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Spurious periodicities in cliometric series: simultaneous testing

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Abstract

In this paper we revisit the methodological aspects of the issue of spurious cycles: using the well-established clinometric data, we apply an empirical strategy to identify spurious periodicities and cross-validate the results. The analysis of cyclical fluctuations involves numerous challenges, including data preparation and detrending. As a result, there is a risk of statistical artifacts to arise: it is known that summation operators and filtering yield a red noise alike spectral signature, amplifying lower frequencies and thus, longer periodicity, whereas detrending using differencing yields a blue noise alike spectral signature, amplifying higher frequencies and thus, shorter periodicity. In our paper we explicitly address this issue. In order to derive the stationary signals to be tested, we perform outlier adjustment, derive cycles from the series with the asymmetric band pass Christiano-Fitzgerald filter using the upper bands of the Kuznets and the Juglar cycles as cut-offs, and obtain detrended prefiltered signals by differencing the series in the absence of fractional integration. Afterwards, we simultaneously test whether the spectral densities of filtered and detrended prefiltered signals are significantly different from the spectral density of the related noise. The periodicities from the Kuznets range were not simultaneously significant, and thus are likely to be spurious; whereas ones of the Juglar and Kitchin ranges were simultaneously significant. The simultaneous significance test helps to identify spurious periodicities and the results, in general, accord with the durations of the business cycles found in other works.

Keywords: business cycles, spectral analysis, spurious cycles, fractional integration, simultaneous testing

JEL classification: E02, E32, E39, F44

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1 Introduction

The motivation for this paper was the works on the spectral analysis of cliometric and economic time-series by Cendejas et al. (2015), Metz (2011, 2010), Pollock (2013, 2014), Diebolt (2014) and the works on the significance testing of spectral peaks by Mann and Lees (1996) and Thomson (1982). In the above-mentioned papers, the issue of spurious cycles was noted, discussed and analyzed to a certain extent. The contribution of this paper is twofold: firstly, we show how the spurious periodicities can arise and demonstrate the exposure of spectral analysis to methods of detrending; secondly, we offer an empirical strategy to conduct a simultaneous significance test for spurious frequencies in filtered and detrended prefiltered stationary signals based on red and blue noise confidence intervals.

The history of empirical observations on periodicity in economic variables exceeds the history of the modern business cycle theory. Whereas the works of Juglar (1862), Kondratjew (1926) and Kuznets (1930) have provided a strong impulse for theoretical and empirical works, Burns and Mitchell (1946) defined the rules of empirical identification of business cycles. In the aftermath two empirical approaches to identifying business cycles and periodicity emerged: spectral analysis of economic time series (Granger and Hatanaka, 1964) and descriptive analysis of local minimum and maximum (Bry and Boschan, 1971). Whereas certain elements of spectral and frequency analysis existed long before the emergence of the business cycle theory, the Bry-Boshan method, including the related procedures, was specifically developed to address the challenges of the National Bureau of Economic Research (NBER). These methods have some common features: they both involve detrending of the time series, application of filters or moving averages, and measuring periodicity. However, there are several fundamental differences: the Bry-Boshan procedures are traditionally applied to quarterly data and application to annual data requires calibrations[1] (see Harding, 2002); spectral analysis can be applied to a broader range of sampling rates without alterations; wheareas Bry-Boshan procedures involve descriptive identification of the turning points, spectral analysis is based on frequency decomposition of the time series. Another difference of the Bry-Boshan method is that according to Burns and Mitchell (1946, p. 3) the business cycles are not divisible into shorter cycles with amplitudes approximating their own ones, whereas spectral analysis is based on the spectral representation theorem, which states that a stochastic process is additively built up by elementary and mutually orthogonal harmonic oscillations

[1] Harding (2002, pp. 7-8) notes that adopting the Bry-Boshan procedure and identification rule to annual data may result into loss of precision. In general, quarterly data allow for a more precise identification of the turning points.

(Cramér and Leadbetter, 1967, p. 129). Therefore, the spectral analysis allows for divisible shorter cycles, although such periodicities can be either spurious (results of spectral leakage) or *hidden*, in terms of Wiener (1930, p. 128). One should note that the spurious nature of cycles does not depend on their length: long as well as short periodicities can be spurious as well.

The main task of the spectral analysis is to separate the dominant frequency from the other ones. In this paper we show that even the dominant frequency can be an outcome of spurious periodicities produced by filtering or differencing and a certain simultaneous significance test has to be applied in order to sort out spurious periodicities. The paper is organized as follows: in Section 2 we present a short overview of relevant literature; in Section 3 we focus on the methodology and data, discuss detrending issues and the testing procedure; in Section 4 we present our spectral densities with related confidence intervals and highlight significant periodicities, including those, which remained significant after simultaneous testing; Section 5 includes critical assertion of our results and comparison with other known estimates of business cycle periodicities; Conclusion summarizes our findings and issues from the discussion.

2 Literature overview

Methodological diversity and data heterogeneity has resulted into different business cycle duration estimates with a very broad band: starting from the long waves of Kondratjew (1926) from 45-60 years; Kuznets (1930) cycles of 15-25 years; Juglar (1862) cycles of 7-11 years and to much shorter Kitchin (1923) cycles of 3-5 years[2].

One should note that the researchers, in honour of whom the cycle periodicities were named, applied different data and methods in their works. Kitchin (1923, p. 10) used the UK and the USA data on clearings, prices and interest and detrended them with a linear trend, including a structural break. Juglar (1862) used the French and the UK data on financial situations of banks and also the data on prices (see Juglar, 1862, pp. 3; 42-43 and 51). A rather descriptive analysis of the data in Juglar (1862, pp. 8 and 15) suggests that not only cycles with duration between 7 and 11 years were detected, but also shorter cycles of around 4-5 years. In Kuznets (1930), detrending with a non-linear logistic curve and smoothing with a moving average was applied on the production and price series for the USA. After detrending and smoothing, primary and secondary secular movements

[2]Kitchin (1923, p. 10 and 14) notes minor and major (trade) cycles of 3.5 years and around 7-8 years duration respectively.

were discovered and the cycles cleared from such movements were analysed (see Kittredge, 1931). Afterwards, the cycles of various duration between 15 and 25 years were obtained. The longest Kondratjew (1926) cycles were derived with a similar methodology: according to Metz (2011), Kondratieff used a quadratic fit to detrend the production series and then applied smoothing with a 9-year moving average. The periodogram analysis after replication of the original method and data, clearly indicates 37-year cycles (see Metz, 2011, p. 211); however, the Kondratieff cycles are known to reach up to 60 years. Last but not the least is the periodicity stated in Burns and Mitchell (1946, p. 3): "in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own". The latter is consistent with the Juglar cycles; or with the Kitchin cycles. The above-mentioned periodicities constitute the starting point of our discussion: which of these cycles are present in the spectrum of the long-run cliometric time series and, if they are present, can they be spurious?

The modern empirical literature on business cycles is often focused on the shorter cycles, whereas the long waves are either left out of the analysis or are not addressed in a proper manner. Considering the application of spectral analysis, interesting exceptions are: Korotayev and Tsirel (2010), Metz (2011), Cendejas et al. (2015) and Diebolt (2014). Whereas Korotayev and Tsirel (2010, p. 28) and Metz (2011, p. 229) do find mixed evidence for long waves, a clear association with the so-called Kondratieff cycles is debated, since these waves can be related to stochastic shocks and structural breaks (see Metz, 2011, p. 236). Diebolt (2014) and Cendejas et al. (2015) use the methodology which allows for long waves; however, the latter authors find evidence only for the periodicities in the Kuznets/Juglar or Kitchin ranges. The authors, who use the Bry-Boschan procedure (see Christoffersen, 2000, Bergman et al., 1998) obtain different periodicities from 19 to 6 years, or from 3 to 5 years, which corresponds to Kuznets, Juglar and Kitchin cycles.

Special attention should be paid to the notion of the spurious cycles. The general robust framework for detecting significant[3] periodicities can be found in Thomson (1982) and Mann and Lees (1996): their approach represents deriving background noise[4] from the data and testing the signal periodicities against it. The idea of spurious periodicites in economic series originates from the work of Nelson and Kang (1981), who proved that randomly generated series can exhibit periodicities which have no underlying reasoning and are spurious. Afterwards,

[3]The idea of a significance test for spectral density values can be traced back to the G-test from Fisher (1929).
[4]Thomson (1982, p. 1085) uses white noise, whereas Mann and Lees (1996, pp. 424-425) use red noise

at least several works explicitly addressed the issue of spurious cycles in the real economic data (e.g., Pollock, 2014, Woitek, 1997). Pollock (2013, p. 113) provides examples of spurious periodicities amplified by different detrending methods: "differencing nullifies the trend and it severely attenuates the elements of the data that are adjacent in frequency to the zero frequency of the trend ... It also amplifies the high frequency elements of the data". The summation operator, on which most statistical filtering tools are based, including moving averages, acts in an opposite way: "the squared gain of the summation operator ... gives unbounded power to the elements that have frequencies in the vicinity of zero". Therefore, filtering is likely to yield spurious periodicity for the low frequencies, whereas differencing is likely to amplify spurious periodicites at higher frequencies. Metz (2011, p. 213) notes the dilemma of comparing filtered and differenced spectral densities which we exploit in the empirical section of our paper. Woitek (1998, p. 6) also highlights the fact that statistical filters generate spurious periodicities. However, the magnitude of such spurious periodicity depends on the filtering methods: Woitek (1998, p. 12) demonstrates that the band-pass filters differ in their performance, e.g., Hodrick-Prescott filter is prone to generate spurious periodicity with higher magnitude comparing to the Baxter-King filter.

In order to proceed to the empirical framework, we should highlight two important assumptions derived from the related literature: empirically estimated periodicities of business cycles vary, with Kondratieff cycles being the most debatable ones; detrending and filtering may generate spurious periodicites. Therefore, it is not sufficient to identify peaks in spectral densities, but rather to test whether the periodicity is likely to be spurious or not.

3 Methods and data

The idea is simple: if a certain frequency is significant related to the confidence interval of noise after filtering and differencing[5], then such frequency is unlikely to be spurious. However, if at least one of the these conditions is violated, the given periodicity is most likely spurious. In this section we focus on the empirical strategy and methods, and formulate the hypotheses for the simultaneous testing.

In order to begin, we eliminate the time series outliers with the help of auto regressive moving average (further ARIMA), as in Metz (2010, p. 57). We account for four different types of outliers: additive outliers (AO), level shifts (LS), temporary changes (TC) and innovational outliers (IO). This allows us to clear the

[5]In addition to differencing we apply detrending with a linear trend, refraining from any nonlinear interference, which can potentially generate spurious periodicities, similar to the ones expected to be found after filtering.

original data from potential distortions driven by structural breaks. The outlier adjustment is performed with the functions from de Lacalle (2015). Afterwards, we perform filtering with the asymmetric Christiano-Fitzgerald (further CF) filter (see Christiano and Fitzgerald, 2003) based on the functions from Balcilar (2007). The choice of given filter is justified because of the advantages of the changing gain function - namely the asymmetric feature - comparing to the Baxter-King filter[6] (see Metz, 2011, p. 215). We expect that the filter will dampen high frequencies, amplify the low frequencies and generate spurious periodicities. Thus, we will need a reference for comparing our findings: the differenced data, to which we will refer as detrended and prefiltered[7]. As we noted previously, differencing may affect the spectral density is a reverse way: it will amplify the high frequencies and dampen the low ones, thus the risk of spurious periodicities still exists (see Salas, 1980, Pollock, 2013, p. 293 and p. 113 respectively). We verify the stationarity of the filtered and differenced data with the Kwiatkowski et al. (1992) test[8] (further, KPSS) using the functions from Trapletti and Hornik (2015).

Whereas for the asymmetric CF filter we use the upper bounds of the Kuznets and the Juglar cycles (25 and 11 years respectively[9]), for the differences we need to check whether fractional integration exists - if so, our signals would be "overdifferenced". If that is the case, then the differenced data would not be the best benchmark because the long-memory features would be corrupted by differencing and fractional differencing should be applied. In case if the fractional difference parameter d is in a proximity of one, the first degree of differencing is justified. We estimate the parameter d with the help of two methods: the unit root log periodogram regression as in Phillips (1999, 2007) and the multivariate log periodogram regression as in Robinson (1995). For these purposes we used the functions from Baum and Wiggins (2000b) and Baum and Wiggins (2000a). Phillips (2007) notes that the standard Geweke-Porter-Hudak estimator of d from Geweke and Porter-Hudak (1983) may be biased for cases $0.5 < d < 1$. Kim and Phillips (2006) show that the log periodogram regression is consistent for such cases when $0.5 < d < 1$ including cases when d=1 (see Hurvich and Ray, 1995). Therefore, the Phillips (2007) test[10] based on the unit root log periodogram regression is an

[6]The original version of the Baxter-King filter (see Baxter and King, 1995, 1999) can be compared to the symmetric CF filter with a specified gain function. One should note that comparing to the well-established Hodrick-Prescott filter (see Hodrick and Prescott, 1981), the simple Baxter-King filter with a specified gain function is less prone to yielding spurious periodicities for annual data as noted in Woitek (1998, Figure 3 on p. 12). There have also been attemptes to introduce an asymmetric extension of the Baxter-King filter (see Buss, 2011).

[7]This data will not be filtered, but only differenced once and detrended with a linear trend exactly as in Woitek (1997, p. 88, footnote 20).

[8]The H_0 of the KPSS test is that the series are stationary.

[9]This explicitly allows the existence of such periodicities in the series, even if they will turn out to be spurious.

[10]The H_0 for the Phillips (2007) test is that d=1, implying that the series contain a unit root and have to be

ideal tool to check whether the data was differenced correctly. Robinson (1995) multivariate test[11] will answer the question whether the same degree of differencing should be applied to all series. The latter test is applied merely as a cross-validation tool for the Phillips test.

Comparing two spectral densities of the filtered and detrended prefiltered signals is not sufficient and we will introduce a reference benchmark spectral density with confidence intervals for blue or red noise[12]. The derivation of these types of noise from the signals will be based on the functions from Bunn et al. (2015) and Schulz and Mudelsee (2002). In addition, for generation of red and blue noise, we have applied certain functions from Borchers (2015) and Zeileis and Grothendieck (2005): for certain countries the autocorrelation parameter was positive whereas for the other countries is was negative. One has to note that Granger (1966) and Levy and Dezhbakhsh (2003)[13] found that most macroeconomic variables follow the spectral density comparable to the red noise; however, there are also other findings: e.g. Bjørnland (2000, pp. 379-380) demonstrated other spectral patterns in the filtered GDP data. Indeed, in case of negative autocorrelation coefficient estimated for the stationary signal, higher frequencies would be stronger yielding a blue noise comparable spectral density; whereas if the coefficient is positive, the spectral density will resemble red noise with emphasis on lower frequencies. Therefore, the appropriate confidence intervals based on the red or blue noise derived from each country's signals would be helpful to test the significance of the peaks of the spectral density function. Thus we will be able to identify spurious cycles which appear only after application of the CF filter or differencing and those periodicities, which are significant relative to the spectral density of the related noise for both types of signals, and thus are unlikely to be spurious. We conduct the test at three levels: 90, 95 and 99%; however, we set 90% level as the lowest threshold for significance[14] for both types of signals. For a given frequency value, the null hypothesis in our case would be that the power of the spectral density of the signal is not significantly different from the confidence interval of the power of the spectral density of the red or blue noise, derived from this signal (by analogy

differenced once. If the H_0 is not rejected, the series are most likely not fractionally integrated. Rejection would mean fractionally integrated series and the need to apply fractional differencing instead of first differencing.

[11] The H_0 for the Robinson (1995) test is that d coefficients are the same for all series.

[12] For theoretical details see Mann and Lees (1996). In our paper a similar test is conducted; however, simultaneously for both types of signals.

[13] Levy and Dezhbakhsh (2003) report various spectral shapes depending on the economic characteristics of the countries: the spectral patterns for developing countries are wider and are saturated around mid-range frequencies, whereas the developed countries exhibit red noise comparable pattern with peaks at lower frequencies.

[14] Although the conventional level of statistical hypothesis tests is usually 95%, we set the 90% benchmark analogous to the last significance level in a regression analysis and denote this level with *. Therefore, if the power of the signal at the given frequency is significant at the 90% level we can reject the null hypothesis that the power of this frequency is not significantly different from the power of the spectral density function of red or blue noise. For all other tests present in this paper, the 5% benchmark is set.

with Bunn et al., 2015, Schulz and Mudelsee, 2002). Therefore, we formulate two nulls for the simultaneous testing:

$$H_{0filtered} : S_{filtered} \leq S_{filt\,noise} \tag{1}$$

$$H_{0prefiltered} : S_{prefiltered} \leq S_{pref\,noise} \tag{2}$$

where $S_{filtered}$ and $S_{prefiltered}$ are the powers of the spectral density of filtered and detrended prefiltered signals; and $S_{filt\,noise}$ and $S_{pref\,noise}$ are the confidence intervals of the powers of the red or blue noise derived from the related signals.

The important feature of the testing strategy is to conduct the same significance test on the filtered and detrended prefiltered data to exclude the periodicities which are obviously spurious. If the null is rejected for a given frequency, but only for one type of a signal, it is likely to be spurious.

The spectral density of the signals is estimated with the general-purpose Blackman-Harris window based on Harris (1978) which can perform very well in suppressing the side lobes thus minimizing spectral leakage (see Prabhu, 2013, p. 306). For a fine resolution we set 7 segments with 50% overlapping. However, since the main lobe would be wide it may complicate the exact comparison of the spectral densities of the filtered and differenced data. Therefore, in case of minor discrepancies between the two densities, we will consider the nearest neighbouring frequency within the 0.15 year range. In the tables such cases will be marked accordingly with a circle.

Finally, in the discussion we will revisit our results and compare them to the findings of other researchers. In addition, we will critically assert the methods applied and briefly describe related issues.

The dataset is taken from Bolt and van Zanden (2013): it is a well-established dataset and the results obtained using these series can be compared with the results of other researchers who also used it, bearing in mind methodological differences. By design, the gain function of the statistical filters as well as the methods of the spectral analysis are exposed to the sample size. Thus our major goal during the selection of an appropriate dataset was to select the longest consistent series available. The countries were selected according to two major criteria: no need to interpolate any observations starting from 1820 to 2010 and no need to divert from one single framework of outlier detection and filtering[15]. There

[15] In order to detect and adjust the data for outliers, the ARIMA models were used - the adjustment for IO outliers caused substantial trend changes for the series on France and Northern Italy, which were excluded from the sample due to necessity of different treatment. A different outlier treatment may hypothetically manifest itself in the spectral densities which is not desirable.

were six countries which fit this criterion: Australia, Denmark, the Netherlands, Sweden, the UK, the USA. The same dataset was used in Cendejas et al. (2015) and Diebolt and Doliger (2005), however starting from 1870, whereas we use the times frames from 1820 to 2010 with 191 annual observations.

4 Results

We start with adjusting the series to AO, LS, TC and IO. As it follows from Figures 4 and 5 adjusting is crucial: for Australia 10 outliers were detected; for Denmark seven were detected; for the Netherlands 12; for Sweden five; for the UK four and for the USA nine. The adjusted data is not stationary and all of the series contain a unit root according to the KPSS test and have to be transformed. The KPSS test results of the adjusted data itself contain little useful information other than the fact that the series are not stationary. Further transformation is needed. This transformation is twofold and we obtain two types of stationary signals: we filter the series with the asymmetric CF filter and apply first differences. In question are the parameters of filtering and differencing: the CF filter is a band-pass filter, where the cut-off frequency is crucial; while for differencing the degree is important. Whereas we decide to set the filter cut-off periodicity to 11 (Juglar cycles) and 25 (Kuznets cycles) as per our goal to test spurious periodicities, the degree of differencing has to be tested. Thus, we first test the presence of fractional integration and whether using first differences is appropriate.

In Table 1 we report the Phillips (2007) and Robinson (1995) test results which point out two facts: the fractional difference parameter d for all countries is in the proximity of one, except only one case for the power of 0.5 which corresponds to only 13 harmonic ordinates for the USA data, which is too few; for all other powers the null that d=1 is not rejected. Robinson (1995) test validates the null of the equality of d for all six cases, which is also close to one. Therefore, using first differences is justified. In Tables 3, 2 and 4 we check whether the filtered and differenced series are stationary: all pass the test.

The fluctuations obtained with the CF filter and differencing exhibit distinct features resembling those, named in Section 2: the filtered cycles with the cut-off periodicity of 25 years from Figure 6 are less dense than the filtered cycles with a cut-off of 11 years from Figure 7. Most dense are the fluctuations obtained by first differencing: the detrended prefiltered data from Figure 8. Recalling that filtering dampens high frequencies and amplifies lower ones (whereas differencing acts the other way around) the figures exhibit exactly these features and we anticipate discrepancies in spectral patterns. The risk of emergence of spurious periodicities generated by the filter is obvious. Considering the autoregressive coefficients for generation of noise (see Table 5), it is obvious, that filtering amplifies lower frequencies, since the coefficients are positive for the filtered fluctuations; whereas for the detrended prefitlered, the coefficients are negative, with one exception to the UK. It is important to note that most of the coefficients are remote from zero, except for the filtered fluctuations for Australia. Therefore, an appropriate modeling of the noise process for each case is preferable rather than setting a white noise benchmark for all cases.

Let us proceed to the spectral analysis and simultaneous significance testing. Figures 1, 2 and 3 display confidence intervals and frequency (periodicity) peaks after applying the Blackman-Harris window. The exact values of significant periodicities are given in Tables 6, 7 and 8. The filtered cycles of Australian data demonstrate that the CF filter functions well and eliminates all periodicities below the cut-off: the first significant periodicity of the CF filtered cycles with the cut-off at 25 years, resembling the Kuznets cycles, is at 17.455; the cycles with the cut-off at 11 years, similar to the Juglar cycles, show a significant peak at 8.348. After examination of the spectrum of the detrended prefiltered data it becomes obvious that the peak of 17.455 is just a leakage from the zero frequency and the second peak is present; however, not significant at any levels. The differenced data are compared to the blue noise, with higher frequencies prevailing. The periodicities, which are significant for the filtered and detrended prefiltered fluctuations, are: 4.085; 2.743 and 2.110 for Australia. For Denmark the situation is similar: the Kuznets cycle peak is at 19.2 years - this frequency can not be confirmed for the detrended prefiltered series; the Juglar cycle peak is simply a leakage from the lower frequency peak and it is not significantly different from the red noise spectrum. The frequencies which are significant for both filtered and detrended prefiltered series are: 5.189 (5.05) and 3.2 years. For the Netherlands the Kuznets and Juglar cycle periodicities (19.2 and 9.143) are significant but are not confirmed by the spectrum of the differenced data. For Sweden the situation is similar, but the periodicity of 5.053 (4.923) appears to be simultaneously significant for both filtered and differenced fluctuations. For the UK the Kuznets periodicity of 14.769 is significant (and can be distinguished in the differenced data, although for the differenced signal it is not significant) and the Juglar peak is at 8.348 - the latter turns to be simultaneously significant, although it may partly capture the leakage from lower frequencies. An intriguing picture is displayed for the USA: both, the Kuznets peak at 24 years and Juglar peak at 9.143 are significant for the filtered series and can be observed in the prefiltered detrended data. They are not simultaneously significant, but can be distinguished. For the USA, the simultaneously significant periodicities are only at 4.085 and 2.133 years.

Since we have established that the series are not fractionally integrated and the first degree of differencing is appropriate, we could argue that the spectral density of differenced data, to which we refer as "detrended prefiltered", is a valid benchmark to eliminate spurious cycles resulting from filters in general, and the asymmetric CF in particular. Although several low frequencies, e.g., 14.769 for the UK, 16 for Sweden, 17.455 for Australia, 19.2 for Denmark and the Netherlands and 24 years for the USA were significantly different from the red noise confidence intervals for the filtered data; they were not validated by the detrended prefiltered data. The latter periodicities could be attributed to the Kuznets range and if we refer to Hypotheses 1 and 2, for these values the nulls are not simultaneously rejected. A similar case is observed for the Juglar periodicities: 8.348 for Australia; 9.143 for the Netherlands; 8.348 for Sweden and 9.143 for the USA. The only exception is the UK data, where 8.348 year periodicity was simultaneously significant: here rejection of Hypotheses 1 and 2 is observed. Concerning the latter case, one should note that this periodicity for the differenced data was significant relative to noise only at the 90% level not even reaching the 95% confidence interval. Therefore, we can only state that the evidence, that the Juglar-like periodicity is not likely to be spurious, is weak. On the contrary, higher frequencies and shorter periodicities are robust: 2.11, 2.743 and 4.085 for Australia; 5.189 (5.053) and 3.2 for Denmark and 4.085 and 2.133 for the USA are simultaneously significant: for these periodicities, Hypotheses 1 and 2 are simultaneously rejected. Therefore, there is strong evidence that the so-called Kitchin periodicities may not be spurious and manifest themselves in filtered and differenced data.

Table 1: Tests on fractional integration, d coefficients and their equality

Phillips (2007) Modified Log Periodogram Regression estimator, deterministic trend removed, H_0: d=1												
	lnAUSTRALIA_adj		lnDENMARK_adj		lnNETHERLANDS_adj		lnSWEDEN_adj		lnUK_adj		lnUSA_adj	
Power	d	P>z	d	P>z	d	P>z	d	P>z	d	P>z	d	P>z
0.50	1.004	0.983	1.032	0.859	1.278	0.118	1.167	0.347	0.987	0.940	0.615	0.030
0.55	1.058	0.710	1.039	0.800	1.096	0.539	1.075	0.628	0.796	0.190	0.789	0.176
0.60	1.122	0.363	0.992	0.949	0.820	0.178	1.134	0.315	0.843	0.240	0.847	0.251
0.65	1.101	0.387	0.999	0.994	0.971	0.805	1.093	0.427	0.818	0.120	0.847	0.192
0.70	1.113	0.273	0.915	0.405	1.029	0.776	1.002	0.987	0.947	0.609	0.920	0.437
Robinson (1995) test for equality of d coefficients, H_0: d coefficients are the same for all six series												
F(5,666) = 0.09726 and P>F = 0.9926												

Table 2: Stationarity test of the filtered Kuznets cycles

CF filtered, Kuznets	KPSS Test for Level Stationarity	
	Test statistic	P value
Australia	0.0139	> 0.1
Denmark	0.0183	> 0.1
The Netherlands	0.0135	> 0.1
Sweden	0.0135	> 0.1
UK	0.0121	> 0.1
USA	0.0164	> 0.1

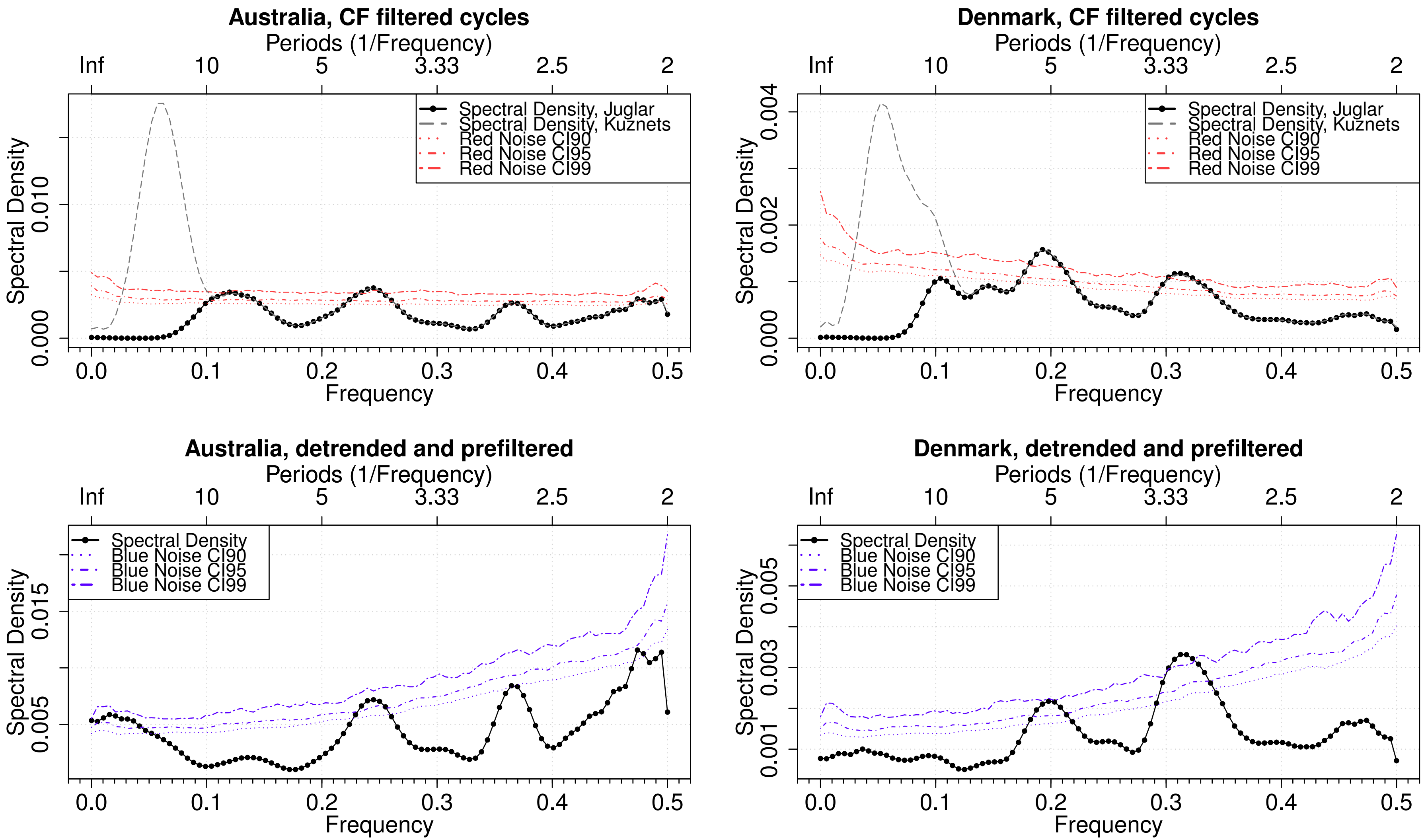
Table 3: Stationarity test of the filtered Juglar cycles

CF filtered, Juglar	KPSS Test for Level Stationarity	
	Test statistic	P value
Australia	0.0089	> 0.1
Denmark	0.0076	> 0.1
The Netherlands	0.0065	> 0.1
Sweden	0.0076	> 0.1
UK	0.0065	> 0.1
USA	0.0065	> 0.1

Table 4: Stationarity test of the detrended prefiltered series

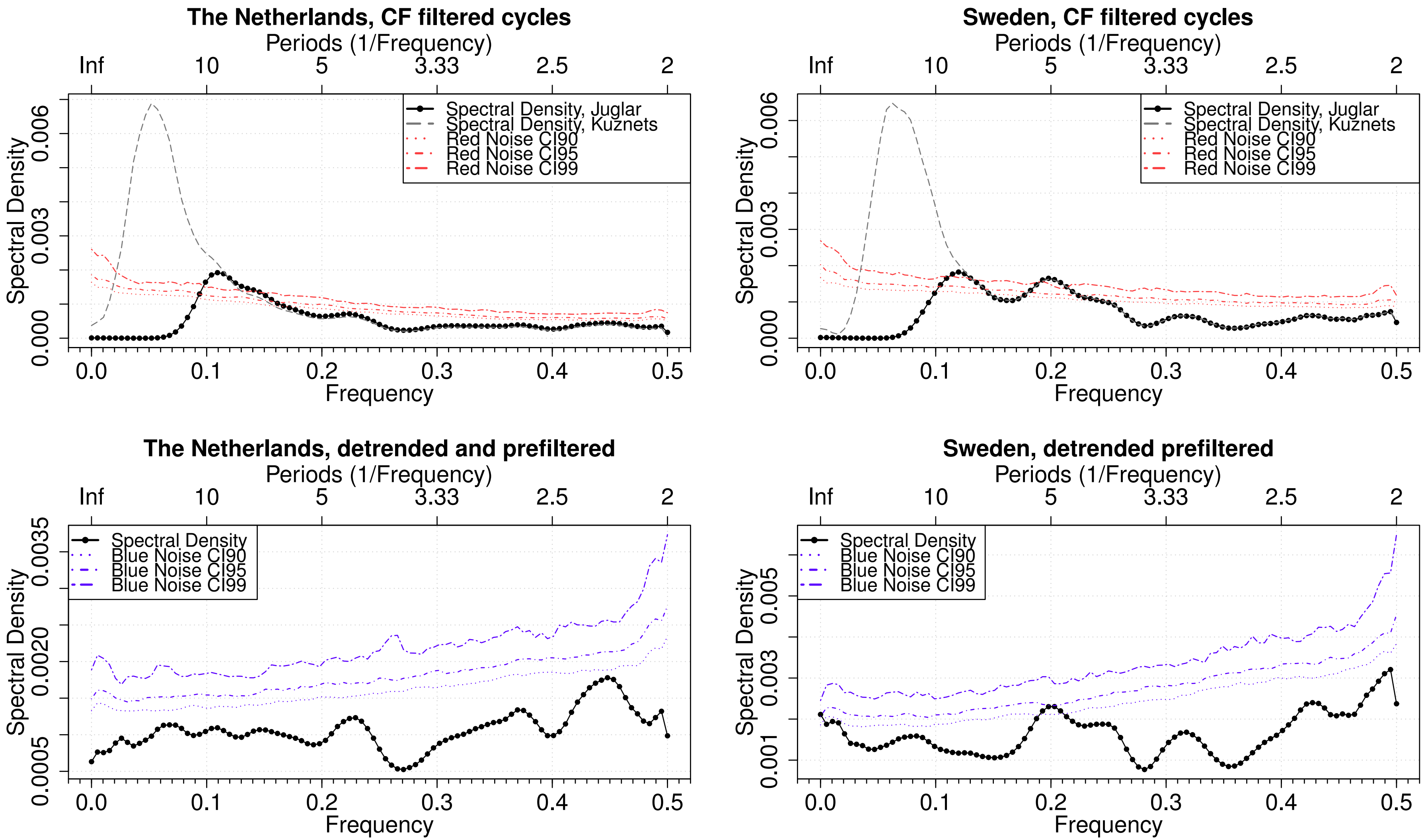
Detrended and prefiltered	KPSS Test for Level Stationarity	
	Test statistic	P value
Australia	0.2151	> 0.1
Denmark	0.1523	> 0.1
The Netherlands	0.188	> 0.1
Sweden	0.1995	> 0.1
UK	0.3279	> 0.1
USA	0.1974	> 0.1

Figure 1: Australia and Denmark: filtered and prefiltered spectral densities



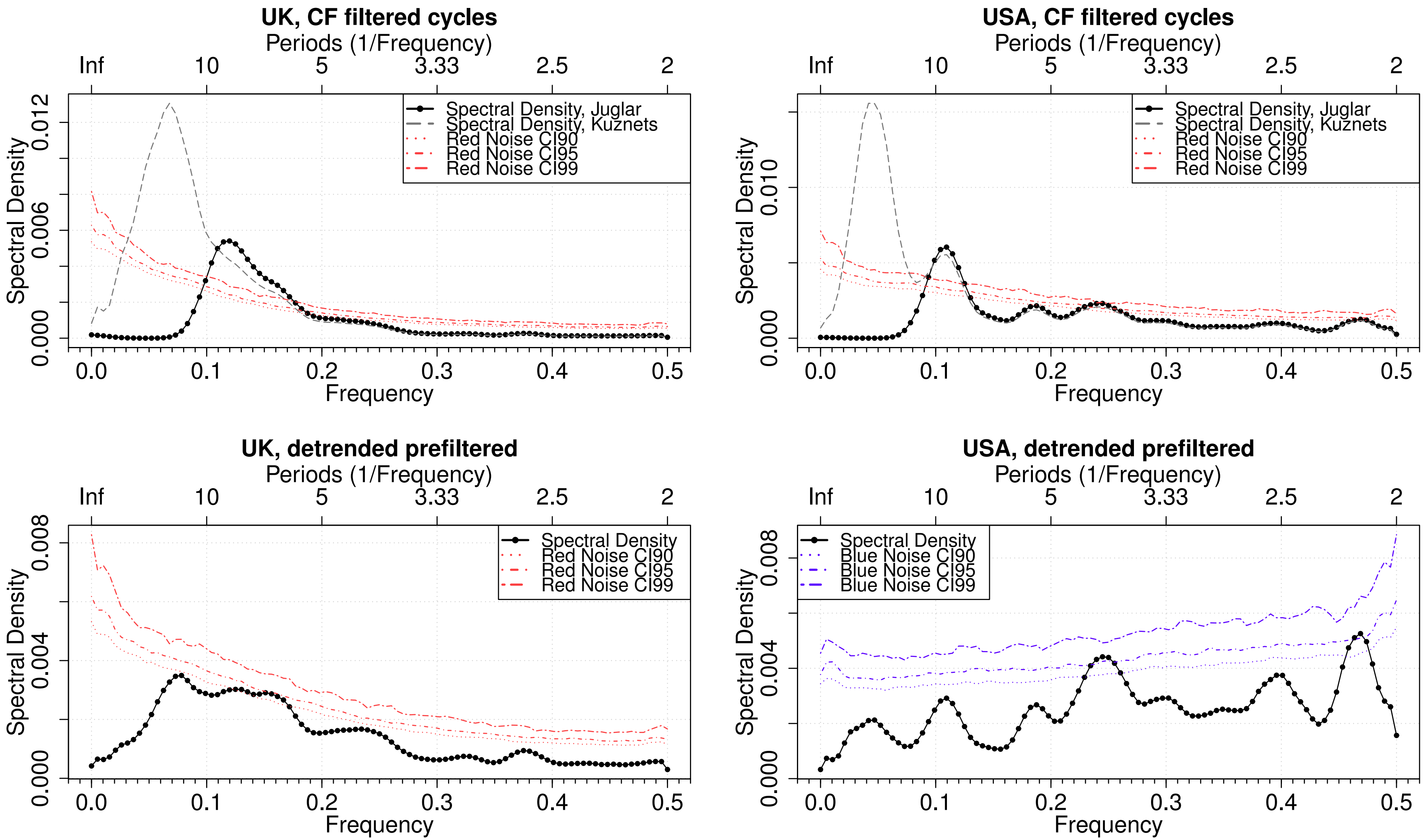
Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Figure 2: The Netherlands and Sweden: filtered and prefiltered spectral densities



Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Figure 3: UK and USA: filtered and prefiltered spectral densities



Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Table 5: Estimated coefficients for generation of noise

	AR(1) coefficient		
	CF (25)†	CF (11)	Prefiltered
Australia	0.488	0.0153	-0.236
Denmark	0.526	0.148	-0.229
The Netherlands	0.662	0.243	-0.0942
Sweden	0.476	0.125	-0.145
UK	0.76	0.499	0.329
USA	0.673	0.281	-0.0815

† for presentation purposes only the background noise for CF (11) and detrended prefiltered signals is displayed on the figures

Table 6: Significant periodicities of CF filtered cycles in years, Kuznets domain

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	17.455	19.2	19.2	16	14.769	24
2nd	8.348	5.189 ○	-	5.053 ○	-	9.143
3rd	4.085 ∗	3.2 ∗	-	-	-	4.085 ∗
4th	2.743 ∗	-	-	-	-	2.133 ∗
5th	2.110 ∗	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level
○ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

Table 7: Significant periodicities of CF filtered cycles in years, Juglar domain

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	8.348	5.189 ○	9.143	8.348	8.348 ∗	9.143
2nd	4.085 ∗	3.2 ∗	-	5.053 ○	-	4.085 ∗
3rd	2.743 ∗	-	-	-	-	2.133 ∗
4th	2.110 ∗	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level
○ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

Table 8: Significant periodicities of detrended and prefiltered cycles

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	4.085 ∗	5.053 ○	-	4.923 ○	8.348 ∗	4.085 ∗
2nd	2.743 ∗	3.2 ∗	-	-	6.621	2.133 ∗
3rd	2.110 ∗	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level
○ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

5 Discussion

The discussion covers certain features of the testing strategy and other methodological or data related issues. We start with comparing the simultaneously significant periodicities with the findings present in other papers and then focus on the possible reasons for similarities and discrepancies.

Woitek (1997, p. 92) also compares filtered and differenced estimates, however without significance testing: for the GDP series of the OECD countries he finds that the cycle duration for the fluctuations obtained with the Hodrick-Prescott filter is around 8.14 years and for the differenced data - around 7.13. In Section 3 we noted, that the given filter is more vulnerable to generation of spurious periodicities than other band-pass filters: in Woitek (1997, pp. 134-142) the issue of spurious periodicities is explicitly discussed. Bergman et al. (1998, p. 74) show cycle durations from 3.8 to 4.6 for Denmark; from 3.4 to 5.5 for the Netherlands; from 4.7 to 5 for Sweden; from 3.5 to 6 for the UK and from 4.1 to 6.3 for the USA using the detection methodology similar to Bry-Boschan coupled with the Baxter-King filter, which, as we previously noted, is less prone to generating spurious periodicities; however, it is symmetric and thus, may be inferior to the asymmetric CF filter for the frequencies below the cut-off. Nevertheless, our findings for Sweden, Denmark and the USA are in the proximity of the above-mentioned values. Cashin and Ouliaris (2001, p. 16) reports lengths for Autralian business cycles using the Bry-Boschan methodology: the values range from 3.2 to 6.1. This range resembles our simultaneously significant findings: 2.743 and 4.085. Cendejas et al. (2015, pp. 22-25) find durations of 6.9 for Australia; 5.3 for Denmark; 3.9 for the Netherlands; 4.5 for Sweden; 3 for the UK and 5.2 for the USA. One has to note that for Sweden and the UK the estimation was slightly altered. These findings also resemble our simultaneously significant periodicities with an exception of the UK. Regarding the UK, Metz (2011, p. 235) finds irregular cycles with a length of around 11 years which is closer to our estimate of 8.348 than the findings of other researchers. In addition, Mills (2007, p. 222), reports cycles of 8.2 years for the UK real interest rates - although, real interest rates are a different variable, it can be used as a proxy for real economic activity. Finally, Diebolt and Guiraud (2000), Diebolt (2014) report longer periodicities, corresponding to Juglar and Kuznets cycles from 7 to 22 years: we detect manifestations of these long cycles in all countries; however, most of them did not turn out to be simultaneously significant with an exception of 8.348 for the UK.

Let us revisit the testing strategy and potential caveats. The adjustment of the series to outliers is related to many risks, e.g., spurious outliers or shifts and thus incorrect adjustment (see the example of such discussion in Metz, 2010, pp. 58-62). This issue is related to our empirical strategy, since we had to apply the same outlier detection methodology, namely the ARIMA models, for the adjustment. Applying different methods for each unique situation would be more appropriate; however in that case, heterogeneity in methodology would increase the exposure of our spectral densities to purely technical features and comparing them would be questionable. The second issue is related to testing: the non-rejection of the null hypothesis as in (1) and (2) has clear implications: the given periodicity is most likely spurious. The implications of rejection of both nulls are more complex. Even if a certain frequency is significant in both cases, there is still a risk of this periodicity to be spurious. This risk comes from two sources: the benchmark spectral density of the noise and the spectral density of the signal itself. For simplicity, we assume that the noise is an autoregressive process of the first order, or AR(1), which is sufficient for the purposes of this paper. One should note that models for the background noise of a higher order, e.g. AR(2), may introduce spurious oscillations due to their design (see Mann and Lees, 1996, pp. 411-412), therefore AR(1) is preferable. The second issue is related to the fact that we compare two cases of amplification: amplified lower frequencies and amplified higher ones. Although the degree of differencing is justified by the test on fractional integration and the asymmetric CF filter is a well-established tool, surpassing the symmetric Hodrick-Prescott and Baxter-King filters in certain aspects[16]; the rejection of the nulls should not be seen as an identification of the true dominant periodicity, but rather an attempt to sort out the ones, likely to be spurious.

Last point to discuss is whether one could resort to wavelets in order to identify spurious periodicities. Indeed, using wavelets, one could estimate the trend (see Gilbert, 1999), remove it by the means of a wavelet-based filter and analyse the deviations. However, the wavelet transform would yield the corresponding spectral density without any distortions only if the choice of the wavelet function was

[16]One has to note, that there are more sophisticated wavelet alternatives, filters with optimal cut-off frequency estimation and extensions to the exiting filters (see Çağrı Akkoyun et al., 2012, Iacobucci and Noullez, 2005, Baubeau and Cazelles, 2008, Buss, 2011); in order to answer our research questions, we deliberately used the upper bounds of the Kuznets and Juglar cycles in order to capture any distinct periodicities in that range and perform simultaneous significance testing. We should also note that despite the superior performance of the asymmetric CF filter, according to Iacobucci and Noullez (2005, pp. 95-96) the CF filter is only nearly optimal and is also prone to generating spurious cycles: the gain function with asymmetric weights allows to assign flexible weights to different frequencies, which successfully dampens frequencies below the cut-off (observed on Figures 6 and 7), but this very feature can induce phase shifts. Even though, that the filtered cycles pass the KPSS test, such anomalies can not be completely ruled out. Nevertheless, for the purpuses of our paper, the asymmetric CF filter performs well and eliminates frequencies below our cut-off points. This leaves the Kondratjew range out; however, as we noted in Section 2, such periodicities are the most debatable ones.

appropriate (see Tabaru and Shin, 2003). Spectral analysis is exposed to a similar risk. Therefore, in case of wavelets the risk of emergence of spurious periodicities during the transformation is not completely eliminated. Another issue with the application of wavelets, would be the simultaneous testing. It would involve a large number of transformed signals, the approximations of their densities and the densities of their noise. Bearing similar risk of emergence of spurious results, there will be other uncertainties related to the testing.

Conclusion

The debates on the periodicity of economic fluctuations involve more than 150 years of fruitful theoretical and empirical research. The problem of spurious periodicities has been accompanying these debates, especially during the period of emergence and evolution of statistical methods of analysis. The well-established periodicities of economic fluctuations are ranged from the long waves of Kondratjew (1926) of 45-60 years; Kuznets (1930) cycles of 15-25 years; Juglar (1862) cycles of 7-11 years and much shorter Kitchin (1923) cycles of 3-5 years. Various data adjustment, filtering and detrending techniques are prone to generating spurious periodicities: filtering based on summation operators may amplify low frequencies and dampen the higher ones; whereas differencing amplifies high frequencies and suppresses the lower ones. In this context, the main research question of this paper can be formulated as follows: which of these cycles are present in the spectrum of the long-run cliometric time series and, if they are present can they be spurious?

In order to address this question, we use the cliometric data for Australia, Denmark, the Netherlands, Sweden, the UK and the USA during 1820-2010 and apply the following empirical strategy: we adjust the series for additive outliers, level shifts, temporary changes and innovational outliers; test on fractional integration; obtain two types of cyclical fluctuations: with the asymmetric Christiano-Fitzgerald filter (filtered series) and using first differences (detrended prefiltered); derive blue and red noise confidence intervals; estimate spectral densities using the Blackman-Harris window and conduct simultaneous testing of the significance of the spectral densities of the filtered and detrended prefiltered series. Those preiodicities which were not simultaneously significant for the filtered and detrended prefiltered series are most likely spurious.

The tests suggest absence of fractional integration and thus first degree of differencing is appropriate. The filtered series allow for Kuznets and Juglar cycles up to 25 and 11 years respectively. After conducting simultaneous significance tests at 90, 95 and 99% levels, we find that even the most distinct peaks at lower frequencies (longer periodicities) are not significantly different from the confidence intervals of the related noise for the detrended prefiltered data. Thus, periodicities from 16 to 24 years, which were significant for the filtered series (as in Diebolt and Guiraud, 2000, Diebolt, 2014), were not simultanoeusly significant for the detrended prefiltered ones. The longest periodicity, which was simultaneously significant relative to noise at least at the 90% level was 8.348 for the UK, resembling the findings of Metz (2011, p. 235); other simultanoeusly significant periodicities are ranged from 2.11 to 5.189 which is close to findings of Woitek (1997), Bergman et al. (1998), Cashin and Ouliaris (2001), Cendejas et al. (2015).

Even though that the Kuznets cycles manifest themselves, we were able to simultaneously find significant evidence only for the Juglar and Kitchin cycle lenghts. Simultaneous testing of the significance of spectral densities of the given series against the noise confidence intervals helps to identify periodicities, which are most likely spurious; however, the exact identification of the true dominant frequency is still an open question. The simultaneous non-rejection of the nulls is straightforward and implies that the given peak is not significantly different from the spectral pattern of the related blue or red noise; whereas the rejection case may still be prone to issues mentioned in the discussion.

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Appendix

Figure 4: Unadjusted series

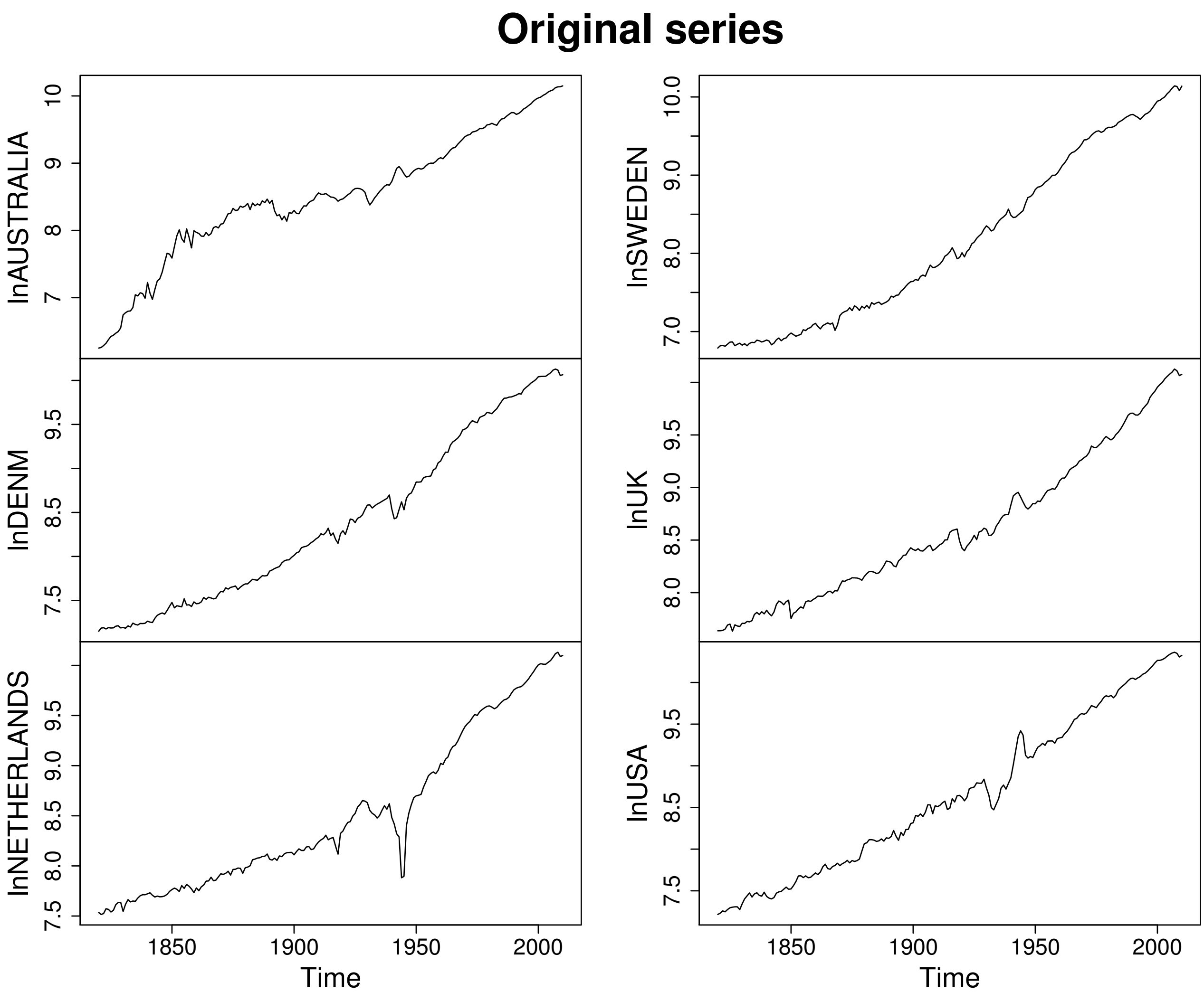


Figure 5: Series, adjusted for outliers using ARIMA models

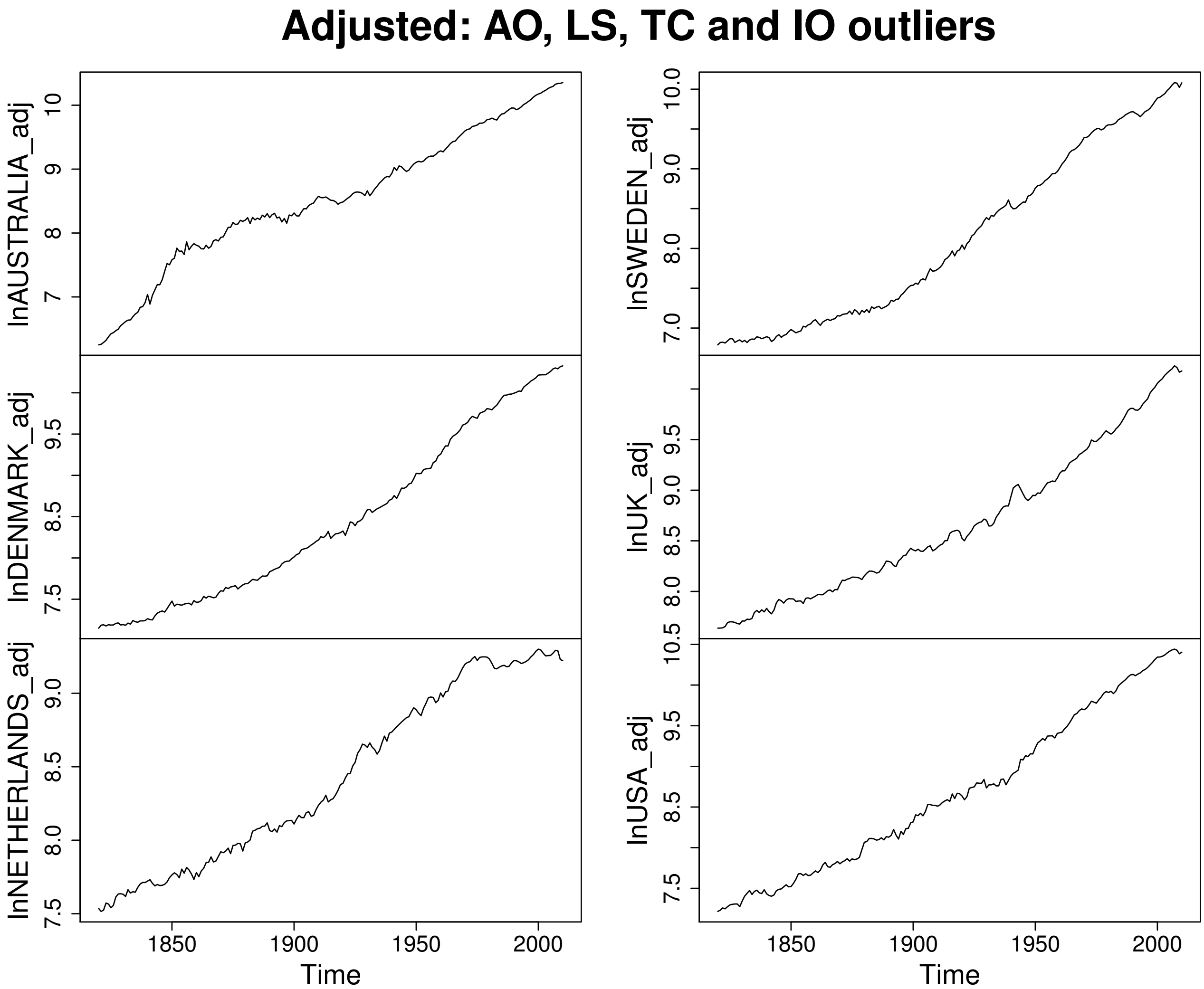


Figure 6: Cyclical deviations obtained with an asymmetric Christiano-Fitzgerald filter

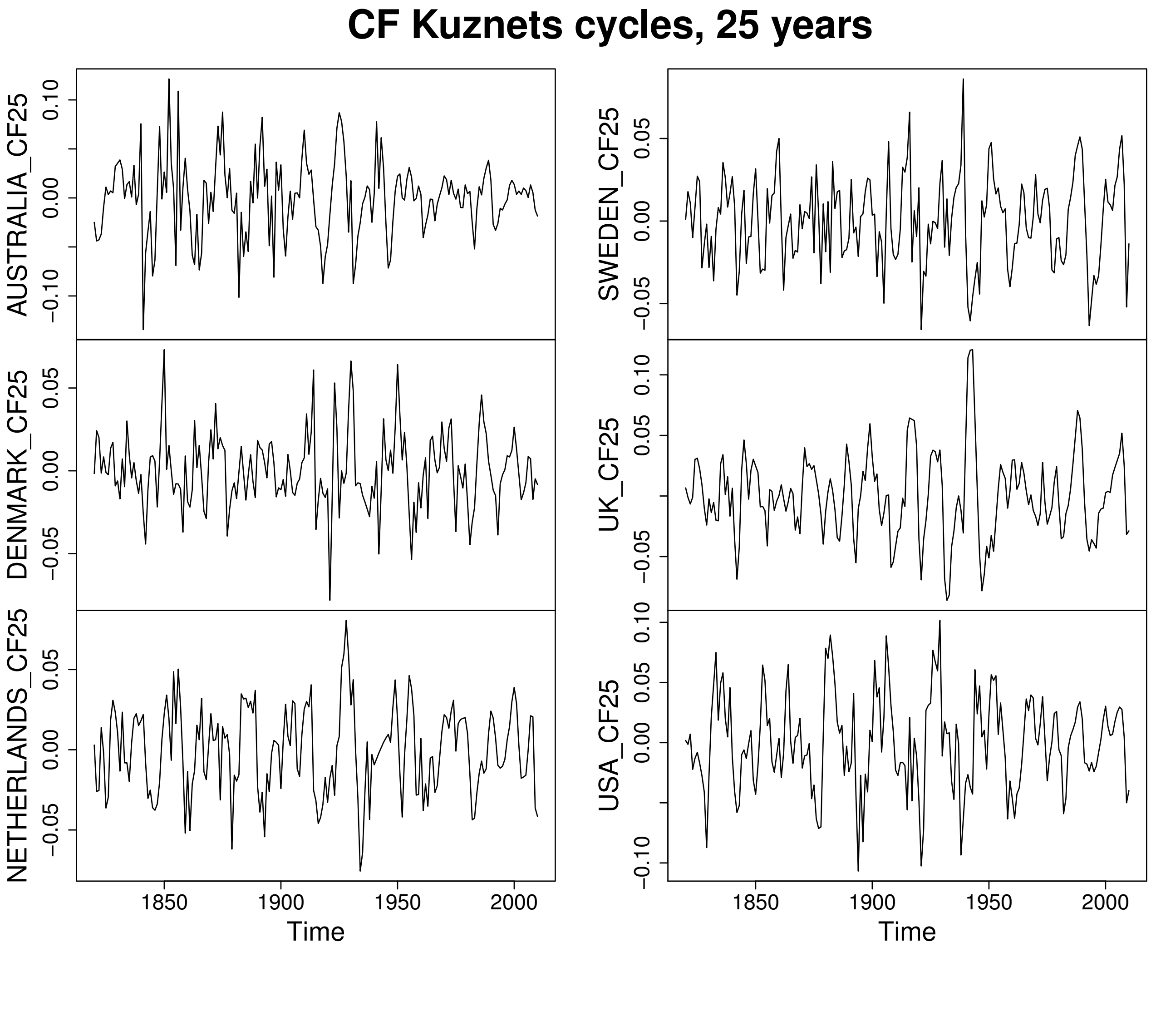


Figure 7: Cyclical deviations obtained with an asymmetric Christiano-Fitzgerald filter

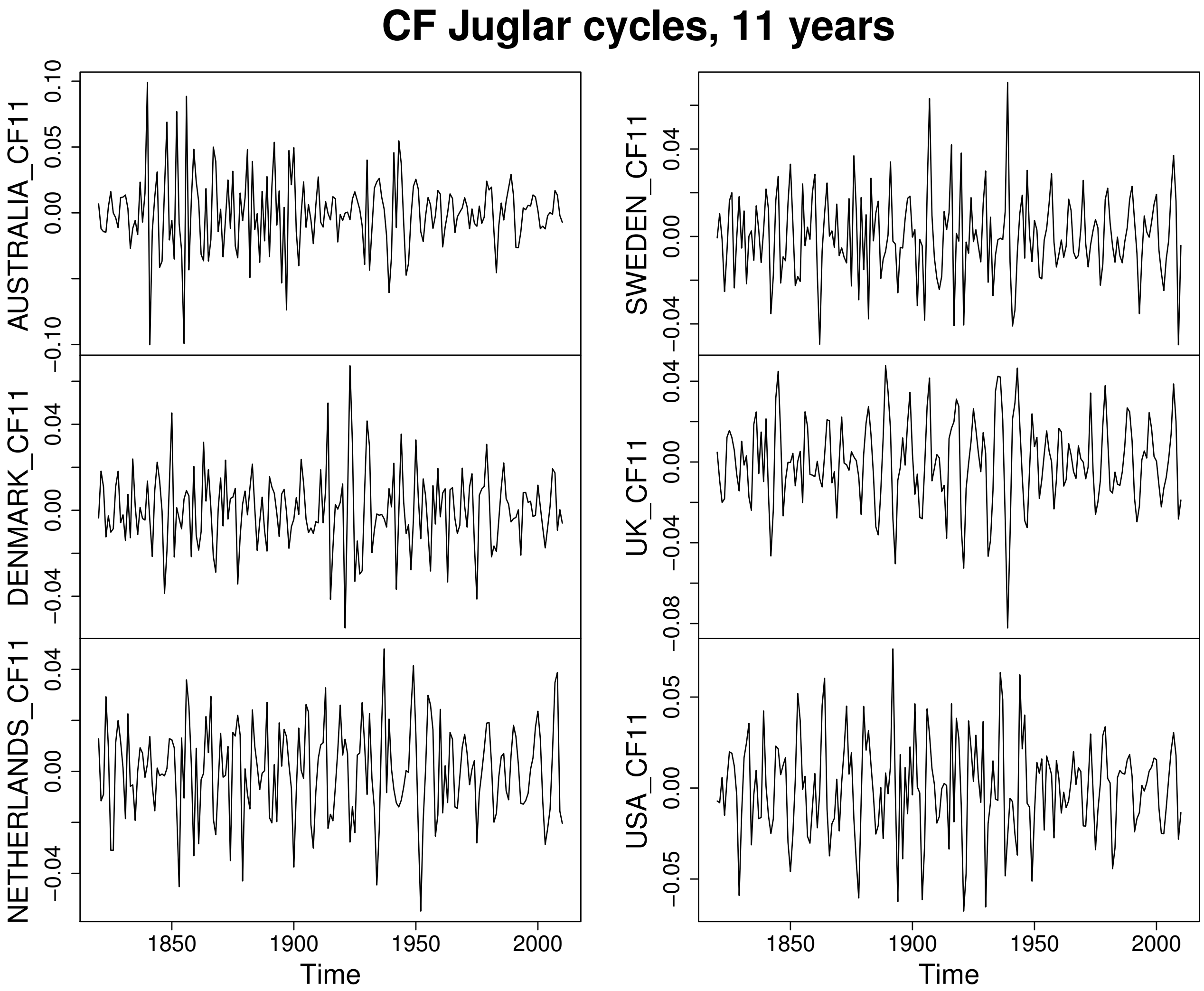
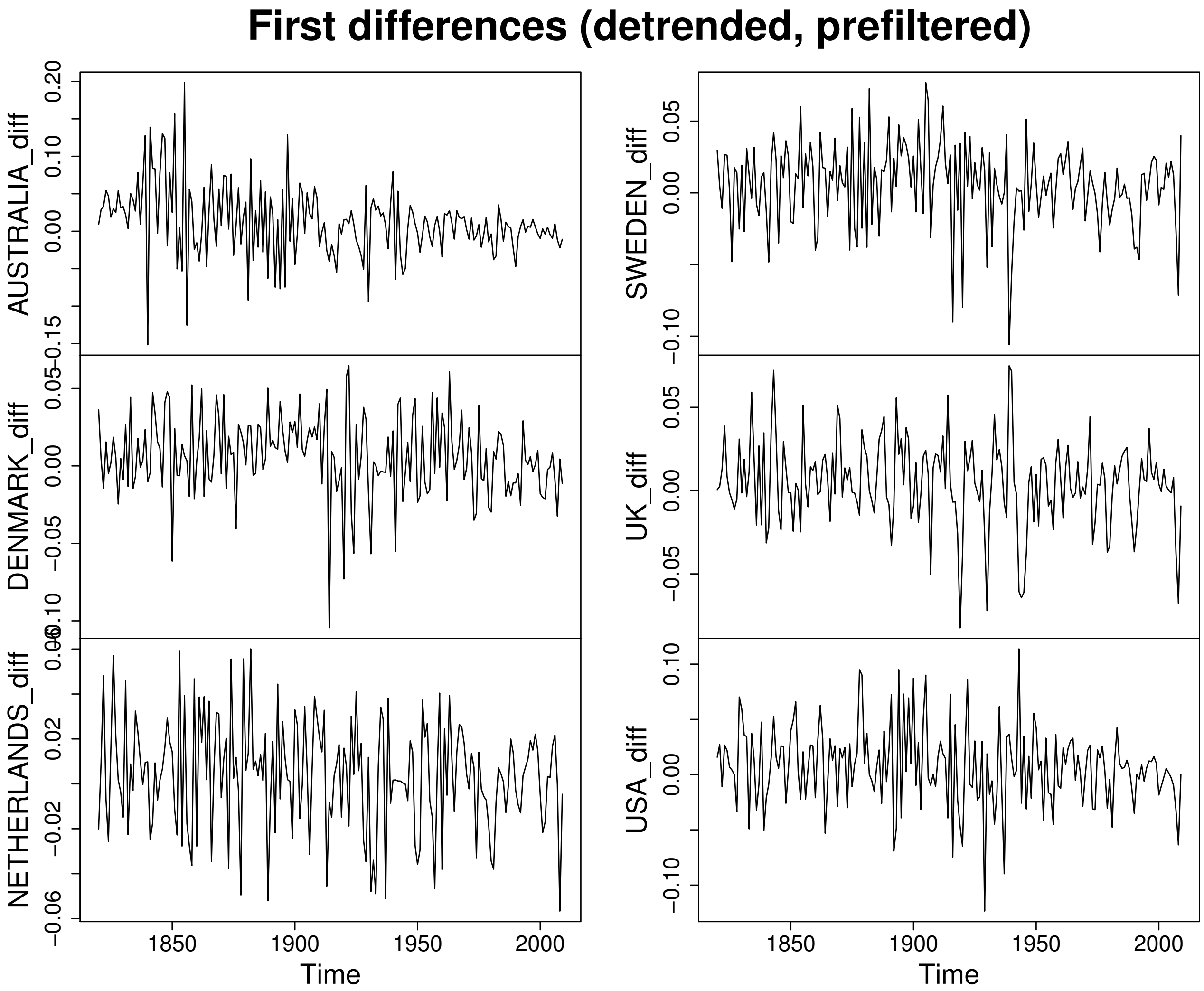


Figure 8: Differenced (detrended prefiltered) series



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