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A Frequency Selective Filter for Short-Length Time Series*

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An effective and easy-to-implement frequency filter is proposed, obtained by convolving a raised-cosine window with the ideal rectangular filter response function. Three other filters, Hodrick-Prescott, Baxter-King, and Christiano-Fitzgerald, are critically reviewed. The behavior of the windowed filter is compared to the others through their frequency responses and by applying them to both an artificial, known-structure series and the Euro zone GDP quarterly series. A bandpass version of the Hodrick-Prescott filter is used. The windowed filter has almost no leakage and is better than the others at eliminating high-frequency components. Its response in the passband is significantly flatter, and its behavior at low frequencies ensures a better removal of undesired long-term components. These improvements are particularly evident when working with short-length time series, which are common in Macroeconomics. The proposed filter is stationary and symmetric, therefore it introduces no phase-shift. It uses all the information contained in the raw data and stationarizes series integrated up to order two. It thus proves to be a good candidate for extracting frequency-defined series components.

Keywords: Spectral methods, frequency selective filters, Hodrick-Prescott, Baxter-King and Christiano-Fitzgerald bandpass filters, business cycles.

JEL codes: C10, C14, E32.

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1 Introduction

There are several ways for formalizing the separation of a signal into different periodic components. One of the most insightful remains the Fourier decomposition, which views the signal as a linear combination of purely harmonic components, each having a time-invariant amplitude and a well-defined frequency. Short-time Fourier analysis and wavelets — which make it possible to represent the frequency content of a series, while keeping the time and scale description parameter respectively — are also an alternative, especially in the case of nonstationary or intermittent signals. These techniques allow a detailed insight into the data structure. However, they are not easily implemented with short-length series and are not broached in this paper.

A selective filtering operation over an infinite continuous signal is defined by specifying the range of individual frequencies that should be extracted and those that should be removed. In the case of finite-length samples, it is impossible to design a filter that preserves all frequencies in a given range and completely removes those outside it (the so called *ideal filter*). Indeed, especially in the case of short-length series, abrupt variations in the frequency response give rise to the *Gibbs phenomenon*, the appearance of spurious artificial fluctuations in the filtered signal (see, among others, Hamming (1998), Oppenheim and Schaffer (1999), and Priestley (1981)). Therefore, it is important to design good approximations to the ideal filter — “good” relative to some optimization criteria, like the (weighted) difference between the desired and the effective response.

We propose here the Hamming/Hanning-windowed (HW) filter, which provides a simple and efficient solution to an ideal filter approximation. It is obtained by *windowing*, which is a well-known technique in engineering (Oppenheim and Schaffer (1999)). It consists in smearing the ideal filter response with a lag window and it leads to good attenuation of the spectral power outside the passband, allowing almost complete removal of undesired frequency components. Its only drawback is a negligible widening of the transition between the selected band (*passband*) and the remaining spectral components (*stopband*), which implies that a negligible part of the frequency components lying near the edge of the chosen band may be present in the filtered series.

To show the qualities and improvements of the HW filter, we compare it to those most widely used in Macroeconomics for trend and cycle extraction, namely the filters in Hodrick and Prescott (1997), Baxter and King (1999), and Christiano and Fitzgerald (2003). We thoroughly review these filters and, in particular, we visualize the time coefficients, gain, and phase of the Christiano-Fitzgerald filter, plotting them as surfaces in three-dimensional space.

In the following section, we briefly recall the issues of optimal filter design. In the third section the HW filter is introduced, together with a sketch of its computing algorithm. The fourth section contains an extensive critical overview of the the Hodrick-Prescott (HP), the Baxter-King (BK), and the Christiano-Fitzgerald (CF) filters. In the fifth section these are compared to the windowed filter, both from a theoretical point of view, by plotting their frequency responses, and from an applied one, by applying them to an artificial series and the Euro zone GDP quarterly series. The sixth section concludes.

2 The Optimal Filtering Problem

It is common knowledge that an infinite series would be required to obtain the ideal (rectangular) frequency selective filter $H^{\text{ideal}}(\nu) = \Theta(\nu - \nu_l)[1 - \Theta(\nu - \nu_h)]$, where $\Theta(x)$ is the Heaviside step function. The aim of optimal filtering theory consists in finding the best approximation to $H^{\text{ideal}}(\nu)$ in the case of finite series.

We deem the essential requirements to be met in solving the optimal filtering problem to be: (i) the approximated filter should leave as much information unaffected as possible over the specified range of periodicities it is supposed to extract; (ii) it should not introduce spurious phase shifts, which would imply a modification of timing relations among different series or among different frequency components within a same series; (iii) its output must be stationary.

Consider the filtering problem for a finite time series u_j of duration $T = N\Delta t$, where N is the number of data points and Δt the sampling periodicity:

$$\begin{aligned} v_j &= h_j \otimes u_j \equiv \sum_{n=0}^{N-1} h_n u_{j-n \bmod N} , \\ &= \frac{1}{N} \sum_{k=-N/2}^{(N-1)/2} H_k U_k e^{i2\pi jk/N} . \end{aligned} \quad (1)$$

Since we are dealing with a finite discrete series, the frequency $\nu_k = k/(N\Delta t)$ and the time $t_j = j\Delta t$ variables are also discrete and indexed by k and j , respectively. Moreover, because of discretization, the absolute value of ν_k is bounded by $\nu_{\text{Nyq}} = (2\Delta t)^{-1}$, the so-called *Nyquist frequency*. It is easy to see from (1) that the filter H_k is not causal, since each point of the output series is computed by means of past as well as future values of the input series.

From the expression of the filter frequency response

$$H_k = \Delta t \sum_{n=-\lfloor N/2 \rfloor}^{\lfloor (N-1)/2 \rfloor} h_n e^{-i2\pi nk/N} , \quad (2)$$

we deduce that a filter that is real in the time domain ($h_j = h_j^*$) is symmetric in the frequency domain ($H_k = H_{-k}$), and *vice versa*. Therefore, if we want real signals to remain real after filtering, both time *and* frequency response functions have to be real and symmetric, to avoid time and/or frequency shifts. Indeed, it is easy to see that, if the filter H_k is a complex function, different frequencies undergo different phase shifts and the timing relations among components are destroyed.

Equation (2) implies that the sum of the windowed filter coefficients h_j is set by the frequency response at the origin

$$H_0 = \Delta t \sum_{n=-\lfloor N/2 \rfloor}^{\lfloor (N-1)/2 \rfloor} h_n . \quad (3)$$

This allows the removal of the signal mean in the case of lowpass and bandpass filters,

$$H_k|_{k=0} = 0 . \quad (4)$$

If we add the following condition on the filter first time derivative:

$$\Delta H_k|_{k=0} = 0 , \quad (5)$$

or its time domain equivalent

$$\sum_{n=-\lfloor N/2 \rfloor}^{\lfloor (N-1)/2 \rfloor} nh_n = 0, \quad (6)$$

then the elimination of two unit roots is ensured.

The circular convolution (\circledast) in (1) implies that the finite signal is replaced by its periodic version $u_{N+j} = u_{j \bmod N}$, the maximum period length being implicitly assumed by the Fourier transform to be $T = N\Delta t$. This imposed T -periodicity is in general false and affects the analysis. Indeed, it introduces an artificial discontinuity at the edges of the time series in the form of the Gibbs effect. As is shown in the next section, these oscillations are due to the form of the discrete Fourier transform of a rectangular window of width $T = N\Delta t$ (see Figure 1).

There are three ways to minimize this effect. The first is to choose the length of the series T as a multiple of the highest period that is likely to occur. This is a very difficult task, since it requires knowledge of the data-generating process and would, in any case, imply some data loss. The second is to choose both cutoff frequencies as integer multiples of T^{-1} , which is easier to do, but might also imply data loss. The third, if the series has a deterministic trend, for instance a polynomial function of time, is to subtract the least-squares fit before filtering. Recall that the operation of detrending and that of filtering do not commute, since a polynomial and a periodic term are not orthogonal. Subtracting the OLS regression line can always be done to reduce the edge discontinuities that appear if there are non-harmonic frequencies in the signal. The effect of this discontinuity is, however, reduced to negligible amplitudes by the use of windowing.

3 The Windowed Filter

The truncation to N of the ideal filter time coefficients

$$\begin{aligned} h_j^{\text{ideal}} &= \frac{\sin(2\pi\nu_h j \Delta t) - \sin(2\pi\nu_l j \Delta t)}{\pi j}, & j = -\infty, \dots, \infty, \\ h_0^{\text{ideal}} &= \lim_{j \rightarrow 0} h_j^{\text{ideal}} = 2\Delta t(\nu_h - \nu_l), \end{aligned} \quad (7)$$

where $j = -\infty, \dots, \infty$, and ν_h and ν_l represent the high and low cutoff frequency, respectively, amounts to multiplying (7) by an N -wide rectangular lag window, yielding

$$\begin{aligned} h_j &= \frac{\sin\left[\frac{2\pi j}{N}\left(k_h + \frac{1}{2}\right)\right] - \sin\left[\frac{2\pi j}{N}\left(k_l - \frac{1}{2}\right)\right]}{N \sin\left(\frac{\pi j}{N}\right)} & j = 1, \dots, N-1, \\ h_0 &= \lim_{j \rightarrow 0} h_j = \frac{2}{N}(k_h - k_l + 1). \end{aligned} \quad (8)$$

The truncation induces fluctuations of large amplitude and slow decay in the response function — the Gibbs effect again —, caused by the discontinuities induced by the lag window, whose $\sin(\pi\nu T)/(\pi\nu T)$ -profile Fourier transform (Figure 1, right panel) disturbs the ideal frequency response. An adjustment to the rectangular lag window shape is thus required to obtain a response that goes faster to zero. For this purpose, the “adjusting” window should

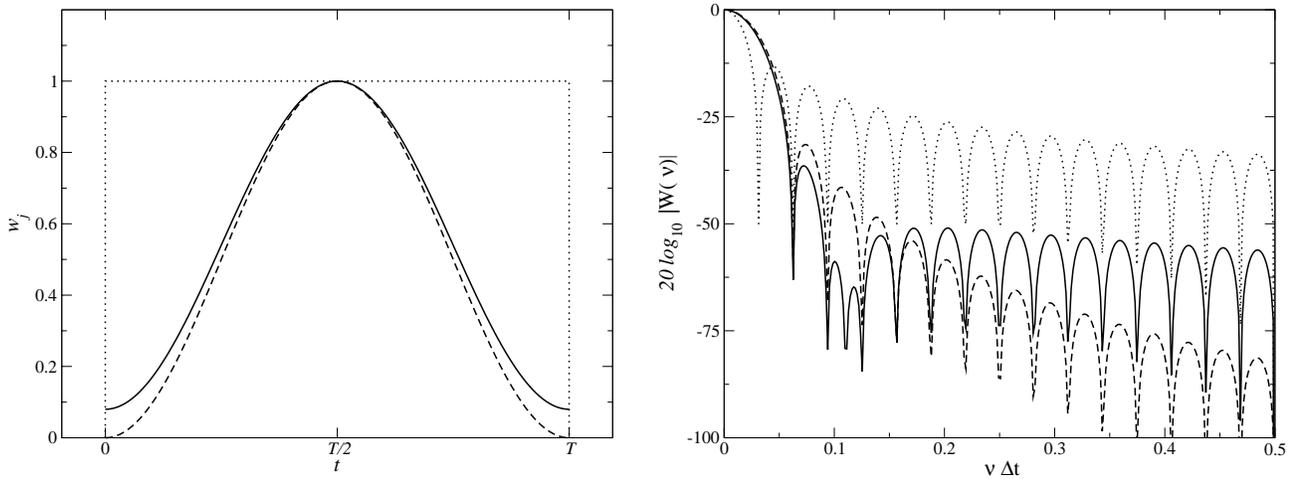


Figure 1: Window Functions and Their Frequency Responses.

be chosen to go to zero continuously with its highest possible order derivatives, at both ends of the observation interval.

The choice of the best window has been thoroughly discussed in the signal processing literature (Jenkins and Watts (2000); Priestley (1981); Oppenheim and Schaffer (1999)) and is not a univocally defined problem because different optimization criteria could be used, among which: (i) the minimization of the *leakage factor*, that is, the ratio of the power in the sidelobes to the total window power (see Fig. 1); (ii) the minimization of the mainlobe width (the highest peak in Figure 1, right panel), which is proportional to the transition band width — the width of the band that arises between the stopband and the passband, as a consequence of the finiteness of real series — ; (iii) the minimization of the highest or the first sidelobe peak height. Notice that there is a trade-off between (i) and (ii): the lower the leakage factor, the wider the mainlobe width, and *vice versa*. This is shown in Figure 1: the rectangular window indeed has the narrower mainlobe width, which implies a steeper transition between the passband and the stopbands, but at the price of a high leakage factor.

From these and other possible criteria, a broad range of windows arise (triangular, Bartlett, Parzen, Blackman, Tuckey-Hanning, Hamming, see Priestley (1981)). We single out the *raised-cosine* (or *general Tuckey*) windows

$$w_j^{\text{Han}} = a - (1 - a) \cos\left(\frac{2\pi j}{N}\right), \quad \frac{1}{2} \leq a < 1, \quad (9)$$

which have spectral windows of the form

$$W(\nu) = \left[(2a - 1) + \frac{2(1 - a)}{1 - (\nu T)^2} \right] \frac{\sin(\pi \nu T)}{\pi \nu T}. \quad (10)$$

More precisely, we consider the so-called Hanning ($a = 0.5$) and Hamming ($a = 0.54$) windows (the H-window in the following, Figure 1), which represent the best compromise for our purposes in building a bandpass filter. Obviously, different windows may perform better as regards one specific criterion. For instance, the Blackman and Parzen windows have a lower leakage

factor and a better sidelobe attenuation than the H-windows, but a wider transition band, that affects the performance of the bandpass filter, especially in the case of short-length series. Not restraining ourselves to “static” windows, we could also consider other windows, like the Gaussian or the Kaiser windows, which have a parameter that allow to establish quantitatively and to modify the ratio between leakage factor and transition (mainlobe) width. Nevertheless, the use of such windows leads to much more complicated computations and a marginal gain with respect to H-windows.

Figure 1 shows the rectangular, Hanning and Hamming windows (left panel) and their corresponding Fourier transforms (right panel). The Hanning window is continuous and vanishes at both zero and N along with its first derivative (see Figure 1, left panel), while the Hamming window is not continuous at the edges of the interval and is obtained by a judicious combination of the Hanning and the rectangular windows. As for their frequency responses, the H-windows have a mainlobe width that is almost twice as wide as that of the rectangular window. This implies that the filters obtained by H-windowing have a transition band approximately twice as wide as that of the ideal filter — the price paid for smoothing. The Hanning spectral window performs better than the Hamming one in the upper part of the spectrum (high ν), and this is useful with long time series with good frequency resolution, like those typical in finance. However, the Hamming spectral window attenuates the first sidelobes amplitude better, and hence, it is the appropriate window to use when frequencies close to the edges of the passband have to be eliminated — especially in the case of short-length series more common in macroeconomics.

Both the Hanning and Hamming spectral windows are real and even, so that the symmetries of the ideal infinite filter are preserved; that is, if the latter is real and even, it remains so through windowing.

3.1 The HW Filter Algorithm

We now introduce the proposed filtering procedure, described by the following algorithm:

- (i) subtract, if needed, the least-square regression line to remove the artificial discontinuities introduced at the edges of the series by the Fourier transform;
- (ii) compute the discrete Fourier transform of the signal u_j

$$U_k = \sum_{j=0}^{N-1} u_j e^{-i2\pi jk/N}, \quad k = 0, \dots, \lfloor N/2 \rfloor;$$

- (iii) apply the Hanning- or Hamming-windowed filter ($W_k * H_k$) to U_k ,

$$\begin{aligned} V_k &= (W_k * H_k) U_k = \sum_{k'=-\lfloor N/2 \rfloor}^{\lfloor N/2 \rfloor} W_{k'} H_{k-k'} U_k \\ &= \left[\left(\frac{1-a}{2} H_{k-1} + a H_k + \frac{1-a}{2} H_{k+1} \right) \right] U_k, \quad k = 0, \dots, \lfloor N/2 \rfloor, \end{aligned}$$

where H_k is defined by the frequency range as

$$H_k = H_k^{\text{ideal}} \equiv \begin{cases} 1 & \text{if } \nu_l N \Delta t \leq |k| \leq \nu_h N \Delta t \\ 0 & \text{otherwise} \end{cases},$$

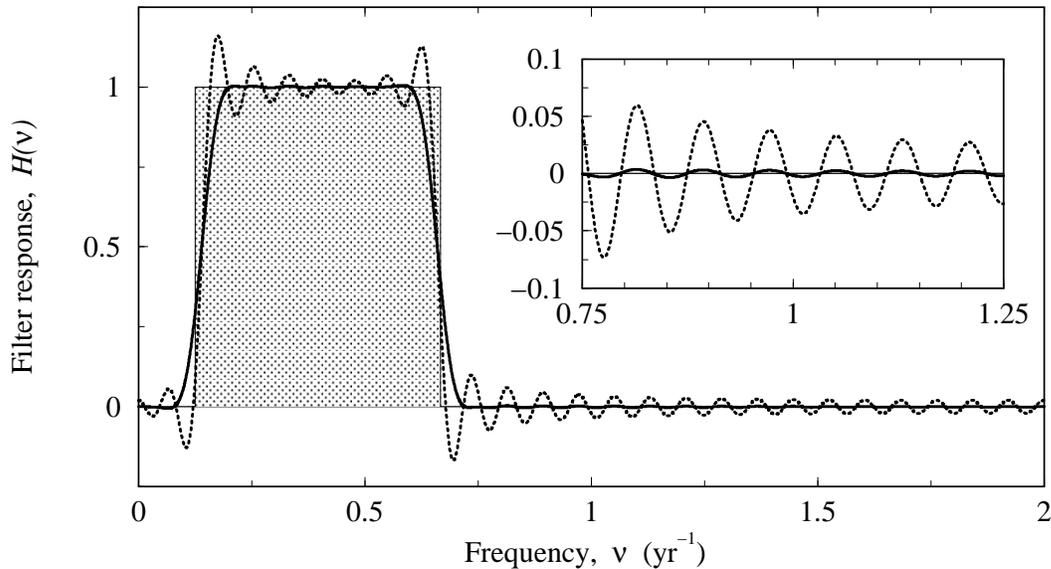


Figure 2: **Windowed Filter Frequency Response.**

and W_k is the discrete window Fourier transform, which has only three non-zero components at frequencies 0 and $\pm(N\Delta t)^{-1}$;

(iv) compute the inverse transform

$$v_j = \frac{1}{N} \left[V_0 + \sum_{k=1}^{\lfloor N/2 \rfloor} \left(V_k e^{i2\pi jk/N} + V_k^* e^{-i2\pi jk/N} \right) \right], \quad j = 0, \dots, N-1.$$

Windowing the filter response in the frequency domain by convolution of the ideal response with the spectral window, as in (iii), is computationally less expensive than time domain multiplication. Indeed, as stressed above, both the Hamming and Hanning discrete spectral windows have only three non-zero components. Also note that the HW filters satisfy conditions (4) and (5), and thus stationarize an $I(2)$ series.

From now on we deal only with the Hamming-windowed filter, since it is more suitable for short macroeconomic series. But the differences between the two filters in comparison with the others are almost imperceptible. Figure 2 shows the frequency response of bandpass filters obtained by direct truncation and by the Hamming-windowing procedure. Note the reduced leakage of the filter obtained by windowing. As for the wider transition band, however, in many applications it is more important to remove most of the undesired frequencies than it is to have a sharp discrimination between frequencies at the edges of the passband. Summing up, this filtering procedure ensures the best possible behavior in the upper part of the spectrum, the complete removal of the signal mean, and a flat response inside the passband.

4 Overview of the Most Popular Bandpass Filters

In this section, we provide a critical review of some of the frequency-selective filters that are widely used in the literature for trend and cycle extraction, namely the HP filter (Hodrick

and Prescott (1997)), the BK filter (Baxter and King (1999)) and CF filter (Christiano and Fitzgerald (2003)). The by-products of this review are essentially four: the finding of an explicit formula for the computation of the HP filter λ -parameter as a function of the sampling periodicity and of the cutoff frequency; the consequent building of a bandpass version of the HP filter, in order to make a fairer comparison among all the filters (see Section 5); the formal expression of the minimum moving-average order of the BK filter (the parameter K), to obtain the appropriate resolution according to the cutoff frequencies values; and the three-dimensional plots of the CF filter time coefficients, gain and phase.

4.1 The Hodrick-Prescott Filter

The Hodrick-Prescott cyclical component v_j^{HP} is defined as the difference between the original signal u_j and a smooth growth component g_j . The latter is the solution of the optimization problem

$$\min_{\{g_j\}} \sum_{j=0}^{N-1} \left[(u_j - g_j)^2 + \lambda (g_{j+1} - 2g_j + g_{j-1})^2 \right], \quad (11)$$

which minimizes the sum of the norm of the cyclical component $\|v_j^{\text{HP}}\| = \|u_j - g_j\|$ and the weighted norm of the rate of the growth component $\|(1 - L)(1 - L^{-1})g_j\|$, where L is the lag operator $Lx_j \equiv x_{j-1}$. The smoothing parameter λ penalizes variations in the growth rate with respect to the differences between filtered and unfiltered series and is usually set to 1600 for quarterly data. For large values of λ , the growth component g_j tends to the OLS line calculated from the data.

The solution of (11) for $N \rightarrow \infty$ can be found explicitly in the frequency domain (King and Rebelo (1993)) and leads to the following expression for the frequency response function

$$\begin{aligned} H^{\text{HP}}(\nu) &= \frac{4\lambda(1 - \cos(2\pi\nu\Delta t))^2}{1 + 4\lambda(1 - \cos(2\pi\nu\Delta t))^2} \\ &= \frac{16\lambda \sin^4(\pi\nu\Delta t)}{1 + 16\lambda \sin^4(\pi\nu\Delta t)}, \end{aligned} \quad (12)$$

where $G(\nu)$ is the Fourier transform of the series growth component g_j .

From this expression and Figure 3, it can be seen that this is in fact a highpass filter, the frequency response rising monotonically from zero at $\nu = 0$ to nearly one at the Nyquist frequency. The transition is rather smooth and occurs at a cutoff frequency — defined as the frequency for which the response is equal to 0.5 — given by

$$\nu_c = (\pi\Delta t)^{-1} \arcsin\left(\frac{\lambda^{-1/4}}{2}\right); \quad (13)$$

that is, $\nu_c = 0.0252(\Delta t)^{-1}$ when $\lambda = 1600$. Hence the HP filter, in the configuration suggested by the authors for quarterly data, selects periodicities shorter than approximately 10 years, but has the disadvantage of a wide transition band (see Figure 3). The frequency response goes as $\lambda(2\pi\nu\Delta t)^4$ at low frequencies; hence it behaves as a fourth-difference filter and can stationarize an $I(4)$ process.

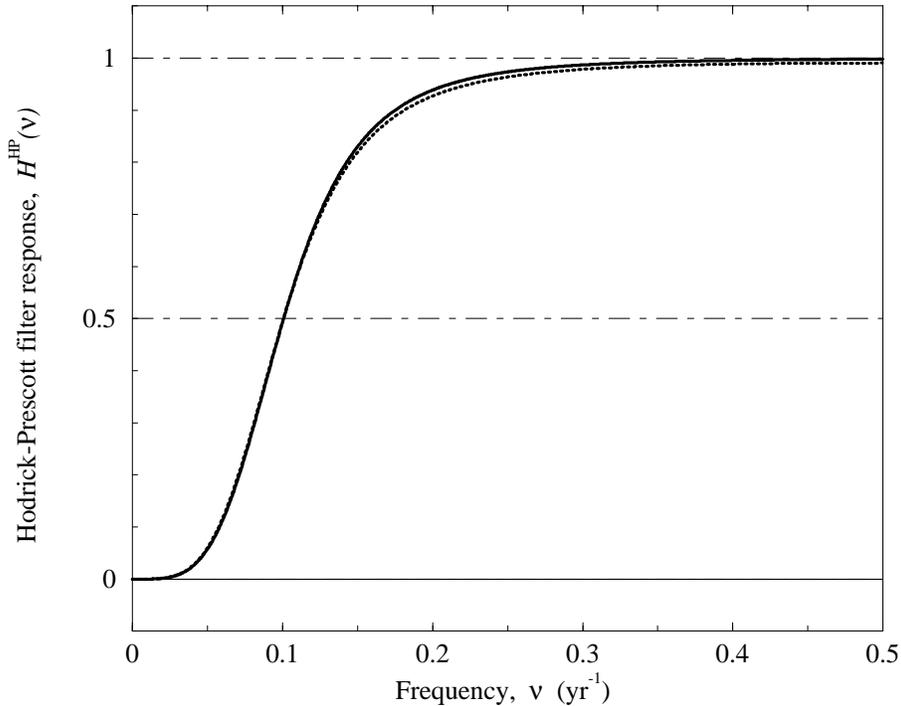


Figure 3: **Hodrick-Prescott Filter Frequency Response.**

A recurring issue when using the HP filter is the value of the parameter λ to use when dealing with annual or monthly data. This has been studied in, among others, Ravn and Uhlig (2002), which finds

$$\lambda_s = s^4 \lambda_q, \quad (14)$$

where λ_q is the value of the parameter for quarterly data (the usual 1600), s is the alternative sampling frequency (equal to 1/4 for annual data and 3 for monthly data), and λ_s the corresponding parameter value. As for the dependence of λ on the cutoff frequency, by noticing that the HP filter belongs to the wider class of Butterworth filters, Gomez (2001) indicates the expression

$$\lambda = [2 \sin(x_c/2)]^{-4}, \quad (15)$$

where x_c stands for the reduced angular frequency. A more general and comprehensive work is Harvey and Trimbur (2003b). This analyzes the dependence of λ on the cutoff frequency and the sampling frequency in a model-based approach to filters. In particular, it examines how the variation of λ can change the structure of an unobserved component model by modifying, for example, the correlation between components.

To find the explicit dependence of λ on both the sampling frequency and the cutoff frequency ν_c , we can directly solve the frequency response (12) for λ . Through (13), we obtain

$$\lambda = [2 \sin(\pi \nu_c \Delta t)]^{-4}. \quad (16)$$

Consequently, for a value of ν_c such that $\lambda = 1600$ for $\Delta t = 4^{-1}$ years, we find that $\lambda = 6.68$ when $\Delta t = 1$ years (see Figure 3) and $\lambda = 129660$ when $\Delta t = 12^{-1}$ years. Equations (15) and (16) are exactly the same, considering that $x_c = 2\pi \nu_c \Delta t$. It is easy to see that, in the

limit of small values for the reduced frequency $\nu_c \Delta t$ (large values of λ), the formula (14) is equivalent to (16) and of course (15), and both are equivalent to

$$\lambda \approx \left(2\pi\nu_c\Delta t + O\left((\nu_c\Delta t)^3\right)\right)^{-4} . \quad (17)$$

Therefore λ varies as the inverse fourth power of ν_c or Δt , as can be guessed by inspection of (11), where λ multiplies the square of the second difference of g_j .

By means of the formula (16) or (17), which allows the tuning of the cutoff frequency, a Hodrick-Prescott *bandpass* filter can be obtained as the difference between two highpass filters with different appropriate λ values, as shown in Gomez (2001) and Harvey and Trimbur (2003a) for Butterworth filters. Figure 4 shows the [2, 8] years bandpass HP filter obtained by (12) for a sample of $N = 128$ quarterly data points. Since the length of this filter, that is, the number of points involved in the calculation of one point of the filtered series, is equal to the total number of data points, the behavior of the filter improves as the number of data available grows. However, as expected, the bandpass HP filter cumulates the compression of two standard HP filters and is thus quite a poor approximation to the ideal bandpass filter. Furthermore, since it is a recursive filter — the initial condition g_{-1} is indeed required for the resolution of the optimization problem (11) —, its finite version is nonsymmetric and introduces a phase shift near the series edges.

4.2 The Baxter-King Filter

The method proposed in Baxter and King (1999) relies on the use of a symmetric finite odd-order $M = 2K + 1$ moving average so that

$$\begin{aligned} v_j &= \sum_{n=-K}^K h_n u_{j-n} \\ &= h_0 u_j + \sum_{n=1}^K h_n (u_{j-n} + u_{j+n}) . \end{aligned} \quad (18)$$

The set of M coefficients $\{h_j^{\text{BK}}\}$ is obtained by truncating the ideal filter coefficients at M under the constraint (3) of the correct amplitude at $\nu = 0$, that is, $H(0) = 0$ for bandpass and highpass filters and $H(0) = 1$ for lowpass filters. The BK filter coefficients thus have to solve the following optimization problem:

$$\begin{aligned} \min_{\{h_n^{\text{BK}}\}_{n=-K,\dots,K}} & \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} d\nu \left| \sum_{n=-K}^K (h_n^{\text{BK}} - h_n^{\text{ideal}}) e^{-i2\pi n\nu\Delta t} \right|^2 , \\ \text{s.t.} & \sum_{n=-K}^K h_n^{\text{BK}} = \frac{H(0)}{\Delta t} . \end{aligned} \quad (19)$$

The solution of the constrained problem simply shifts all ideal coefficients by the same constant quantity

$$h_j^{\text{BK}} = h_j^{\text{ideal}} + \frac{H(0) - \Delta t \sum_{n=-K}^K h_n^{\text{ideal}}}{M\Delta t} . \quad (20)$$

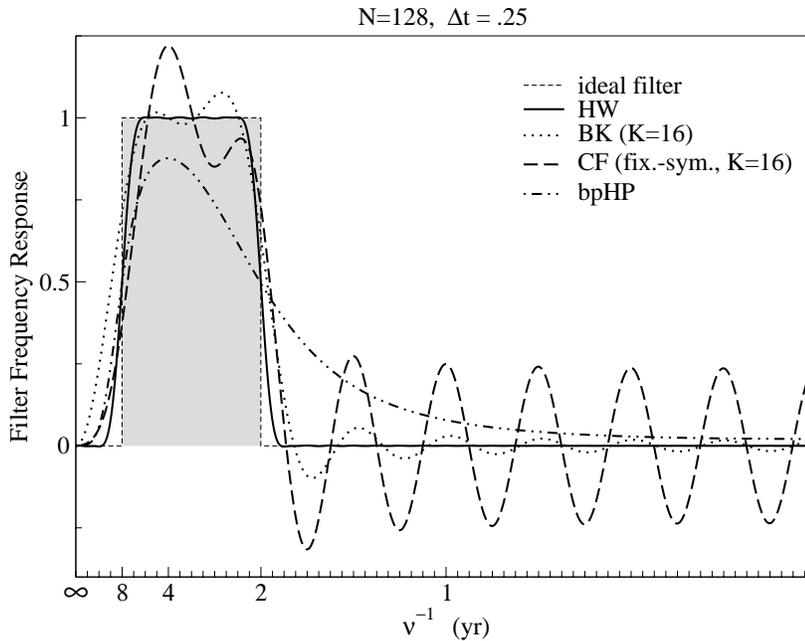


Figure 4: Comparison of Different Filters.

The frequency response of the BK filter with $K = 16$ selecting the band $[2, 8]$ years is reported in Figure 4, together with the responses of the other filters examined in this paper. The length of the BK filter is $M = 2K + 1$, so it does not depend on N . This implies that, unless we vary M , no “automatic” improvement of the filter performance is expected as more data become available.

Beside being optimal for the constrained problem (19), the BK filter has many desirable properties. First, since it is real and symmetric, it does not introduce phase shifts and leaves the extracted components unaffected except for their amplitude. Second, being of constant finite length and time-invariant, the filter is stationary. Third, the filter is symmetric and satisfies (3), thus correctly eliminating the signal mean. Moreover, the bandpass and highpass filter response behave at least as ν^2 for low ν , which allows the removal of up to two unit roots (see (4) and (5)). Fourth, the filter is insensitive to deterministic linear trends, provided that $M < N$, so that it is not used near the edges of the series.

On the other hand, filtering in time domain using moving averages, involves the loss of $2K$ data values, but, if K is chosen too small, the filter resolution $[(2K + 1)\Delta t]^{-1}$ would worsen. In Baxter and King (1999), a value of $K = 12$ for the passband $[1.5, 8]$ years is found to be basically equivalent to higher values, such as 16 or 20, even if it is not the case, as is shown hereafter. As a consequence, the authors suggest putting $K \geq 12$ irrespective of N , the sampling frequency Δt or the band to be extracted. This may cause significant compression and high leakage in the obtained filter response. Such drawbacks are, of course, consequences of the truncation, but they are undoubtedly amplified by the constraint imposition in (19), which, by adding a constant to the ideal filter coefficients (see (20)), causes an extra discontinuity at the endpoints of the filter, worsening the leakage at high frequencies.

In our opinion, the correct procedure is to take into account the filter resolution, once we have fixed the cutoff frequencies. In fact, M must be such that $\nu_h - \nu_l > (M\Delta t)^{-1}$,

otherwise the filter is unable to select the band with enough accuracy. In particular, filters with $\nu_l > (M\Delta t)^{-1}$ — filters whose length M is smaller than the longest period they try to extract — will perform very poorly at low frequencies. This implies that an accurate selection of periods equal to or smaller than 8 years from quarterly data requires using *at least* a 32-point filter ($K = 16$). Thus, the low limit value of $K \geq 12$ suggested in Baxter and King (1999) in the case of a passband of [1.5, 8] years is definitely too low.

Furthermore, Baxter and King argue that a good filter must not depend on the amount of data available, because this would imply a new computation of all the filter coefficients each time new data become available. Thus, time-domain filtering should be preferred to frequency-domain filtering. In our opinion, it is not wise to neglect the new information that becomes available when N increases; as more information is added, it is crucial to take it into account to improve the quality of the filtered signal. This is particularly true with short-length time series.

Finally, it is worth noting that the same “right” behavior (Equation (3)) at the origin is ensured with the truncated filter (8) with no additional constraint beyond the requirement of harmonic cutoff frequencies, that is, cutoff frequencies $\nu_{\{l,h\}}$ that are both chosen to be integer multiples of T^{-1} . Actually, it is easy to check from inspection of the frequency response that, apart from the constraint on the values of $\nu_{\{l,h\}}$, this much simpler filter performs better in the higher part of the spectrum than the Baxter-King filter.

4.3 The Christiano-Fitzgerald Filter

Christiano and Fitzgerald (2003) build a filter using two new ingredients: (i) accounting for the assumed spectral density of the original data, and (ii) dropping the stationarity and symmetry conditions on the filter coefficients.

If the exact spectral density of the original data $U^{\text{exact}}(\nu)$ is known beforehand, the set of coefficients $\{h_j\}$ is given by the solution of the optimization problem:

$$\min_{\{h_j\}} \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} d\nu \left| \sum_{\{j\}} (h_j - h_j^{\text{ideal}}) e^{-i2\pi j\nu\Delta t} \right|^2 |U^{\text{exact}}(\nu)|^2, \quad (21)$$

which is equivalent to the minimization of

$$|v_j - v_j^{\text{ideal}}|^2 = \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} d\nu |H(\nu) - H^{\text{ideal}}(\nu)|^2 |U^{\text{exact}}(\nu)|^2; \quad (22)$$

that is, of the discrepancy between the ideally filtered data and the effectively filtered ones.

According to different types of optimization problems, which give rise to different filters, the set of indexes $\{j\}$ could be constant symmetric $j = -K, \dots, K$, constant asymmetric $j = -K, \dots, K'$, or even general time-varying like $j = -(N - j), \dots, j - 1$. To obtain explicit solutions, Christiano and Fitzgerald assume different spectral density shapes. For instance, if $|U^{\text{exact}}(\nu)|^2$ is chosen as independent of frequency (white noise, referred to as *IID case* in Christiano and Fitzgerald (2003)), the solution is simply given by truncating the ideal filter coefficients (7). If u_j has one unit root and $|U^{\text{exact}}(\nu)|^2$ goes as ν^{-2} for low frequencies but tends to a constant at high frequencies (the *near-IID case* in Christiano and Fitzgerald (2003)), it is shown that the optimal coefficients are again obtained by truncating the ideal ones, but then

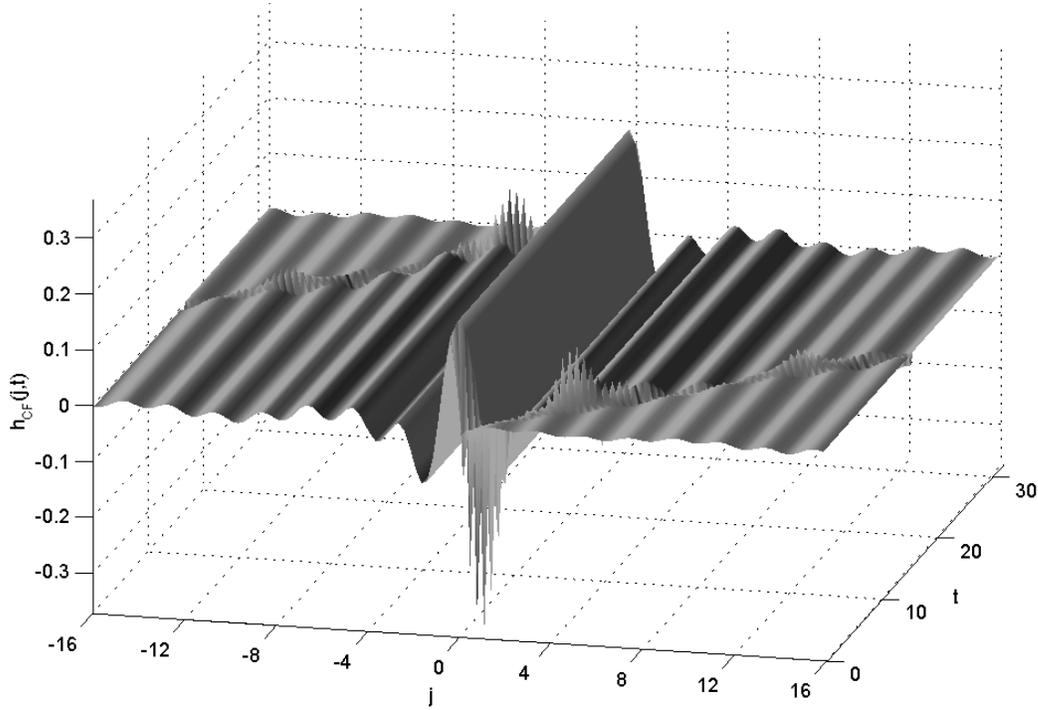


Figure 5: CF Random Walk Filter (I): Coefficients.

subtracting from each coefficient the same constant to make their sum equal to zero and cancel the unit root. For a constant symmetric set of indexes, this gives the Baxter-King filter.

In the end, what is called the Christiano-Fitzgerald filter is obtained by taking the power spectral density $|U^{\text{exact}}(\nu)|^2 \propto \nu^{-2}$ for all frequencies, which is the case for a random walk process. The coefficients can be obtained explicitly and are given by truncating the ideal filter ones and then adjusting only h_{-K} and $h_{K'}$. In this way the sum of the left coefficients ($j = -K, \dots, 0$) and the sum of the right coefficients ($j = 0, \dots, K'$) are both zero and Equation (3) is satisfied. The filtering operation is

$$\begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_{N-1} \\ v_N \end{bmatrix} = \begin{bmatrix} \hat{h} & h_1 & h_2 & \dots & h_{N-3} & h_{N-2} & h_{N-1} \\ \hat{h} - h_0 & h_0 & h_1 & \dots & h_{N-4} & h_{N-3} & \hat{h} - h_{\{0,N-3\}} \\ \hat{h} - h_{\{0,1\}} & h_1 & h_0 & \dots & h_{N-5} & h_{N-4} & \hat{h} - h_{\{0,N-4\}} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \hat{h} - h_{\{0,N-4\}} & h_{N-4} & h_{N-5} & \dots & h_0 & h_1 & \hat{h} - h_{\{0,1\}} \\ \hat{h} - h_{\{0,N-3\}} & h_{N-3} & h_{N-4} & \dots & h_1 & h_0 & \hat{h} - h_0 \\ h_{N-1} & h_{N-2} & h_{N-3} & \dots & h_2 & h_1 & \hat{h} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{N-1} \\ u_N \end{bmatrix}, \quad (23)$$

where the h_j 's are the ideal filter coefficients (8), $\hat{h} = h_0/2$, and we define $h_{\{0,j\}} = h_0 + h_1 + \dots + h_j$ to simplify the notation. Remark that, the series u_j in (23) has been *previously detrended by linear regression*. It is evident — as the authors themselves stress — that this filter acts differently on each date, so that we actually have N different filters, represented by the rows of the matrix in (23). The CF filter is time-varying and is thus nonstationary. Moreover, as is shown in Figure 5, at each time, the coefficients are asymmetric with respect to past and future

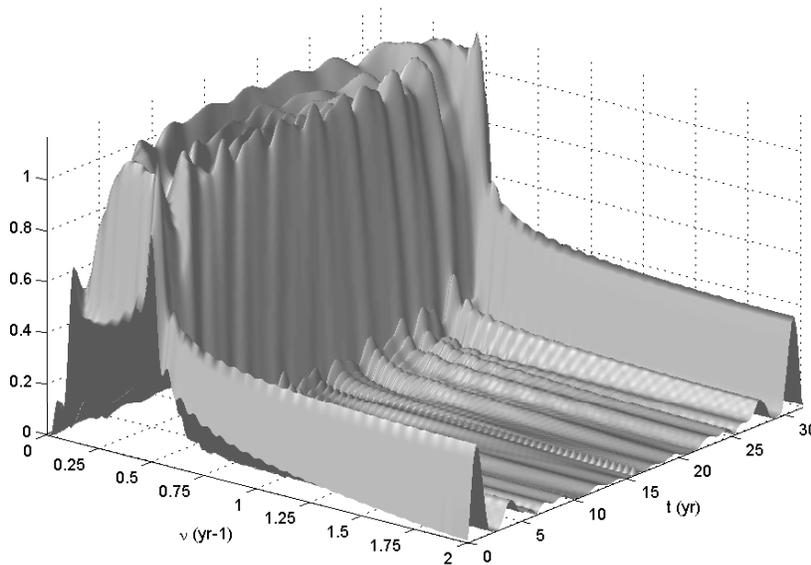


Figure 6: **CF Random Walk Filter (II): Gain.**

data, considering, of course, periodic boundary conditions $u_{N+j} = u_{j \bmod N}$. The asymmetry causes the CF filter response to be complex, and have a nonzero phase. Nonstationarity causes the phase, as well as the real part of the frequency response, to depend on both frequency *and* time.

The gain $G(\nu, t) = \sqrt{(\Re H_{CF}(\nu, t))^2 + (\Im H_{CF}(\nu, t))^2}$ of the CF filter frequency response and its standardized phase

$$\tilde{\Phi}_{CF}(\nu, t) = \frac{\Phi_{CF}(\nu, t)}{2\pi\nu} = \frac{1}{2\pi\nu} \arctan \left(\frac{\Im H_{CF}(\nu, t)}{\Re H_{CF}(\nu, t)} \right), \quad (24)$$

which measures the number of lags in units of Δt , are reported in Figures 6 and 7, respectively. The figures have been obtained for 128 points of quarterly data and a passband of $[2, 8]$ years. By looking at the gain (Figure 6), we notice some leakage in the upper part of the spectrum that is particularly pronounced for at least the first and last three years of data, which should therefore be discarded.

As for the phase, Figure 7 shows the spurious shifts induced in the signal by the CF filter. The absolute value of the phase reaches a maximum of approximately 1.6 quarters for certain components inside the passband. Some components can thus experience shifts up to ± 5 months, causing a maximum *relative* shift of almost one year. With the introduction of a spurious time- and frequency-dependent phase, timing and correlation properties among different frequency components within the series are irreversibly modified and cannot be recovered. The same happens to the correlation and causality relations among different series.

To make direct comparisons with the “two-dimensional” filters, we also plot the frequency response of the *symmetric fixed-length* version of the Christiano-Fitzgerald random-walk filter in Figure 4. Note that also the frequency response plots in Christiano and Fitzgerald (2003) are obtained for this version of the filter. Because of the divergence of the random-walk spectral

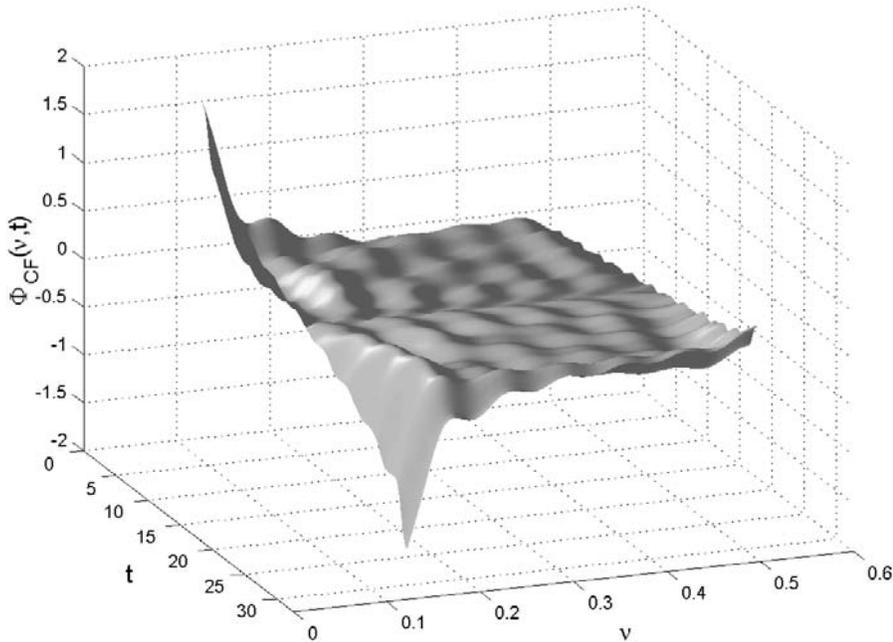


Figure 7: CF Random Walk Filter (IV): Phase.

density at low frequencies, the optimization puts strong emphasis on the behavior near the origin and attenuates these components well (see Figures 4 and 6). This comes at the price of a mediocre removal of high-frequency components. As in the case of BK filter, the poor performance at high frequencies stems from the increased discontinuity at the edges of the filter, once the spurious nonzero amplitude in the origin $H(0)$ has been transferred there. Of course, if the input signal has very small components at high frequencies, as is indeed the case of a real random walk, their leaking in the passband is irrelevant. On the other hand, if it is not clear whether the data can really be modeled as a random walk, as in the case of a growth rate, this filter is a rather poor approximation to the ideal one.

In our opinion, the advantages of the CF random-walk filter are minimal compared to its shortcomings. First of all, the introduction of the assumed spectral density in (21) to find the *optimal* filter adds a step in the computation of the filtered series (and not an easy one), specifically, the estimation of the data-generating model. This is a radical change from the “philosophy” of the other three filters: from a purely descriptive tool to a model-based methodology. But this is its least problem: there is a whole stream of research on model-based filtering (Gomez (2001); Harvey and Trimbur (2003a)). In fact, the filter finally proposed by Christiano and Fitzgerald is not optimal, but *nearly optimal*: the one they obtain by keeping the hypothesis of a random-walk for any time series. This procedure is dubious for at least two reasons: (i) the plausibility of the hypothesis, since, as they write themselves, “This approach uses the approximation that is optimal under the (*in many cases false*) assumption that the data are generated by a pure random walk” (in Christiano and Fitzgerald (2003), p.436, emphasis added); and (ii) if all the beauty and improvement of the method were in the search for the optimal filter for a given series, why spoil it by choosing the same spectral

density, irrespective of the series? What is the point of using such a complex method to obtain a filter that might work *ex post*, but for obscure (at least to us) reasons?

In a few words, besides the standard leakage and compression problems, this filter has two serious shortcomings: it is time-varying and asymmetric. This has at least two consequences. The first is that nothing can be said about the stationarity of the output signal, even if the input is itself stationary. The second is that the time- and frequency-dependent phase shift implies the loss of all timing relations between two series, a loss that can be crucial, as in, for example, the case of the Phillips curve. A fair amount of work has been done on the issue of its “reappearance” in business cycle components (Haldane and Quah (1999); Gaffard and Iacobucci (2001) and Stock and Watson (1999); Christiano and Fitzgerald (2003)), but one must be aware that, once a phase shift is introduced like that of the CF filter, it changes the correlation function between inflation and unemployment. This may modify the form of the Phillips curve, making any further investigation meaningless.

Finally, we remark that nonstationary filters do not preserve purely harmonic signals, as we show in Section 5.1.

5 Applications

5.1 Comparison on the Basis of an Artificial Series

To test the performance of all the previously considered filters on known grounds, we apply them to an artificial series given by a simple harmonic, thus stationary, signal containing only two periods, that is, 6 years and 1.5 years

$$u_j = \sin\left(\frac{2\pi j}{24}\right) - 0.15 \sin\left(\frac{2\pi j}{6}\right), \quad (25)$$

where $j = 1, \dots, 120$ and the data are supposed quarterly, that is, 30 years of data. We filter (25) on the band [1.5, 6] years, so that both cutoff frequencies are submultiples of the signal duration.

The results are shown in Figure 8. The first thing we notice is that the HW filtered series suffers less from compression than the others, while the HP filtered series loses approximately 50% of the original amplitude. Second, ignoring for obvious reasons the BK filtered series, the edges of the HW-filtered series follow those of the original series remarkably well, as is expected for harmonic series, while both the CF-filtered and the HP-filtered series depart from them. Third, the HP-filtered series shows, as we expected, a slight phase shift at the edges, whereas the CF-filtered series has a progressive phase drift that affects each frequency component differently, since the shape of the original signal is not preserved. Thus, not surprisingly, a stationary signal containing 1.5 years and 6 years components is turned, after application of the CF filter, into a nonstationary one, the phase between the two components varying with time while their *mean* frequencies have been increased to $(1.49 \text{ years})^{-1}$ and $(5.7 \text{ years})^{-1}$ respectively.

All these shortcomings become less important when the series length is increased, but operationally the CF filter, rather than being a filter in the acknowledged sense, is best described as a smoothing procedure whose effect on frequency components can hardly be established.

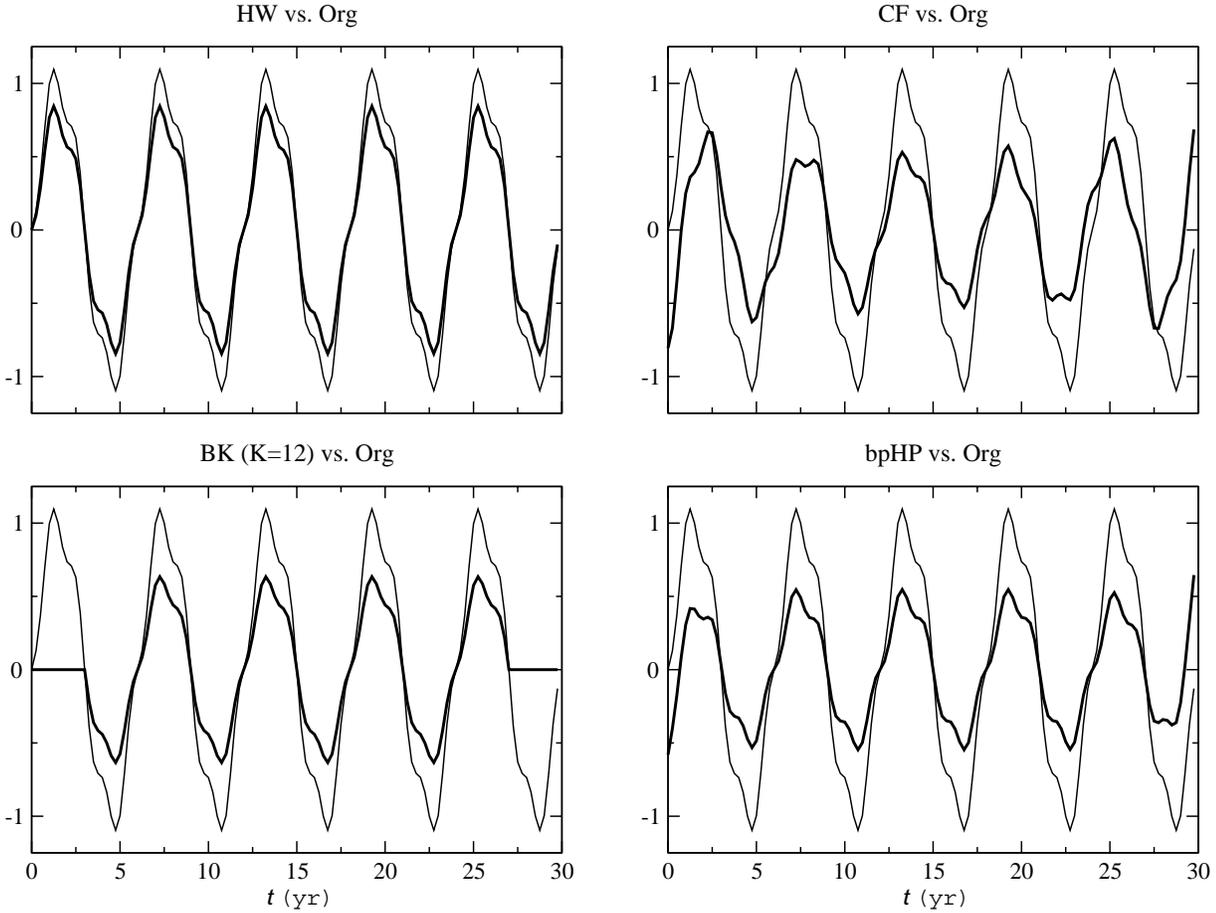


Figure 8: **Application to an Artificial Series.**

5.2 Application to the Euro Zone Gross Domestic Product

In this section, we show the effect of different filters on real data. We choose as an example the quarterly series of Euro zone gross domestic product (Figure 9, left panel), from 1970:I to 2001:IV, thus 32 years (128 data points). The chosen band is $[2, 8]$ years, thus the frequency responses of the applied filters are exactly those plotted in Figures 4, 6, and 7. We emphasize that we choose the above-mentioned band since it is virtually equivalent to the “definition” of the business cycle ($[1.5, 8]$ years) given in Baxter and King (1999), and the duration of the series is multiple of both cutoff frequencies, which are thus harmonic with respect to the signal. The length of the series is also modified for this purpose. The condition of harmonicity of the cutoff frequencies with respect to the signal duration ensures the best performance of frequency filters.

We choose the CF random-walk filter in its recommended non-symmetric, non-stationary version. For the BK filter we choose $K = 16$ instead of 12, the value suggested in Baxter and King (1999), for reasons stated in Section 4.2. As for the HP filter, we choose its original, time-domain recursive version (11). We apply it twice, once with $\lambda \approx 677$ (677.1298) to obtain an 8 year-cutoff highpass filter and the other with $\lambda \approx 3$ (2.9142) for the 2 year-cutoff

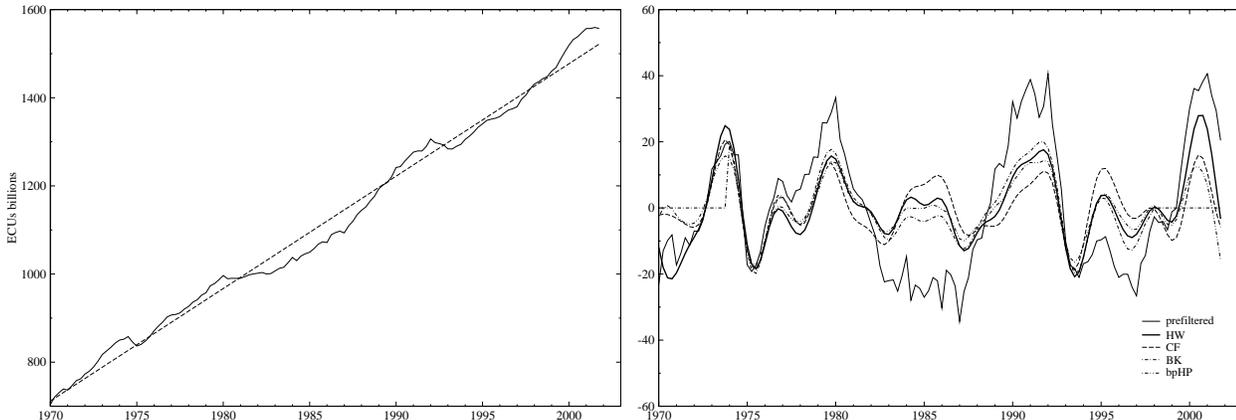


Figure 9: Raw and Filtered Euro Zone GDP series.

highpass filter. We subtract the second series from the first, so that we finally select the desired frequency band from the original series. For both the HW and the CF filters, the data are linearly detrended prior to filtering. The least squares line is shown in Figure 9 (left panel); it is highly significant. The detrended series is then *prefiltered* by means of a lowpass HW filter with $\nu_L = (16 \text{ years})^{-1}$, to ensure covariance stationarity and allowing the definition of the spectrum (dotted line in Figure 10). Finally, we apply the four bandpass filters to the resulting series.

The filtered series are shown in Figure 9 (right panel). Despite the fact that they have similar shapes, the amplitude of their fluctuations differs, especially near the edges. In the HP case, this is due both to the strong filter compression and to the introduced phase shift, whereas in the BK case, it is evidence of both the compression and the truncation of the coefficients. Instead, it reflects the non-stationarity of the CF filter, whose response amplitude decreases close to the ends of the data set (see Figure 6).

To assess the quality of the filtering procedures, we plot, as an estimate of the true spectra, their periodograms

$$\begin{aligned}
 P_u(k) &= \Delta t \sum_{J=-(N-1)}^{N-1} \gamma_{uu}(J) e^{-i2\pi Jk/N} \\
 &= \Delta t \sum_{J=-(N-1)}^{N-1} \gamma_{uu}(J) \cos \frac{2\pi Jk}{N}, \tag{26}
 \end{aligned}$$

where $\gamma_{uu}(J) = \gamma_{uu}(-J) = N^{-1} \sum_{j=-(N-J)}^{N-J} (u(j) - \bar{u})(u(j+J) - \bar{u})$ is the estimator of the series autocovariance function at lag J . Of course, one may object to the non consistency of the chosen spectral estimator. Nevertheless, each filter actually operates on the periodogram, and, besides, the comparison is made at constant N . For these reasons we believe that the periodogram can be used to check which, among the four filters, is the best approximation to the ideal filter.

The periodograms of the four filtered series are plotted against those of the prefiltered in Figure 10. The HW filtered series spectrum (top-left panel) almost exactly reproduces the original frequency components inside the selected band and vanishes outside, except for the frequency components near the band edges, which are compressed by the (necessary) smoothing

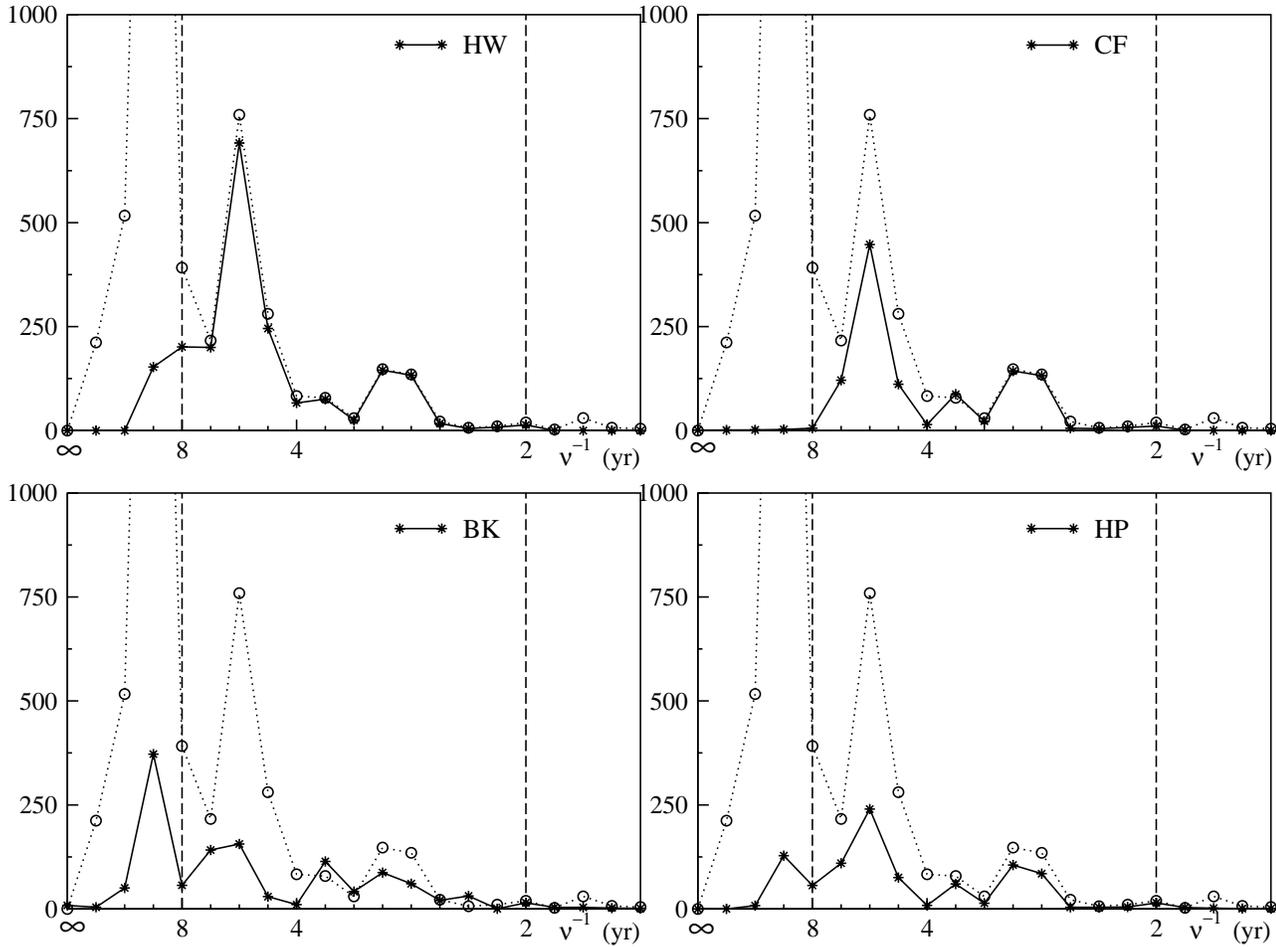


Figure 10: Spectra Obtained by the Different Filtering Operations.

of the rectangular window. The CF filter causes significant compression (top right panel) in the left part of the band. Moreover, though it performs a better attenuation than the HW filter near the lower bound of the frequency band, there is a bothering leakage left at low frequencies (high periods), between $\nu = \nu_l$ and $\nu = 0$. Apart from compression, which is, however, more pronounced than in the case of the CF filter, the BK filter (bottom left panel) does not preserve the relative amplitudes of the components. This is due to the fluctuation of its frequency response in the passband. Furthermore, the BK filtered series spectrum shows high leakage in the low-frequency stopband. Contrary to the previous one, the HP filter, instead, leaves the proportion among components unaffected inside the passband. Furthermore, it has a much lower leakage at low frequencies compared to the BK filter. This is visible also in Figure 4.

6 Conclusions

To obtain an “ideal” filter, one filter selecting a finite range of frequencies with infinite resolution, requires an infinite number of data. With finite data, which is like having a lag window on an infinite-length signal, an ideal filter cannot be realized, and compromise is necessary. Simply truncating the filter coefficients to match the signal length produces a filter that is optimal in the least-squares sense, but displays strong leakage and large ripples in its frequency response. Most often, one is prepared to give up a faster transition between passband and stopband to obtain a more reduced leakage. This is the aim of the windowed filters we propose here. In particular, the HW filter attenuates undesired components by a factor of more than 100, even for short-length time series.

The windowed filters can be designed for a given signal length and used to filter either in the time or in the frequency domain. We prefer the latter, since using the whole signal length to compute filtered values, improves the frequency resolution by exploiting all available information. The resulting filters are both stationary and symmetric, which are fundamental properties for preserving *all* timing relations among frequency components within the same series or across different series. Moreover, bandpass and highpass windowed filters are able to stationarize at least an $I(2)$ process.

The good performance of the HW filter in rejecting the off-band frequency components is checked by means of a comparison with the BK, the CF, and the HP filters. We present a critical, in-depth review of these last three filters and confront them with the HW filter. This is done on the basis of their frequency response and their action on both artificial and macroeconomic time series. The HW filter proves to be a better performing tool for the empirical study of business cycle and for establishing the correlation properties of the variables of interest.

Finally, for the seek of completeness, we deem it advisable to mention the main limit of these nonparametric filtering procedures, that is, their inability to extract the cycle component if the series is known to have an integrated trend (Benati (2001); Murray (2003)). Indeed, the integrated trend spectral amplitudes are non-zero over the whole frequency range and they inevitably add to those of the cycle. Once the spectra have melted together, the only way to separate the different (trend and cycle) contributions *within* the individual frequency component is model-based filtering, since a nonparametric bandpass filter can perform separation only among *different* components. Nevertheless, if we have no prior information on the data-generating process, the non-structural method of spectral filtering has, in our opinion, equal dignity as the model-based approach in extracting the business cycle. In the end, it is a matter of business cycle definition, a thorny subject that has a long history in empirical economics (Mills (2003)), but goes beyond the scope of this paper.

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