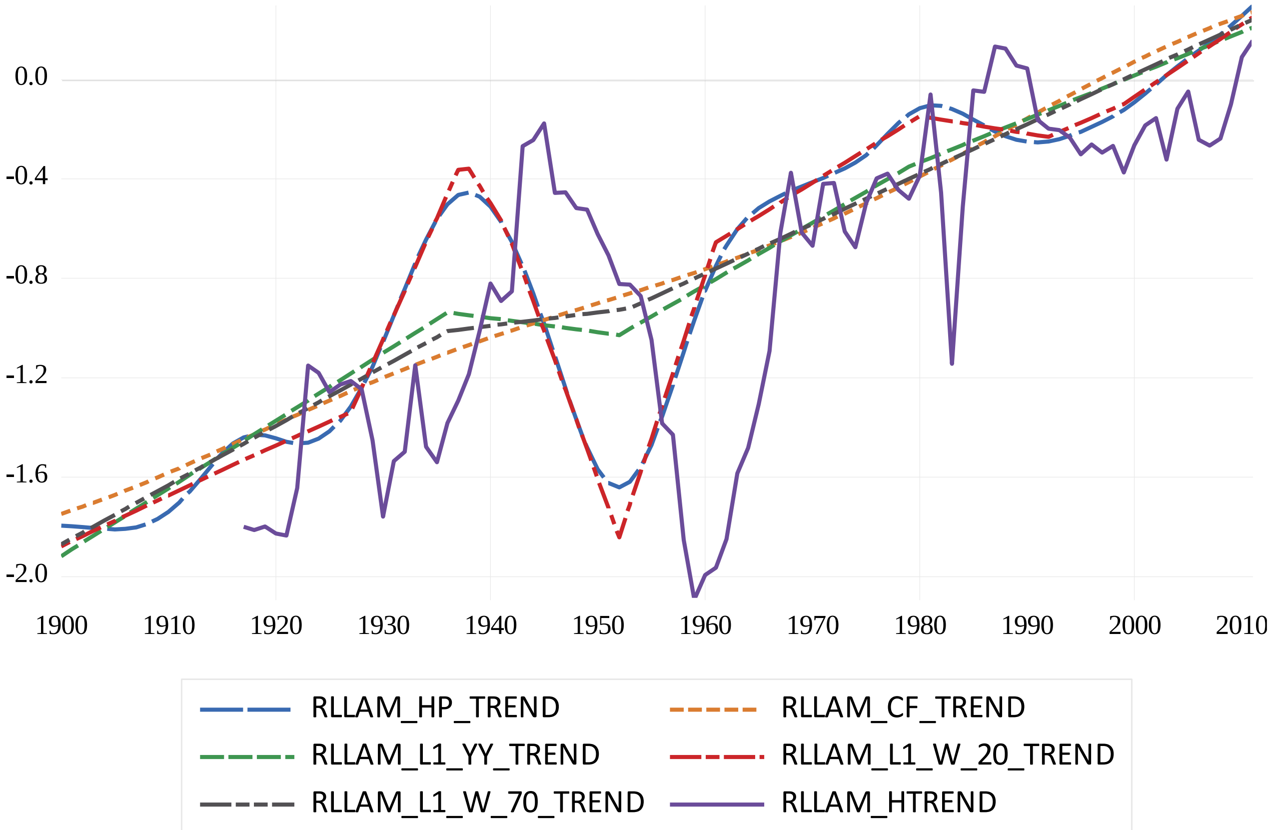

Figure B36 : Cycle representation of Lamb

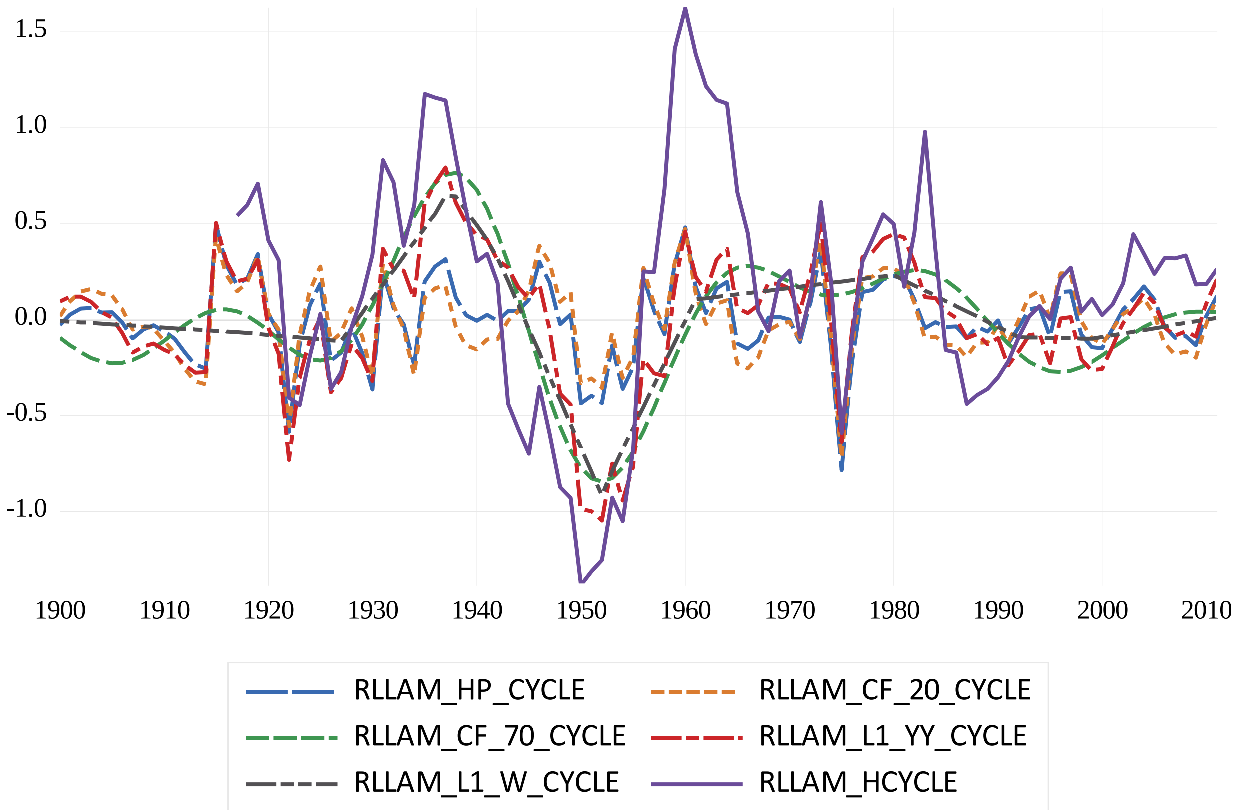

Figure B37 : Trend representation of Lead

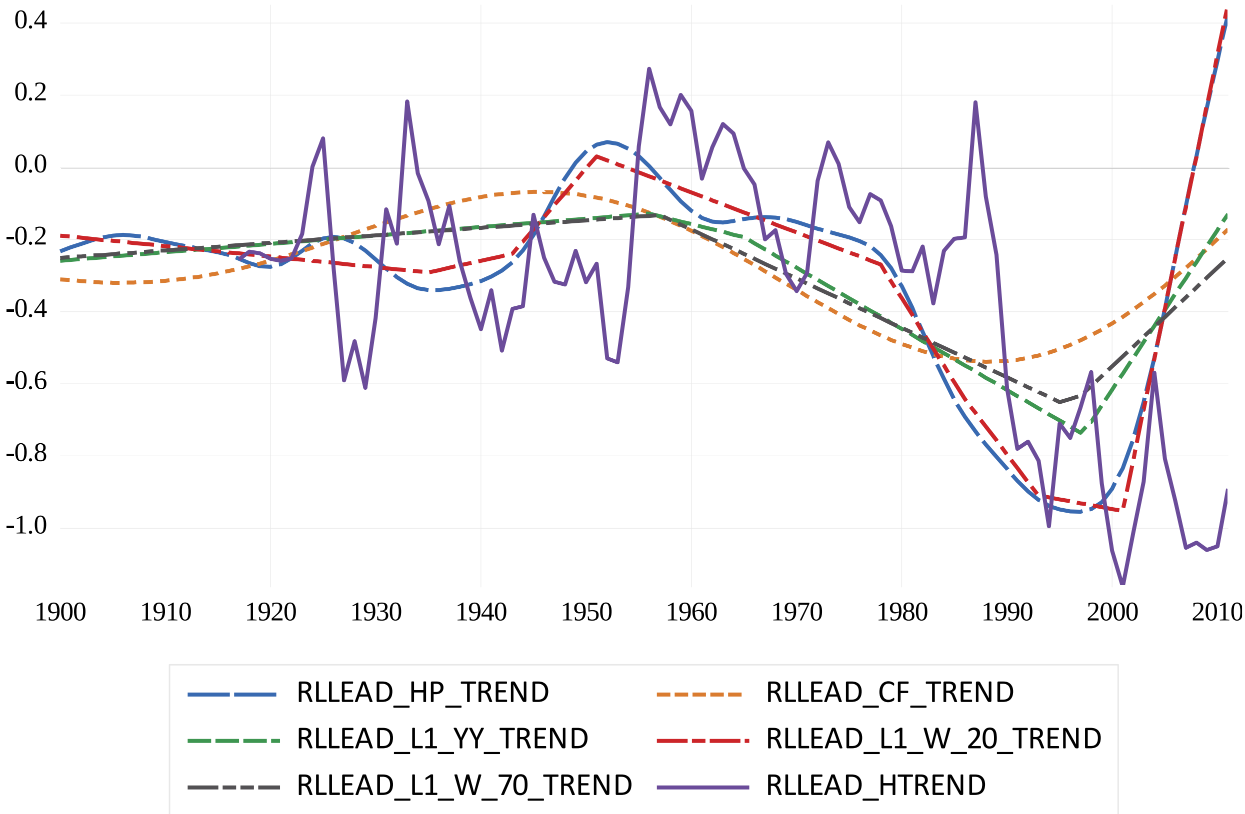

Figure B38 : Cycle representation of Lead

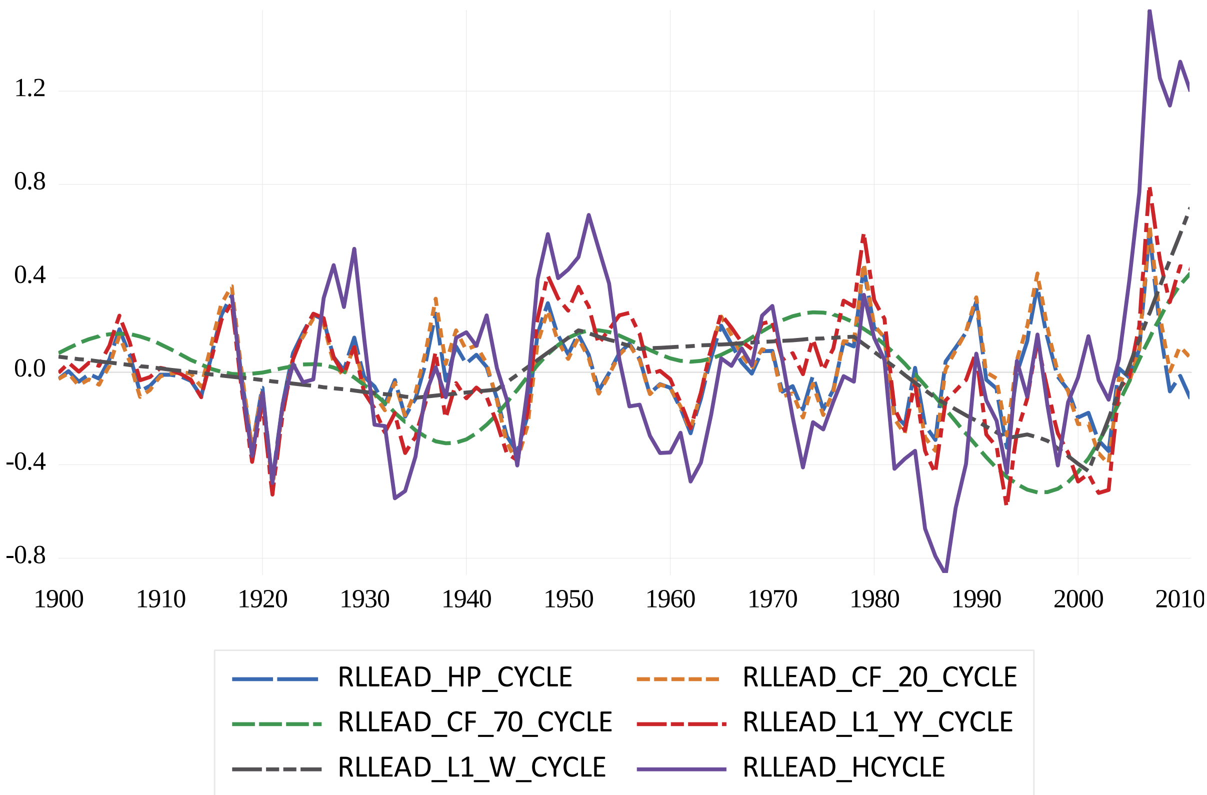

Figure B39 : Trend representation of Maize

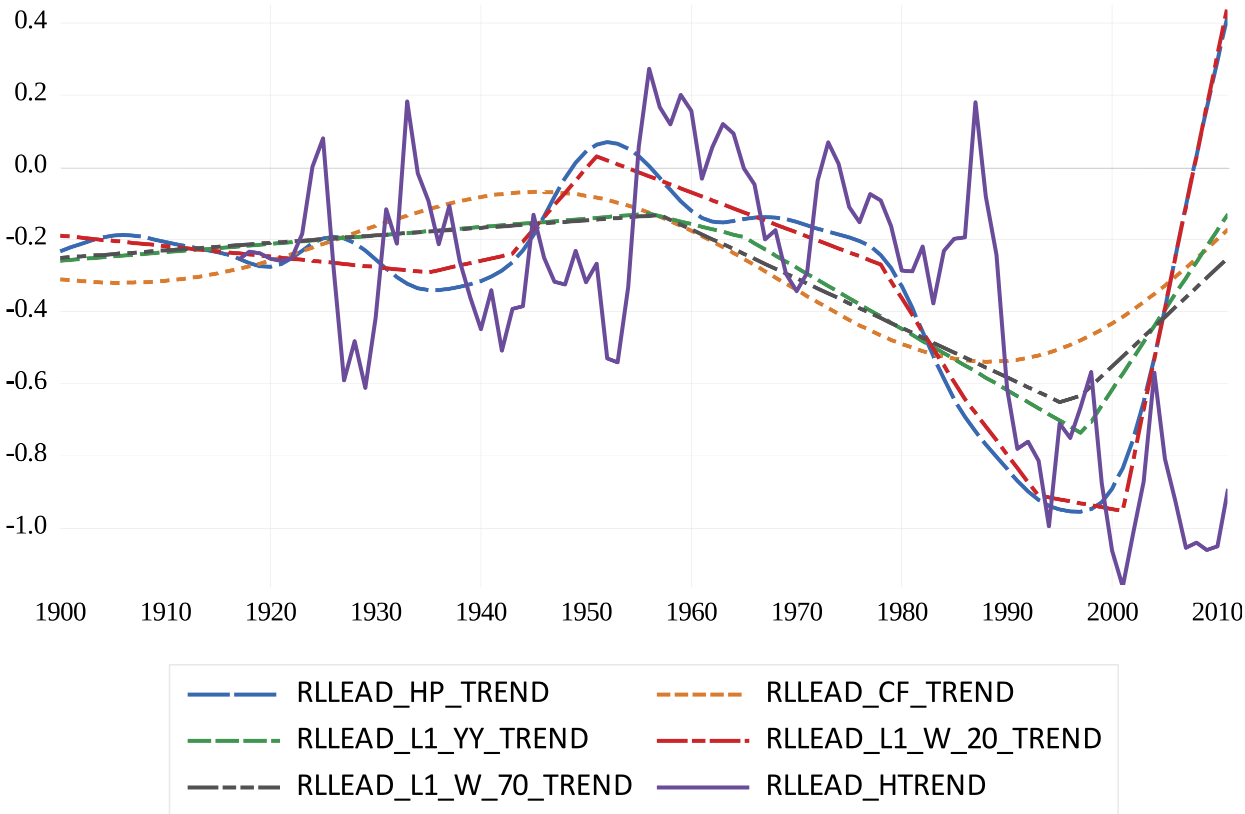

Figure B40 : Cycle representation of Maize

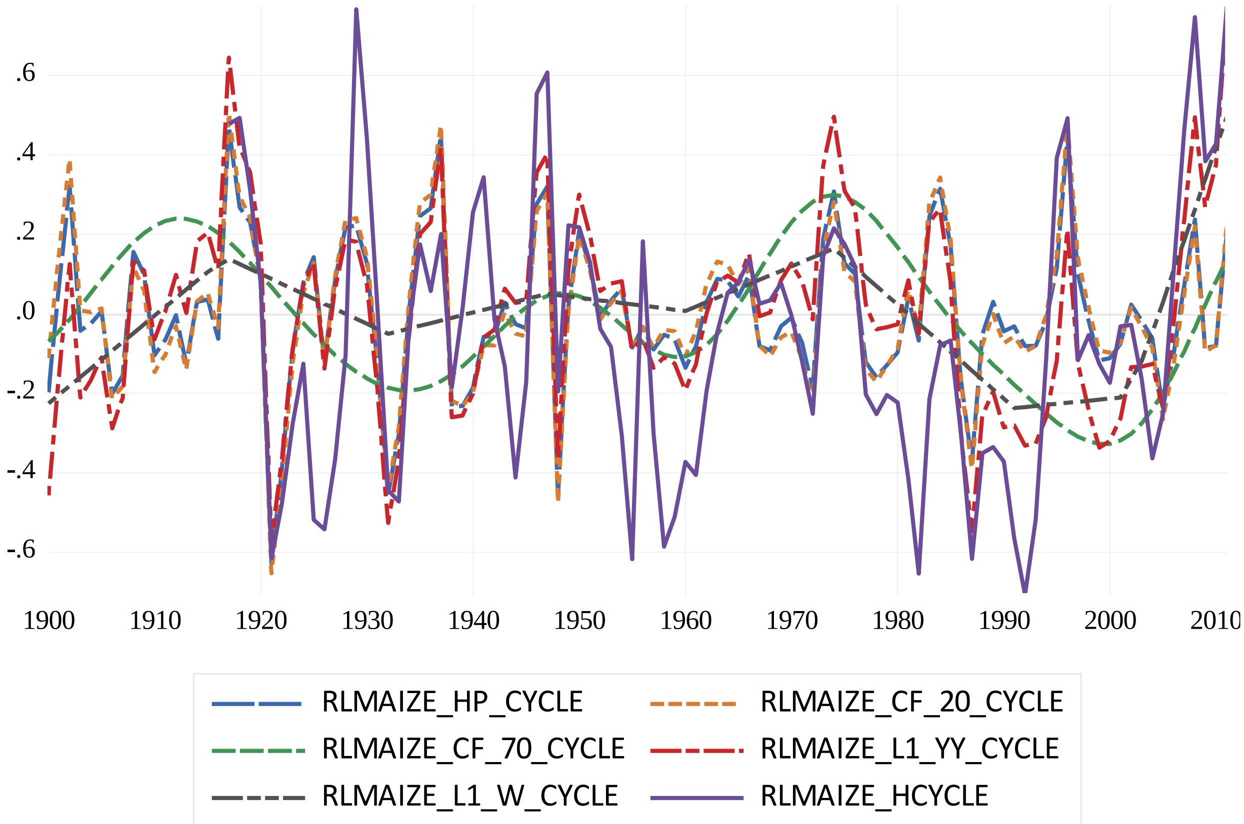

Figure B41 : Trend representation of Palm Oil

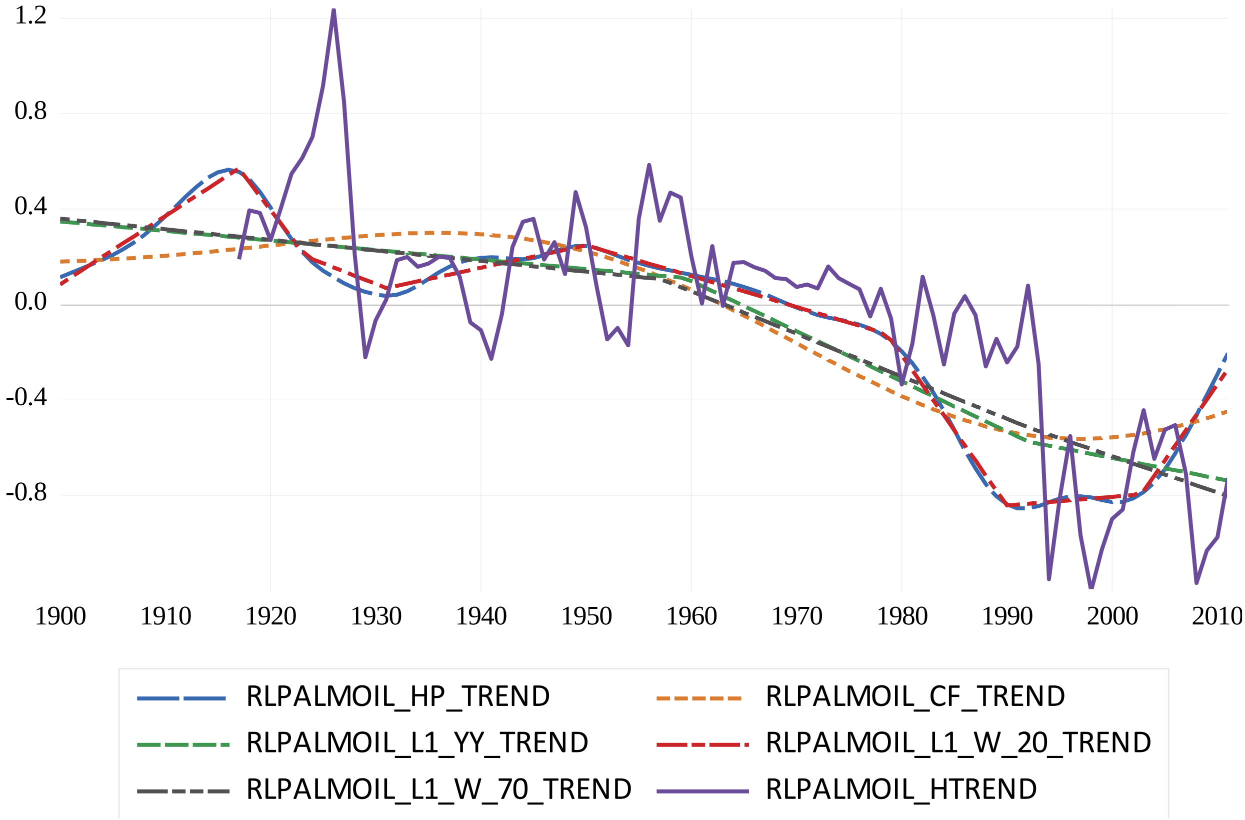

Figure B42 : Cycle representation of Palm Oil

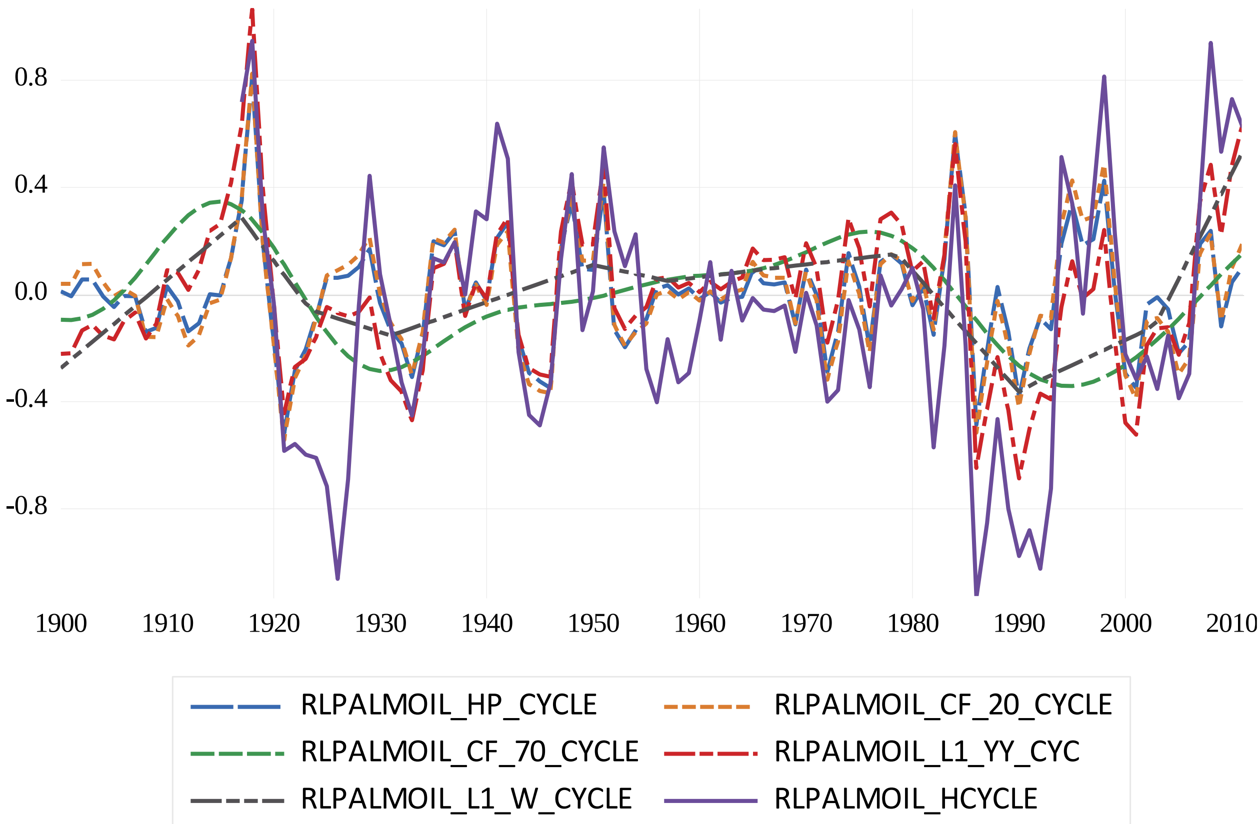

Figure B43 : Trend representation of Rice

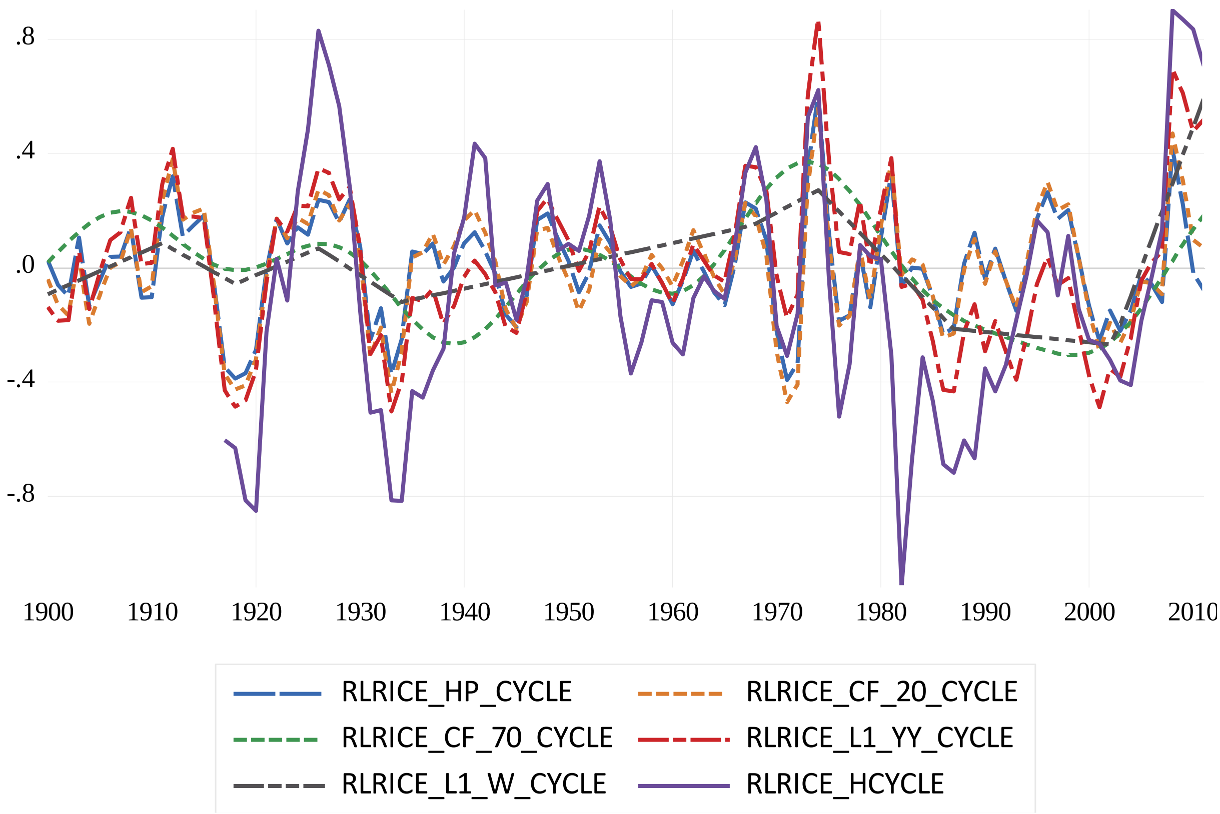

Figure B44 : Cycle representation of Rice

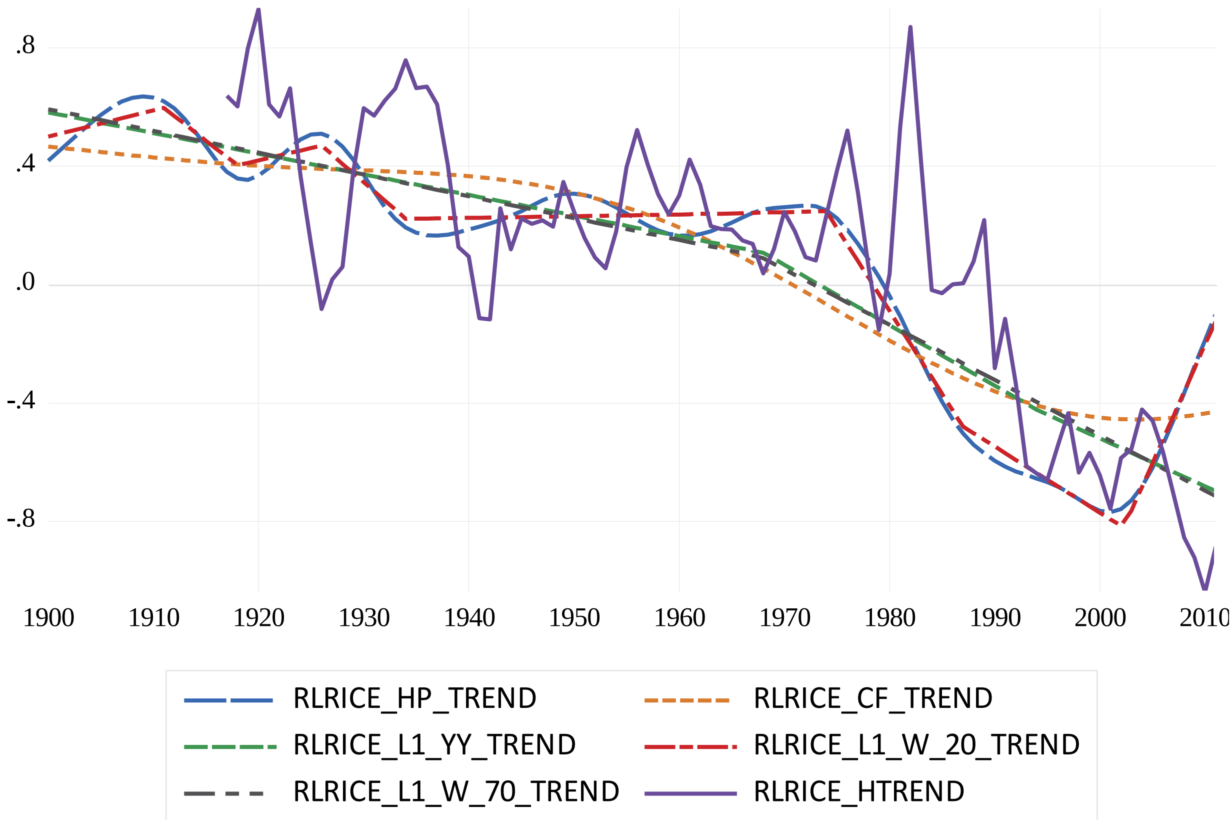

Figure B45 : Trend representation of Rubber

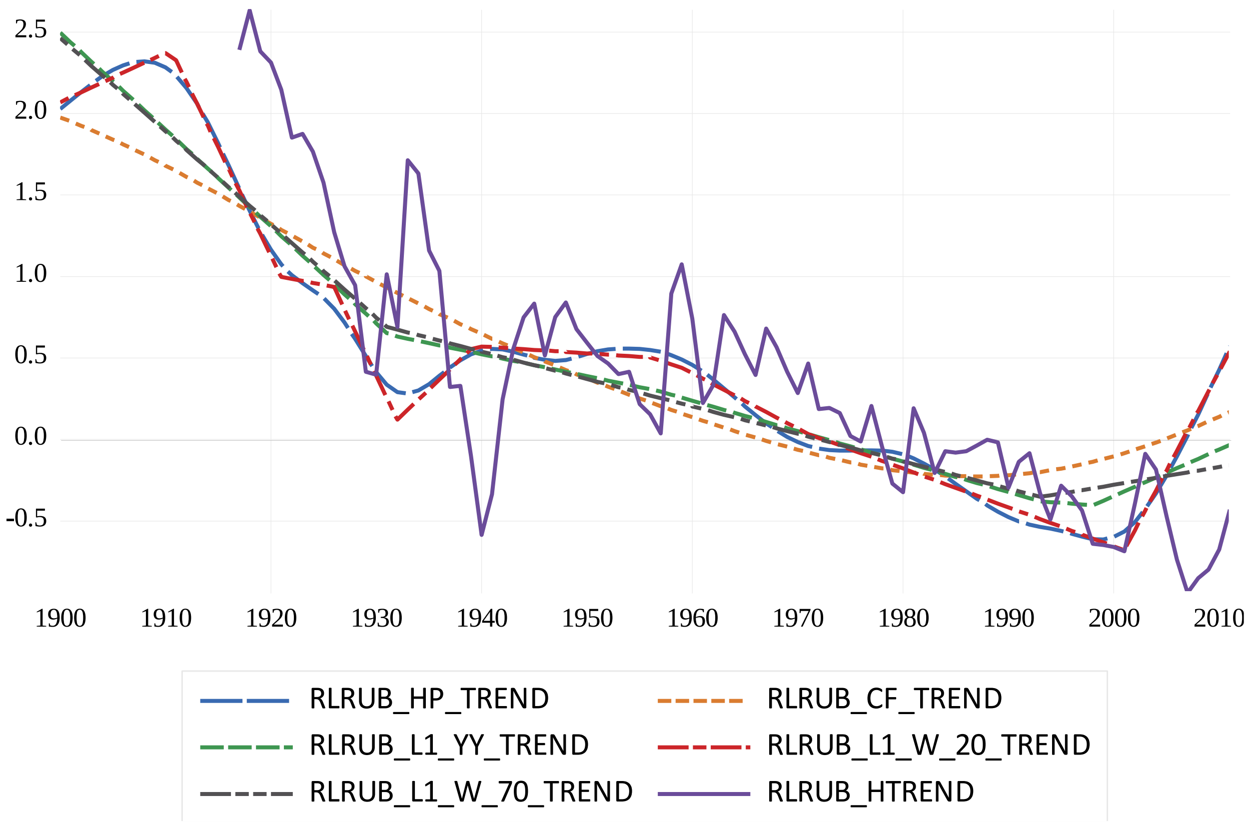

Figure B46 : Cycle representation of Rubber

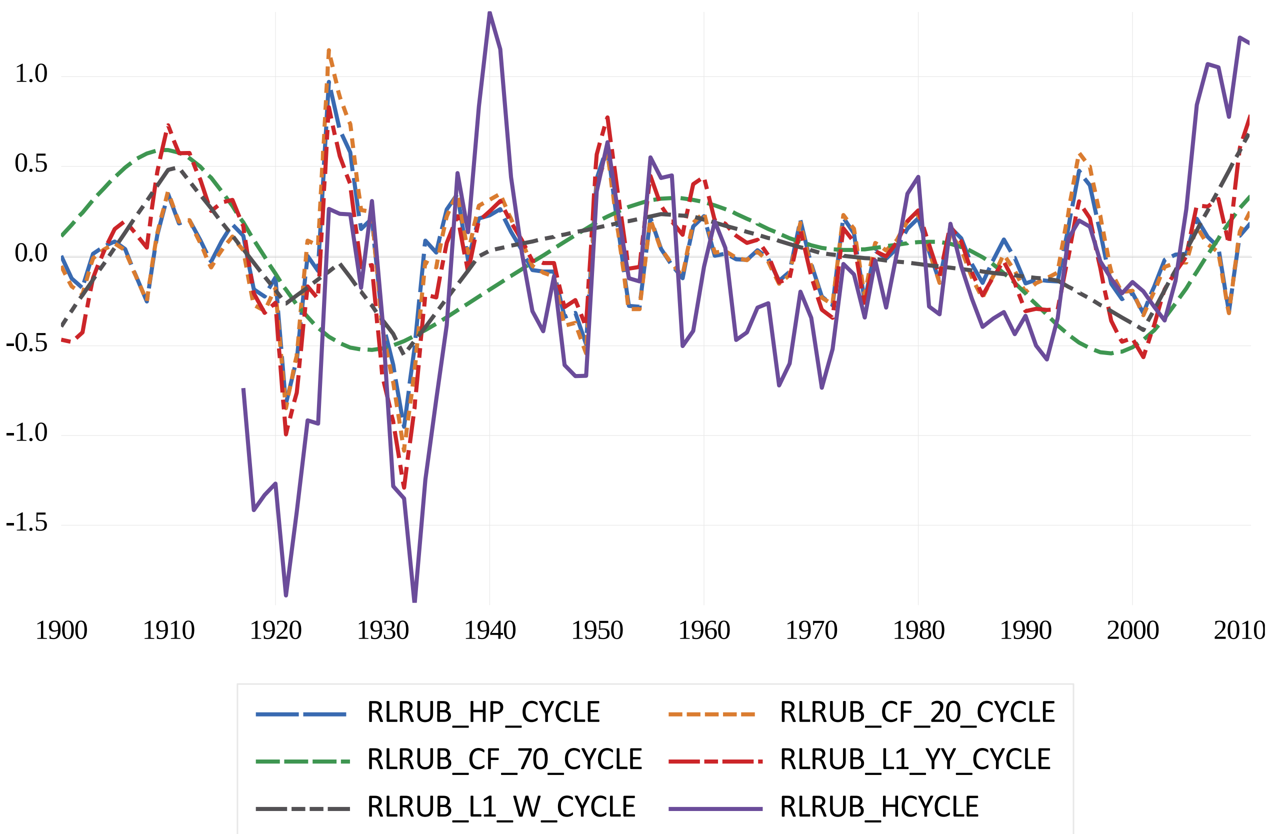

Figure B47 : Trend representation of Silver

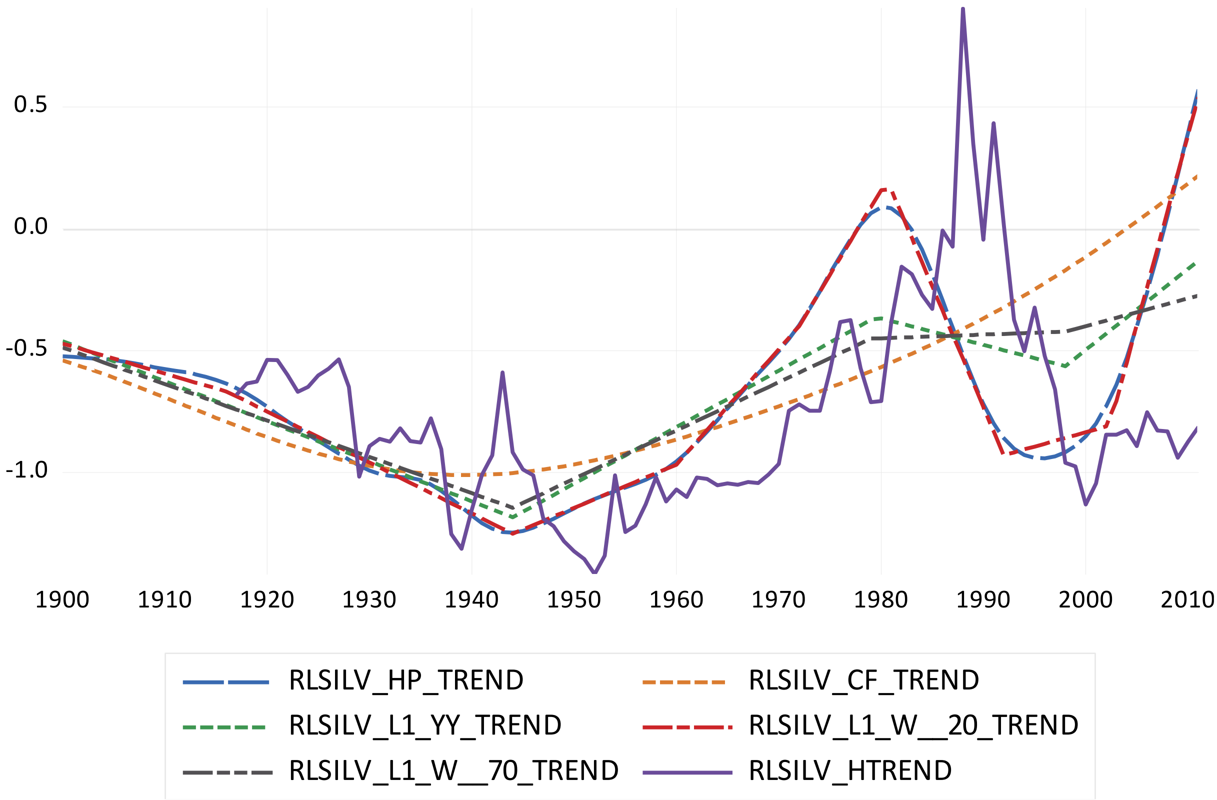

Figure B48 : Cycle representation of Silver

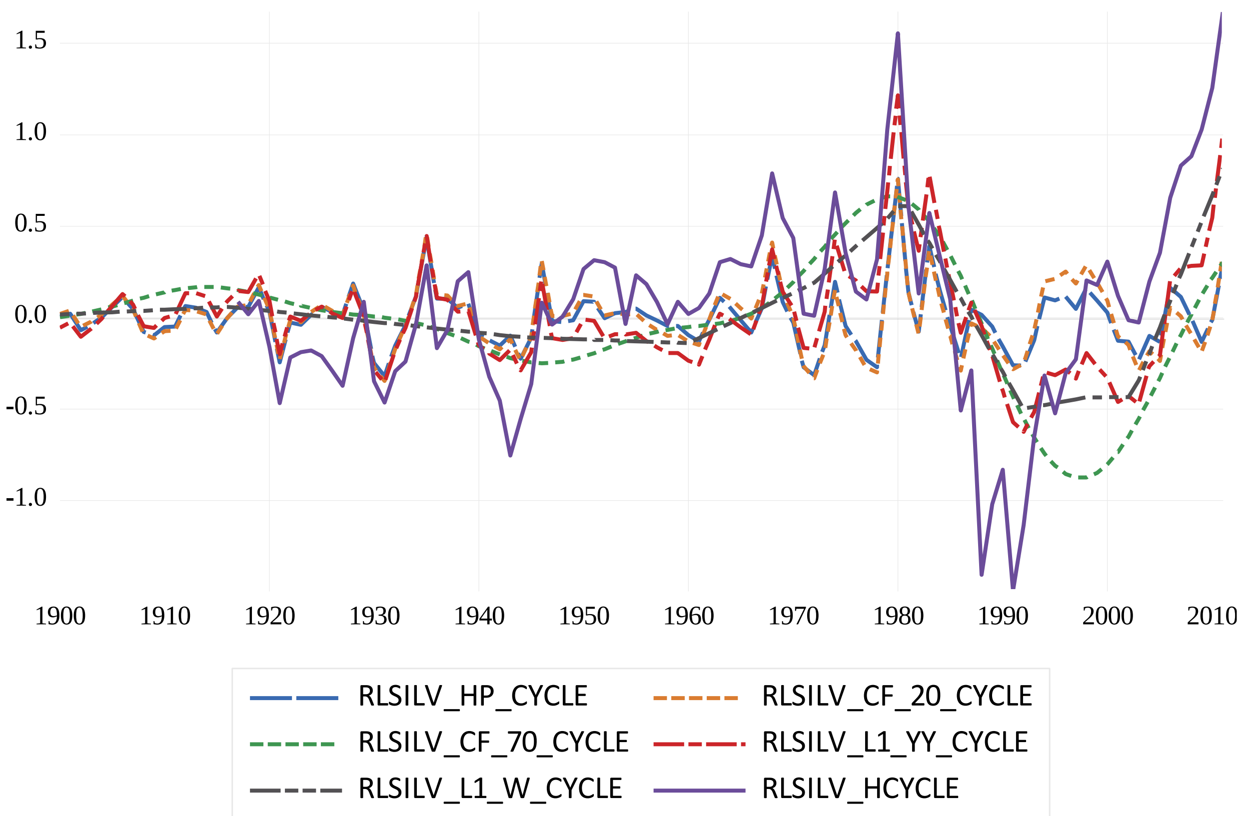

Figure B49 : Trend representation of Sugar

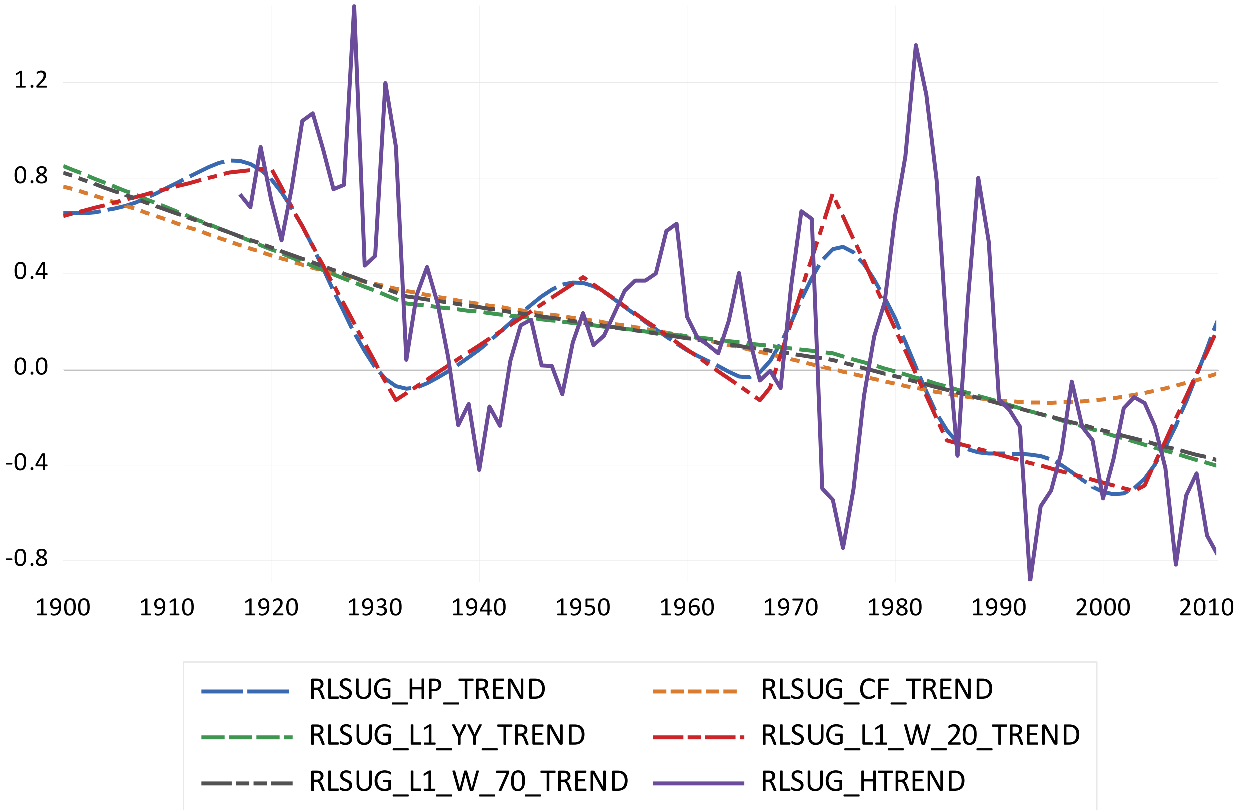

Figure B50 : Cycle representation of Sugar

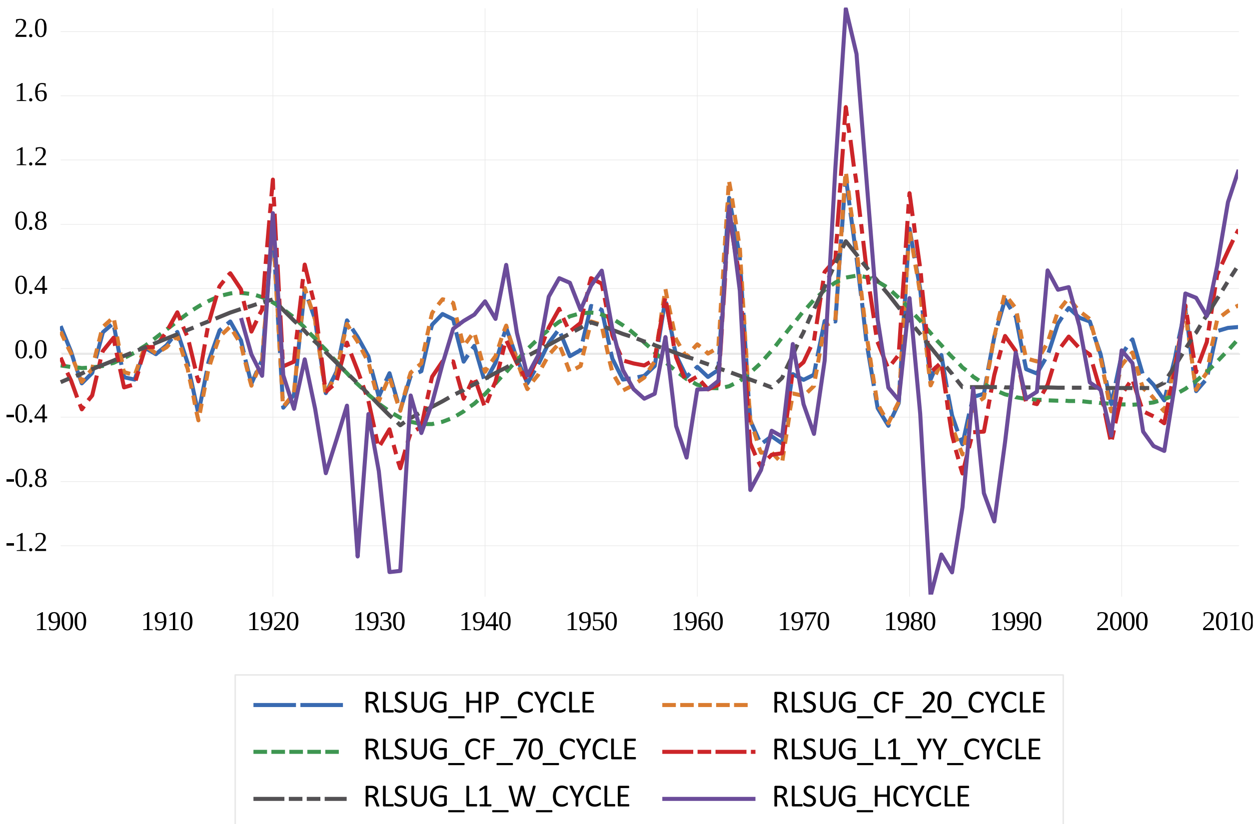

Figure B51 : Trend representation of Tea

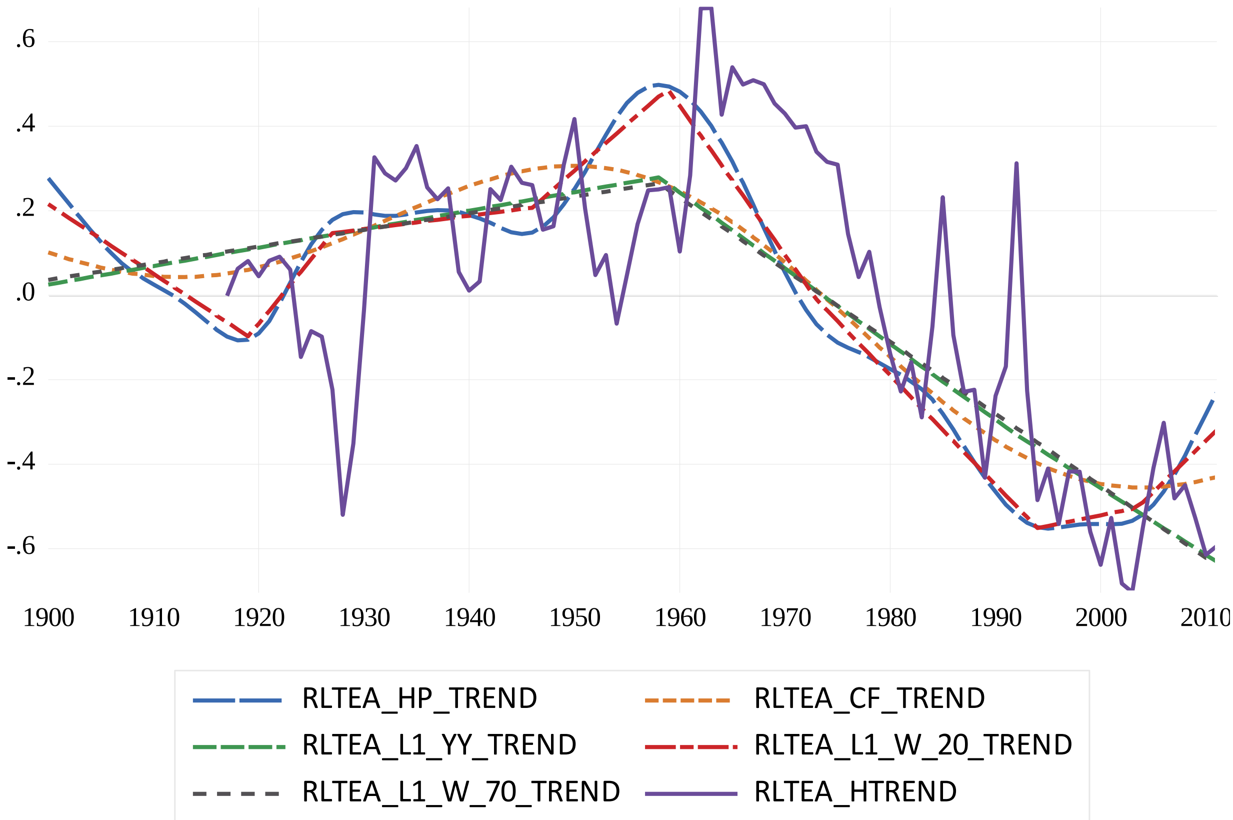

Figure B52 : Cycle representation of Tea

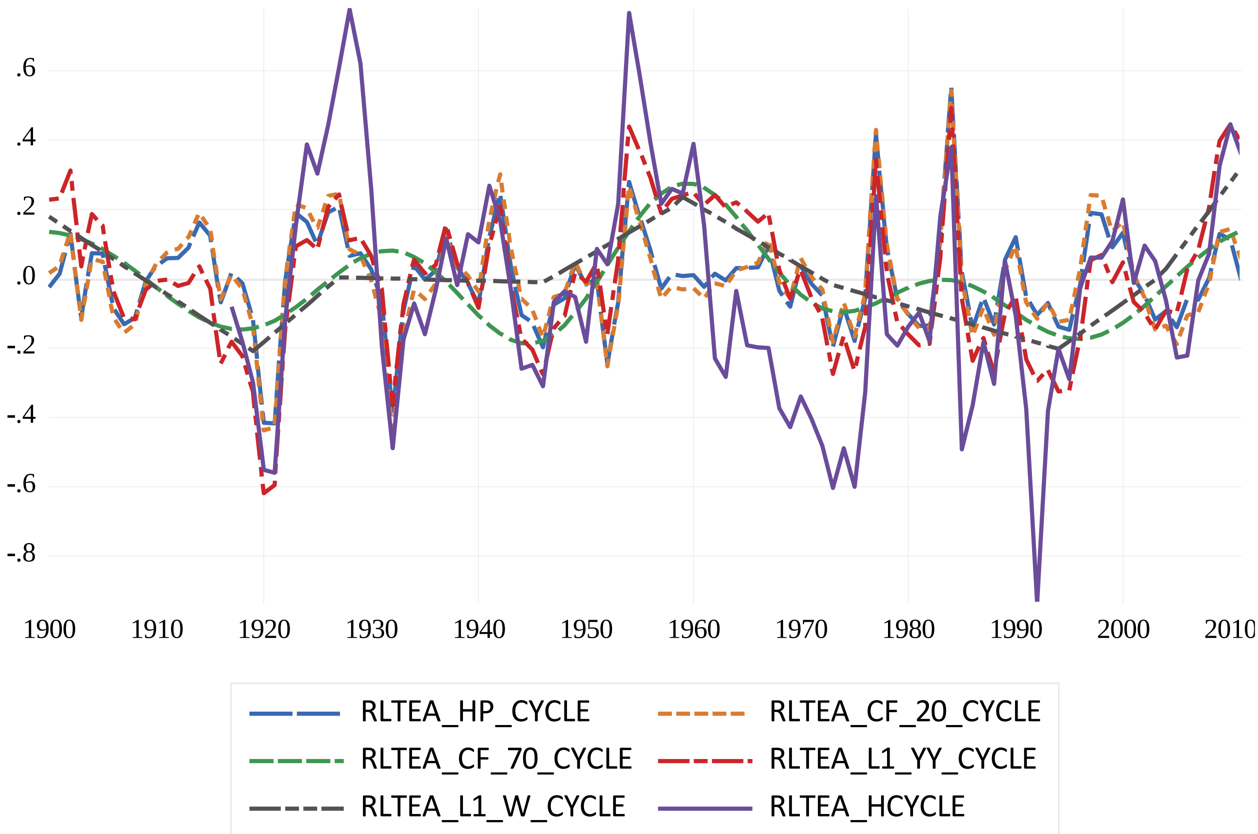

Figure B53 : Trend representation of Timber

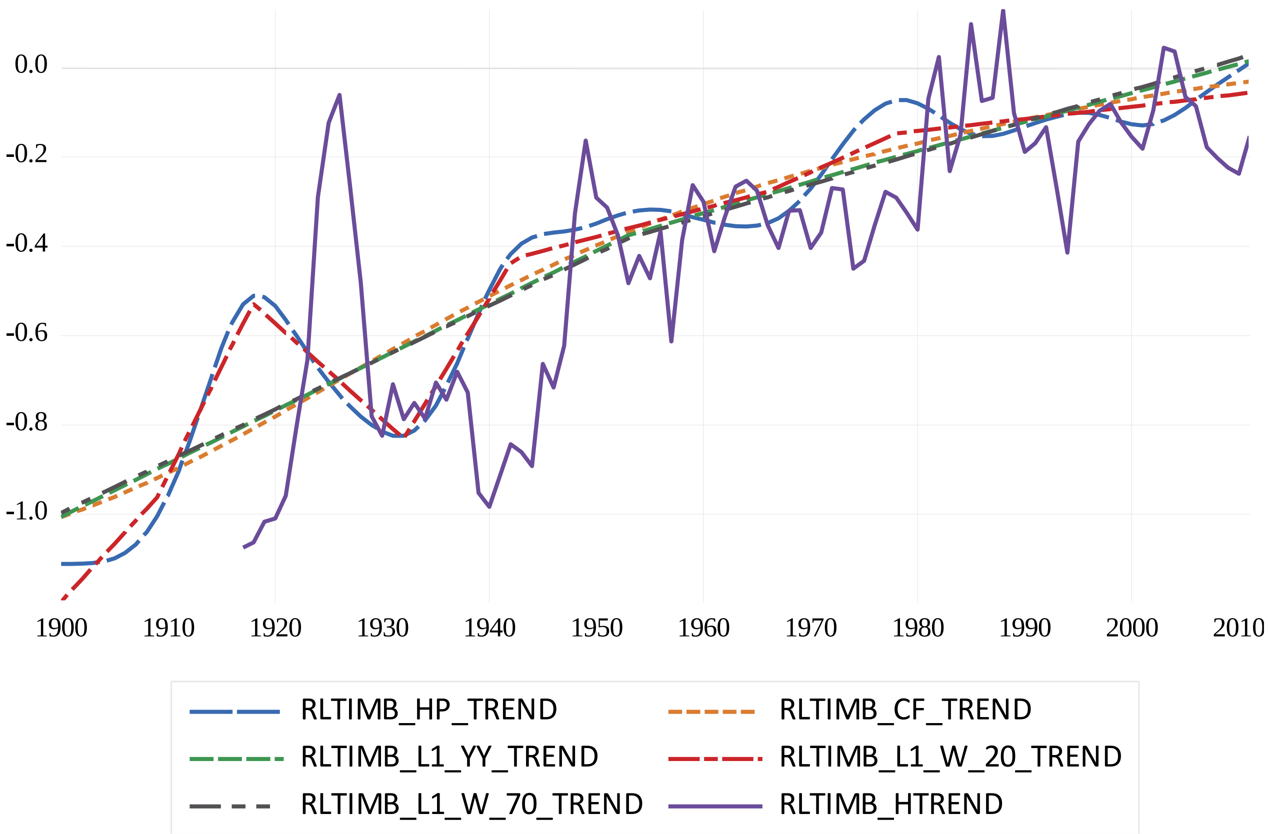

Figure B54 : Cycle representation of Timber

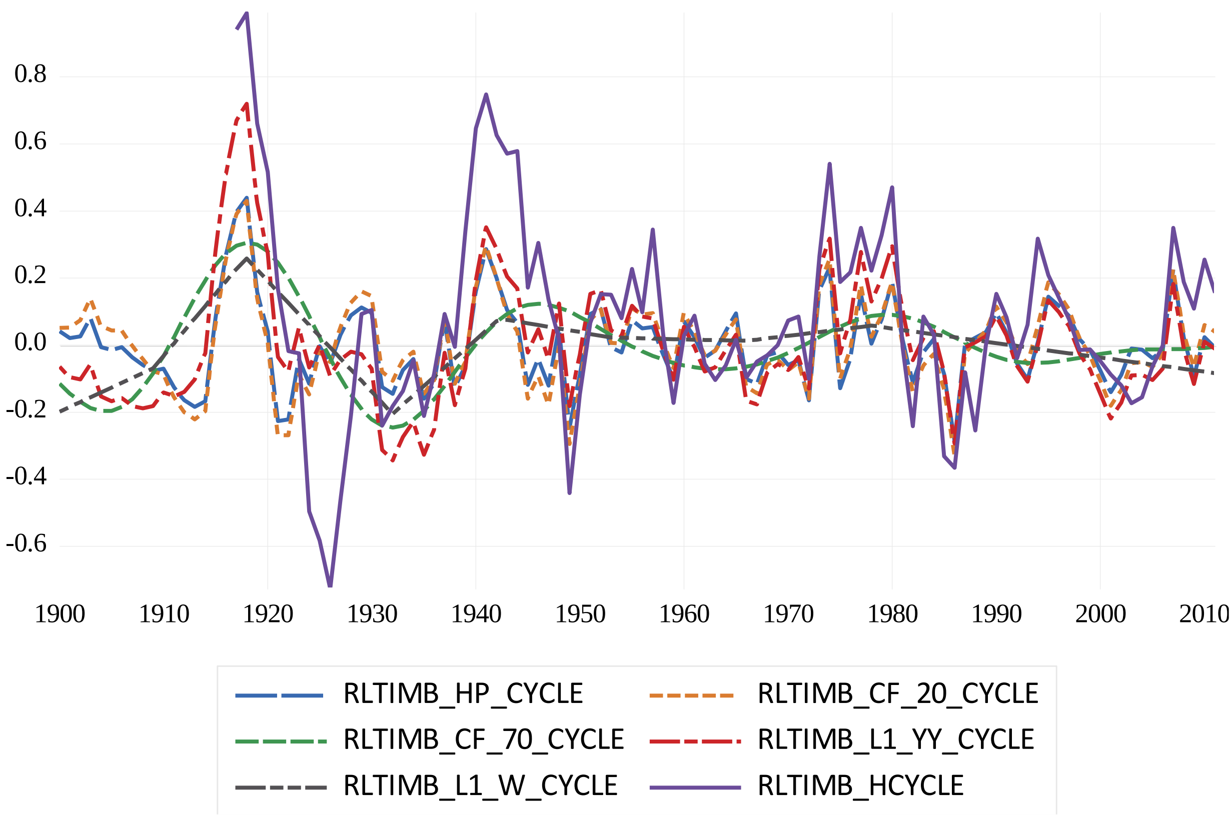

Figure B55 : Trend representation of Tin

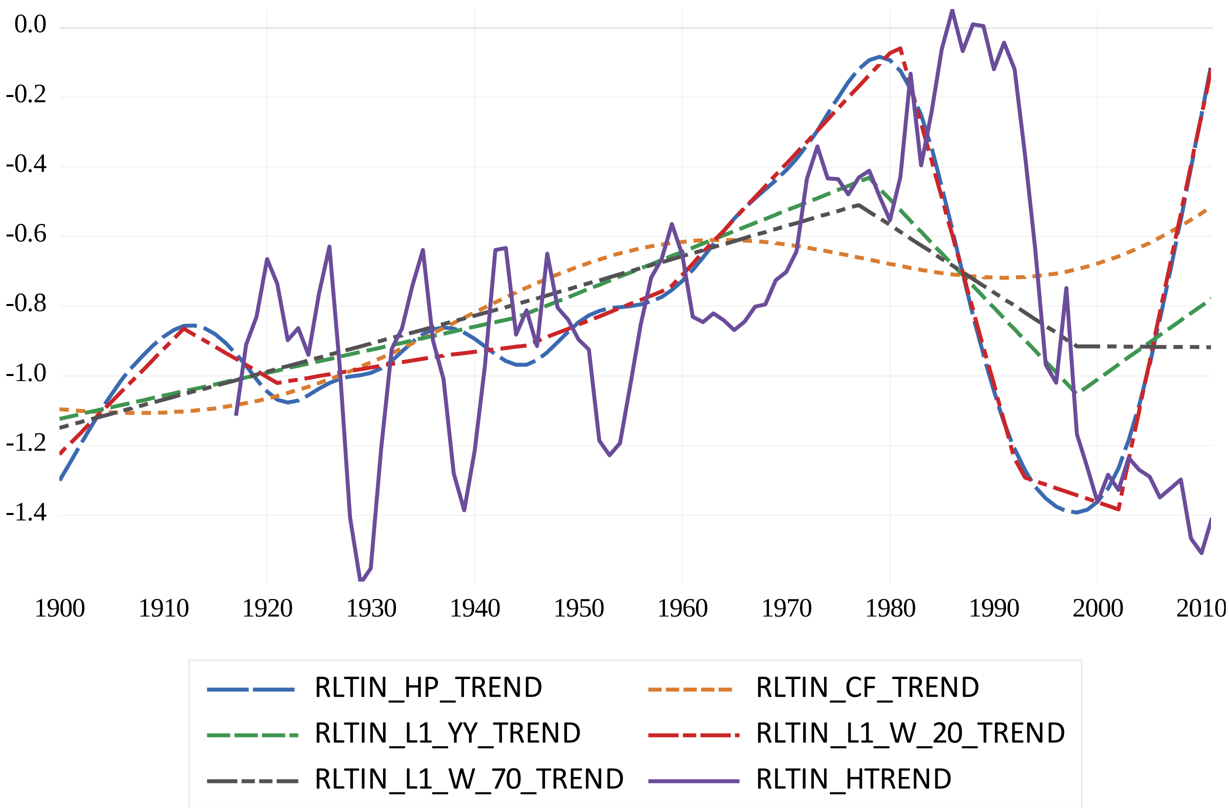

Figure B56 : Cycle representation of Tin

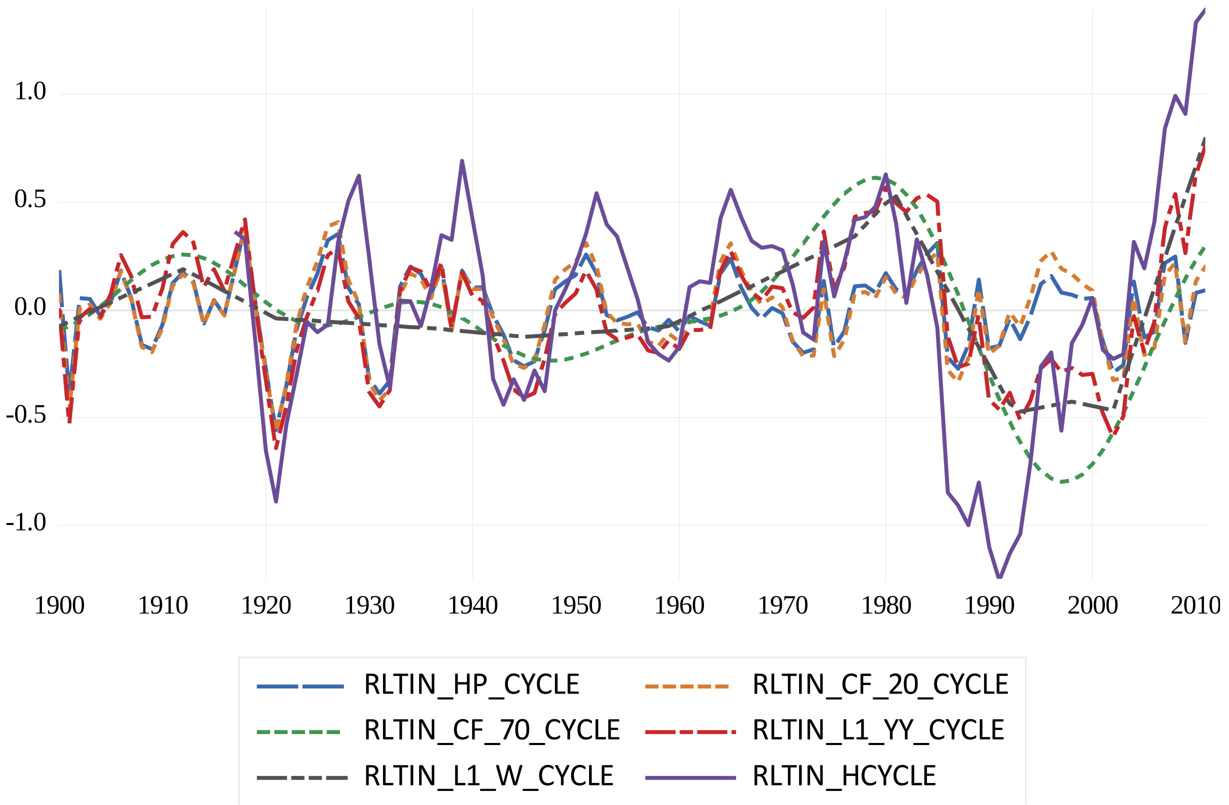

Figure B57 : Trend representation of Tobacco

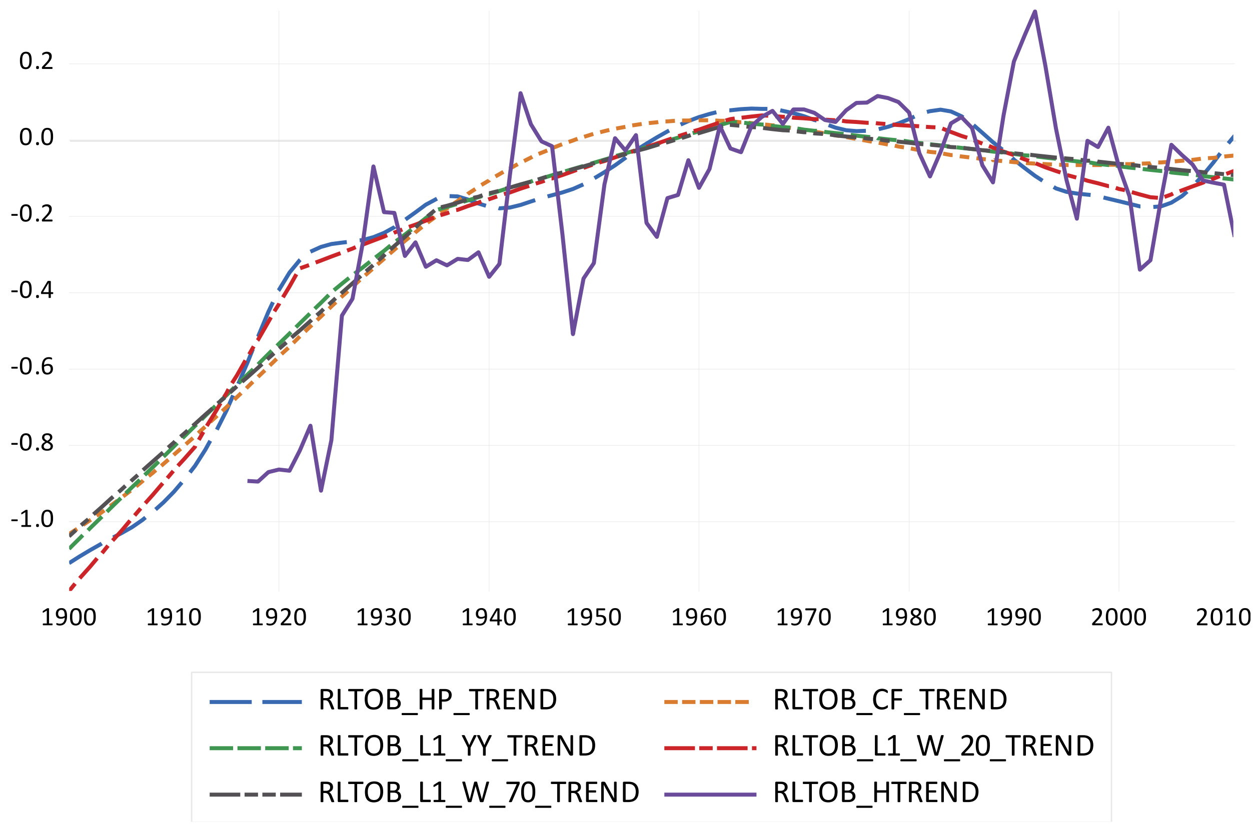

Figure B58 : Cycle representation of Tobacco

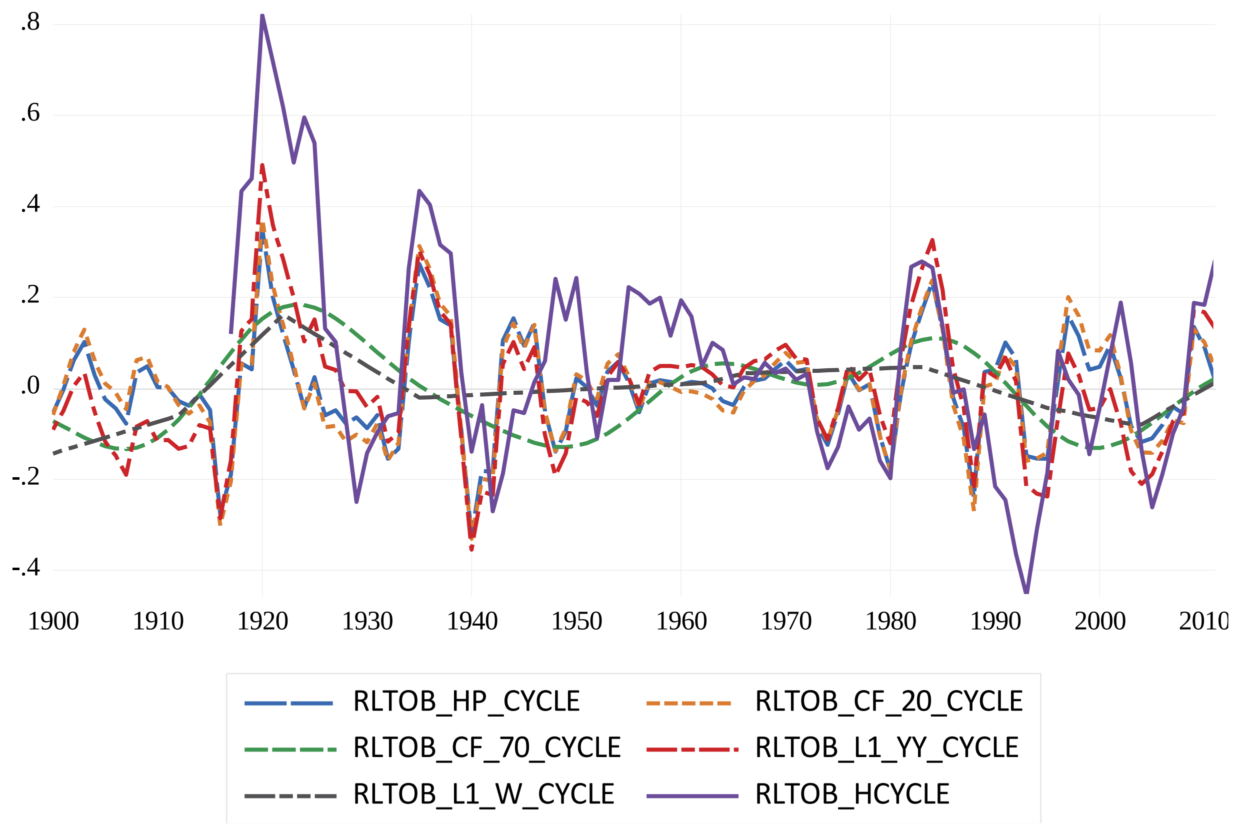

Figure B59 : Trend representation of Wheat

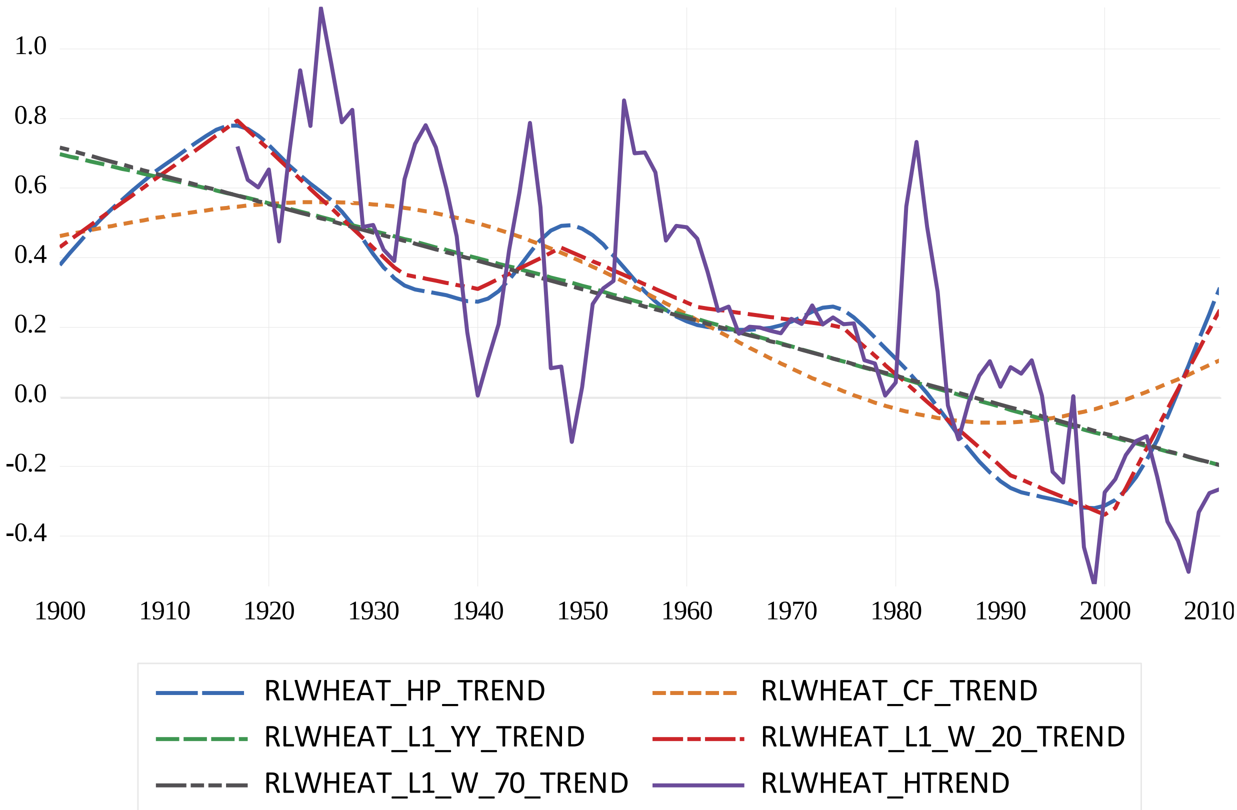

Figure B60 : Cycle representation of Wheat

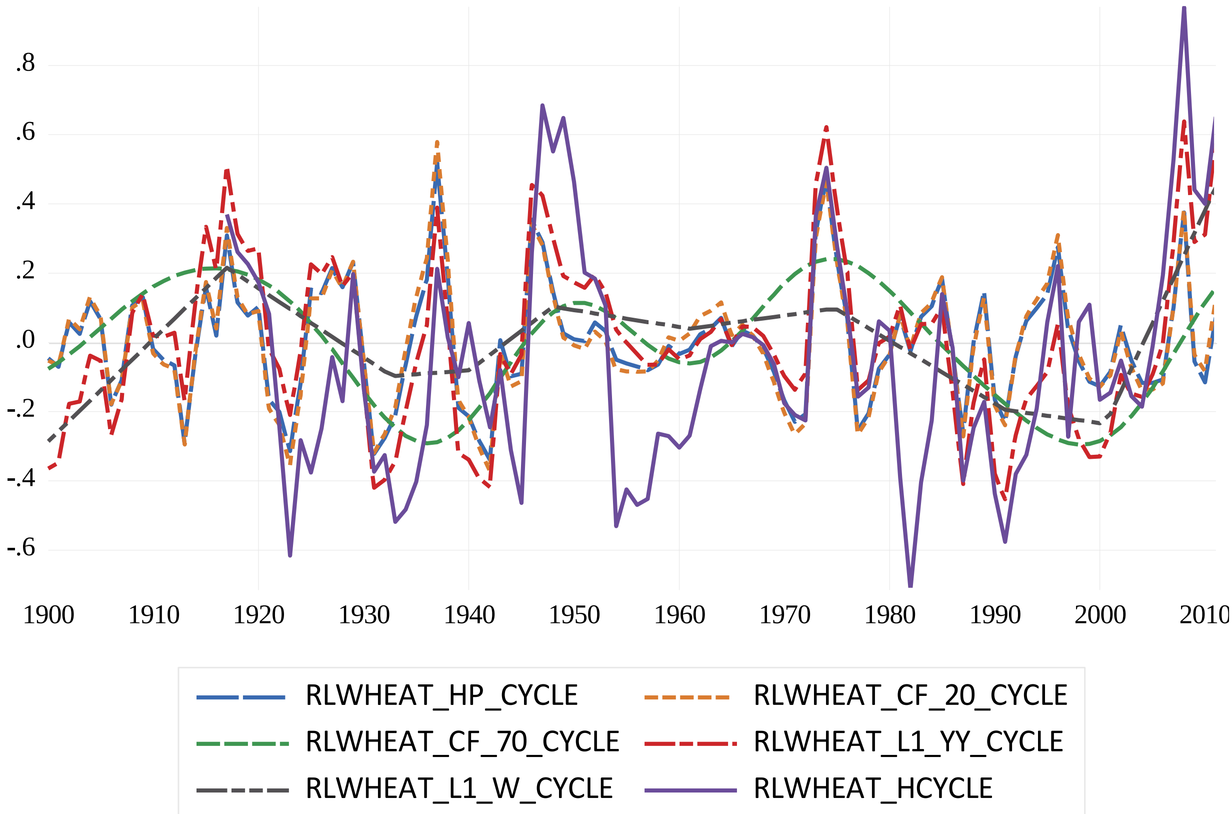

Figure B61 : Trend representation of Wool

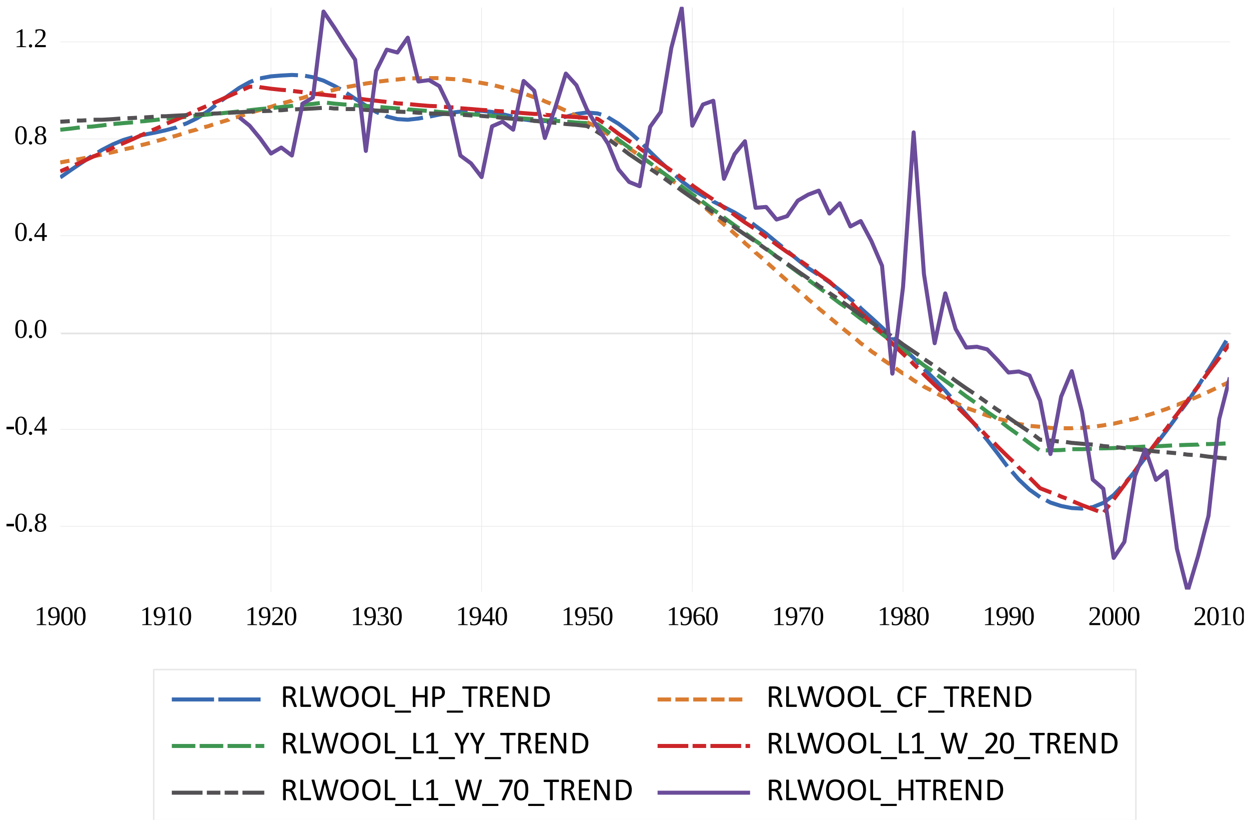

Figure B62 : Cycle representation of Wool

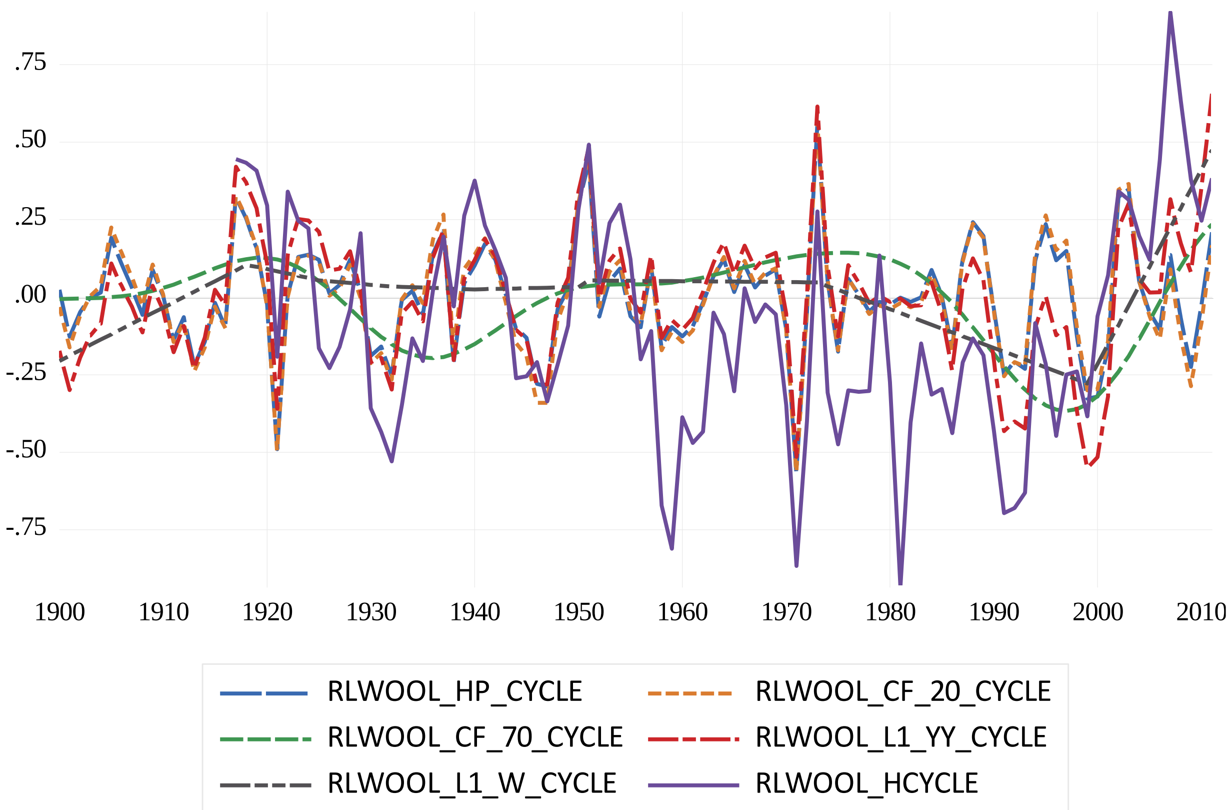

Figure B63 : Trend representation of Zinc

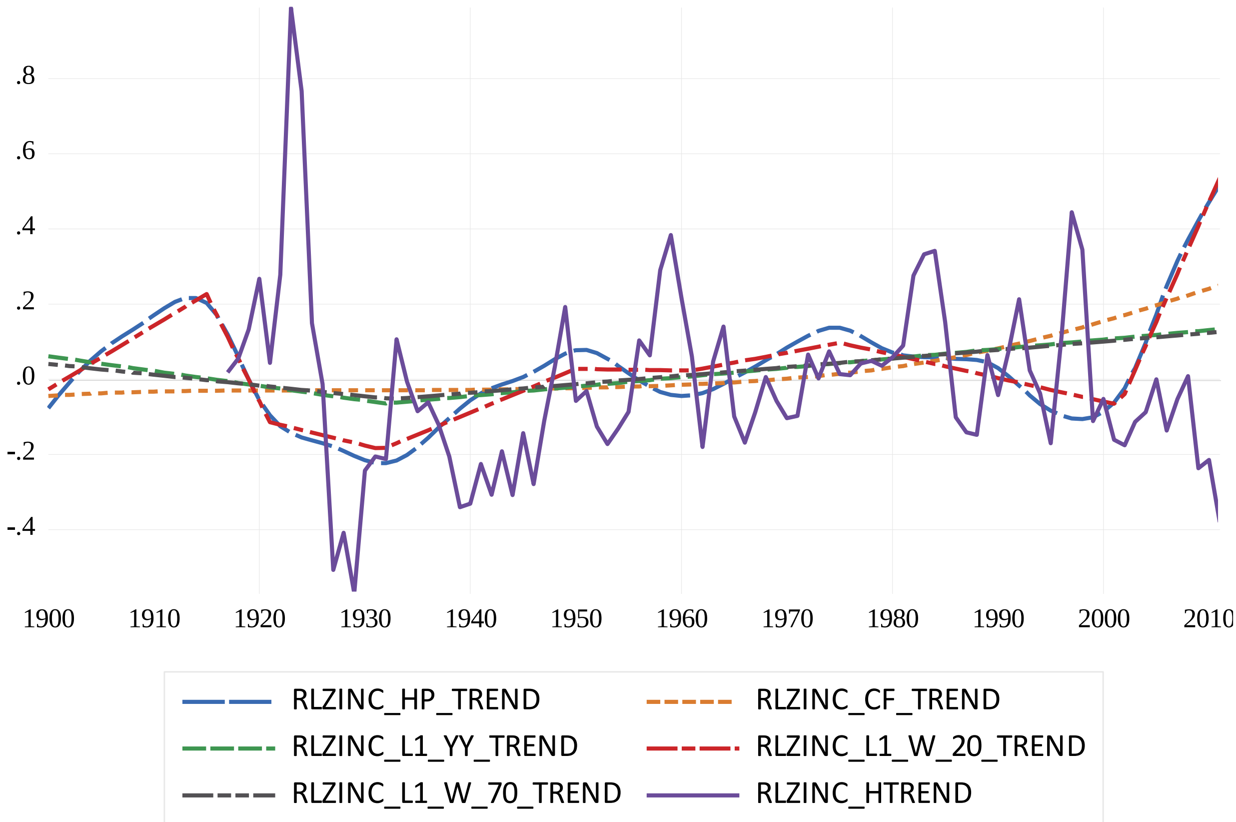

Figure B64 : Cycle representation of Zinc