Growth Cycles in Argentina's: The Recent Behavior | Daniel E. Perrotti | Revista Económica La Plata, Vol. LXVII, Nro. 1 | Enero-Diciembre 2021 | ISSN 1852-1649 | https://doi.org/10.24215/18521649e23 | https://revistas.unlp.edu.ar/economica | Facultad de Ciencias Económicas, Universidad Nacional de La Plata | La Plata | Buenos Aires | Argentina

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Growth Cycles in Argentina: The Recent Behavior

Ciclos de crecimiento en Argentina: comportamiento reciente

Daniel E. Perrotti[1]

ABSTRACT

This article presents a characterization of Argentina's gross domestic product (GDP) cycles of the last four decades. The extraction strategy follows two well-known approaches: the classic and the growth cycle. Both approaches show related results in terms of the number of cycles; cycles' duration; the prevalence of expansions to contractions' duration; cycles' dating; and, the intensity of the different phases. The selection criteria used in the literature allowed the Christiano and Fitzgerald (CF) filter to stand out with desirable characteristics for Argentina's GDP series over the rest of the alternatives considered in the growth cycle analysis.

Keywords: Business Fluctuations, Cycles, Latin America, Caribbean

RESUMEN

Este artículo presenta una caracterización de los ciclos de crecimiento de Argentina de las últimas cuatro décadas. La estrategia de extracción reposó en dos métodos ampliamente conocidos: el enfoque clásico y el enfoque del ciclo de crecimiento. Ambos enfoques muestran resultados similares en términos de: el número de ciclos, la duración de los mismos, la prevalencia de duración de las expansiones por sobre las contracciones, la datación de los ciclos, y la intensidad de las diferentes fases. En el enfoque del ciclo de crecimiento, el filtro de Christiano y Fitzgerald (CF), en su aplicación empírica sobre el producto interno bruto (PIB) de Argentina, exhibió ciertas características deseables en comparación con otros filtros también contemplados en el análisis.

Palabras claves: Ciclos, Fluctuaciones Económicas, América Latina, Caribe

Recibido: 28/04/2020. Aceptado: 13/07/2021
Clasificación JEL: E32, N16

Acknowledgments: The author would like to thank the valuable comments and suggestions on previous versions of this article by anonymous reviewers, Mr. Daniel Sotelsek, Mr. Ricardo Sánchez, and Mr. Jorge Streb.

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I. INTRODUCTION

Over the last decades, Argentina's economy experienced high macroeconomic volatility that provides fertile ground for business cycles (BCs) analysis. This document carries out a partial approximation of Argentina's BCs by extracting and characterizing the GDP cycle. With this goal in mind, two approaches have been applied: the classic and the growth cycles. Comparing the quarterly GDP cycles characterization of these two methodologies and selecting based on previous literature criteria between different univariate filters are two contributions of this study to Argentina's literature on the subject.

The GDP's cycle is a partial approximation to a broader concept of BCs that rests on the concept of *aggregate economic activity*. Consequently, this research's findings should be taken cautiously as a proxy of Argentina's BCs, requiring of future corroboration by studies with a set of variables compatible with a comprehensive representation of the BCs.

The main findings are: 1) the use of the Christiano and Fitzgerald filter for extracting Argentina's GDP cycles stands out as the one with the most desirable characteristics compared with three alternative univariate filters; 2) Argentina's GDP for the period 1980q1 to 2018q2 shows cycles with an average duration between three and a half and four years, where expansions surpass contractions in terms of duration and, in the classic approach, also in amplitude. These findings are in line with those of former studies in the subject.

The rest of the paper is organized as follows: the next section introduces the concepts behind BCs, including a literature review of Argentina's BCs and references to cycles extraction comparison. Section 3 presents the four selected univariate filters applied in the article. Empirical findings are presented in section 4. A comparison with the results from two previous articles is done in section 5. Finally, section 6 highlights some conclusions. The article is complemented with annexes.

II. BUSINESS CYCLES

The interest in BCs has a long tradition in economics that could be traced as back as 1819 (Škare and Stjepanovic, 2015). In the modern era was Burns and Mitchell (1946) and Burns and Mitchell (1935) who placed the concept as follows:

"*BCs are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions and revivals which merge into the expansion phase of the next cycle*".

This definition presents the cycle as movements in the aggregate level of economic activity. Under this approach—defined as the *classic approach* by Zarnowitz and Ozyildirim (2006)—only fluctuations with frequencies higher than cyclical (seasonal, irregular, and outliers) are smoothed out before the analysis. Besides, the identification of the BCs is based on absolute changes in the general level of the economic series by identifying of its turning points. As a result, a BCs upswing (downswing) requires an increase (decline) in the absolute level of the aggregate economic activity index, i.e., positive or negative rates.

Pater (2014) describes four important characteristics of the classic approach: 1) BCs are fluctuations in the economic activity lasting from 1.5 to 8 years; 2) BCs are not periodic but have a finite frequency interval; 3) the amplitudes of the BCs are irregular; 4) there are differences between general behavior and cyclicity of different macroeconomic aggregates.

In the 1960s emerged a divergent approach that would be later known as the *deviation or growth cycle approach* (i.e. Mintz (1974)). In contrast with the classic, this approach considers the cycles as deviations from the economic potential or *long-run trend*. A fundamental related decision lays on selecting the methodology for detrending the data, being several available methods depending on the assumptions about

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the nature and characteristics of the time series' Data Generating Process (DGP). This approach is also related to the literature pioneered by Lucas (1972) and Kydland and Prescott (1982) on Real Business Cycles (RBCs) in the sense that RBCs describes cyclical fluctuations as deviations from the GDP trend. However, a substantial difference is that RBCs seeks to explain the causes behind BCs fluctuations rather than dating them.

There are pros and cons of each methodology. For example, Pater (2014) highlights that the cycles are not clearly visible and distinguishable from their trend in the classic approach. In addition, van Ruth et al. (2005) mention that if there is a continuous positive growth there is little track of the characteristics of the BCs development: *it seems rather arbitrary to define a small decline as a slowdown or recession, but not an almost zero, but still positive growth*. Moreover, the definition of the classic BCs accounts for changes in the aggregate economic activity but does not define which set of variables should be included in it.

The growth cycles approach is not free of criticisms. Perhaps, the most important pitfall is highlighted by Canova (1994, 1999), who demonstrates that the statistical properties of the extracted cycles are sensitive to both the detrending procedure and the dating rule. Moreover, Morsink et al. (2002) highlights that methodology of growth cycles tends to overestimate the frequency of turning points and underestimate their amplitude compared with the classic approach.

II.1 BUSINESS CYCLES IN ARGENTINA

Following a chronological order, highlights the document by Kydland and Zarazaga (1997) where the authors analyze whether the BCs of Argentina presents regularities like those observed in the United States (US) and Europe. These authors maintain that Latin America's academic tradition has favored the explanation of cycles produced by nominal shocks (mainly monetarist), which would be refuted empirically. In this sense, they find that after the implementation of Exchange Rate Base Stabilization (ERBS) programs no real effects on consumption were observed.

The document applies the Hodrick-Prescott (HP) filter to two different Argentina's GDP series before seasonally adjusting them using the X-11 methodology. They use two GDP series (one by Argentina's Central Bank and the other from a private research center) because, as common in several developing countries, there exists problems with data reliability to the point that *"BCs features of Argentina can change substantially from one national account estimate to the next"*. They find that the volatility in Argentina's GDP is higher than in the United States and some European countries, and emphasize that RBCs models could explain much of it (Kydland and Zarazaga, 1997).

The paper by Cerro (1999) measures and describes the main characteristics of the Argentina's growth cycle for 1820-1998. The author merges quarterly annual data from various sources, using both the GDP and the industrial production. She finds for 1970-1998, eight cycles of an average duration of 3.2 years, and an average amplitude of 0.09. The dissection between trend and cycle is achieved by applying the HP filter following the growth trend approach.

Trajtenberg (2004) studies Argentina's GDP cycles by extracting them from the quarterly period 1980-2001 using deterministic and stochastic methods (linear and polynomial trends in the former, Beveridge and Nelson, and Hodrick-Prescott in the later). The author highlights the primary conclusion that it does not exist a unique method for decomposing a macroeconomic time series. The election between one method over others depends on the type of faced problem and the properties of the DGP of the series.

The document by Baccino (2005) studies the cycles of the Monthly Economic Activity Estimator (EMAE), the Gross Agricultural Product, and the value added (VA) in Manufactures, for the period January 1993–February 2006. He models these series' dynamic by disaggregating them into their principal components and estimating models for each component. A characteristic of this document is that, although it uses frequency domain concepts, trends are smoothed by applying first differences.

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The chapter by Jorrat (2005) presents a comprehensive analysis and construction of monthly composite coincident and leading indexes of Argentina. The chapter shows the turning points of Argentina's business and economic cycles detected from the coincident index[2] for the period 1970-2005. The main characteristics of the BCs are[3] : 7 expansions (with a duration of between 5 and 19 quarters, and a median of 10 quarters) and 6 recessions (with a duration of between 2 and 17 quarters, and a median of 5 quarters). The median duration of the BCs is 13 quarters (with a minimum of 10 and a maximum of 29).

Díaz (2007) analyzes the BCs using quarterly data for the period 1988-2006 and applies the HP filter for extracting the cycles. As in the Kydland and Zarazaga's paper, she compares the regularities of Argentina's BCs with other economies finding similarities, although, the volatility of Argentina's GDP is higher again. The paper also describes the BCs using a set of economic series where the GDP is the benchmark.

Finally, a recent work by Gadea and Sanz-Villarroya (2020) analyses Argentina's BCs in a long-run approach for the period 1870-2015, finding that frequent deep busts and short booms characterize Argentina's cycle, offsetting its long-term growth potential. For reaching this conclusion, they study for Argentina, Australia, and Canada, the influence of short-term shocks (cyclical factors) on the long-term behavior (secular factors). They try to explain what happened with Argentina after the middle of the 20*th* century, when the country started a divergence path with the other two, following the methodological approach by Harding and Pagan (2002) which dissects the short and long-term growth through parameters representing mean growth, persistence, volatility, and the ratio between mean growth and volatility. They find that this last ratio is lower for Argentina in the whole period because of lower growth rate and higher volatility; also, Argentina shows less persistence than Australia and Canada.

Gadea and Sanz-Villarroya (2020) then estimate the turning points on the GDP series of these three countries, and present some standard cyclical measures (duration, amplitude, cumulation, and excess of the phases) and specific recovery measures. With these statistics, they find that Argentina shows a differential cyclical behavior after 1945, when expansions are characterized for starting vigorously but vanishing rapidly, with less durability and amplitude than those of Australia and Canada, resulting in a lesser ability for Argentina to resume the long-term trend after a recession (which reflects an influence from the short to the long-term).

II.2 LITERATURE REGARDING CYCLES EXTRACTION'S COMPARISON

Below is presented a short review of articles that deal with comparing results from different extraction methods.

Begining with Cochrane (1988, 1991), who studies the long-run properties (persistence of fluctuations) of the US Gross National Product (GNP) series. He finds dissimilar results compared with previous literature in the sense that the GNP reverts toward a trend following a shock, but after several years, which is consistent with a small random walk component in the GNP series. This result is achieved after studying how long-term forecasts respond to shocks, where the alternatives range from a pure trend stationary process to a pure random walk process. The methodology proposed in the article, that follows the work by Lo and MacKinlay (1989), consists of analyzing the variance of the GNP series' long differences, and allows to conclude that the GNP behavior is consistent with a blend of the two mentioned pure processes. He reaches a similar conclusion by measuring the importance of the permanent (random walk) component

[2] This index is constructed with a set of coincident series that represent the general level of economic activity of the economic cycle. The series are seasonally adjusted and corrected by amplitude and tendency.

[3] Jorrat (2005)'s findings are presented in quarterly terms instead of the original monthly values, in order to facilitate comparison with the results of this document. Likewise, Jorrat's monthly results have been rounded to the nearest quarter.

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of the GNP relative to the variance of GNP annual growth rates. In summary, the US GNP series can be characterized as a series that "*returns toward a trend in the far future but does not get all the way there.*" Finally, one crucial aspect of this methodology is that *"the approach may provide a better approximation in a given small sample than the theory based on a unit root."* This methodology is applied in section 3.4.3.

In Canova (1994), the author employs different detrending methods to compare the extracted cyclical behavior of the US GDP with that from the National Bureau of Economic Research (NBER). He uses 11 detrending methods applied to the US quarterly seasonal adjusted (SA) GDP for the period 1955q3 to 1990q1 and extracts the turning points of the cyclical components using two alternative dating algorithms (which varies in terms of the degree that they capture mild expansions/recessions) that provide substantially different results in terms of path properties. With the milder dating algorithm, *"there are two NBER turning points which are missed by all methods,"* and *"all methods record many false peaks, and many generate cyclical components whose troughs do not line up with standard classifications."* However, with the alternative dating algorithm, *"there is a generalized tendency to miss many turning points of the standard classification."* All in all, the author highlights the importance of both selections: dating algorithm and filtering method.

Park (1996) examines cycles distortion of stylized BCs facts when the time series are integrated by applying three different filters: Hodrick-Prescott, Beveridge-Nelson (BN), and the linear in time (LIT) filter. He affirms that theoretically, the HP filter could be considered between the BN filter (which assumes a unit root component) and the LIT filter (which assumes a deterministic trend). Park finds that the HP filter results in BCs that do not exist in the prefiltered data, situation that deepens with the degree of integration of the prefiltered series: *"HP filter is vulnerable to the unit root components included in the prefiltered series and calls for a precaution against the possible existence of unit roots when the HP filter is applied."* Moreover, the author shows that the stylized facts of the US economy are sensitive to the applied method for detrending the raw series. Another important finding is that the differences between the HP filter and the other two appear to be invariant whether they are applied to the actual or simulated data, being the distortions of stylized facts symmetric.

In Canova (1998a, b), the author presents cyclical properties of a set of real series using different detrending methods. He founds that the second-order properties of the estimated cyclical components vary widely across detrending procedures (with small differential effects at higher moments). He also states that, accordingly, stylized facts of US BCs differ widely across the different detrending methods. In conclusion, the paper indicates that the second moments of the cyclical components are highly sensitive to the filters' choice.

The paper by Burnside (1998) is a reaction to Canova (1998a, b) findings that second moments of cyclical components are susceptible to filters' choices for extracting cycles. Burnside shows that some stylized facts remain robust despite the method selected for detrending. For reaching this conclusion, and after linearly detrending the data, the author introduces estimates of the time series' spectra, indicating that most of the power lies in the low frequencies (declining as the frequency increases). Then, focusing on the cycles between 6q and 32q, he analyses volatility in four macroeconomic series in relation to the output (coherences of cross spectra), highlighting some variability properties presented on these interactions. Finally, he evaluates the phase shifts of the series with the output, concluding that outside the BCs frequencies, there is little tendency for any of the variables to lead or lag cycles in production; however, for some of the variables, the situation reverts inside the BCs frequencies. The main finding is that stylized facts are robust to the filtering method if it removes at least as many variations in the series as the linear detrending method does.

Later in the same article, Burnside explores the results of applying the HP filter and the first differences method to simulated data (where he also proposes a symmetrical treatment of model and data), reporting second–moment properties of the extracted cycles and testing for power in model's selection (between two alternatives DGP). He finds that despite the first differences method provides more power, the HP filter does well enough. Both methods do not have difficulty distinguishing between the true DGP among the

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alternative simulated models. In summary, according to Burnside *"different filters provide different windows through which economists can examine their models and data."* As mentioned before, stylized facts or regularities remain true, despite that the filters may alter some of the second moments.

Guay and St.-Amant (2005) compare, for a set of variables, the spectra of unfiltered series at BCs frequencies with those of their filtered counterparts extracted with the HP and Baxter and King univariate (BK) filters analyzing the dynamics of the cyclical components. They find that the two filters perform adequately when the original series' spectrum peaks at BCs frequencies. However, when low frequencies dominate the spectrum and the spectrum decreases sharply and monotonically at higher frequencies (which is known as Granger shape), the filters induce spurious dynamic properties and extract a cyclical component that fails to capture a significant fraction of the variance contained in the BCs frequencies, being problematic the use of these filters.

In an article split into two issues, Iparraguirre (2009) applies several filters (with deterministic and stochastic approaches) to extract the cycle of Argentina's per capita GDP series for the annual period 1950-2006. The comparison between the different filters is presented in terms of the standard deviations, kurtosis and asymmetry of each filter, the correlation between them, and the estimation of the non-parametric statistic by *Kolmogorov-Smirnov*. Within the results, the Kalman filter shows a lower standard deviation, and most of the methods perform well in terms of kurtosis and symmetry. The correlation analysis indicates that the HP and the linear tendency with structural breaks show the most of it. For its part, the non-parametric test shows that in nineteen of the possible forty-five correlation pairs between the approaches, it cannot be dismissed the null hypothesis of equivalence between the pairs (both samples could be drawn from the same distribution). In conclusion, the author highlights that selecting one method over others relies on the knowledge of historical facts and economic theory in contrast with statistics techniques.

Another important reference that focuses on Argentina is Rabanal and Baronio (2010).

In their article, and after testing for unit root in Argentina's GDP annual series for the period 1880-2009, the authors proceed to extract the GDP cycle by applying different filters with deterministic (polynomic trends and ARIMA with structural changes) and stochastic (BN decomposition, HP filter, and BK Filter) approaches. After extracting the cycles, they compare them in terms of the statistical moments, their co-movement, and the correlation with the GDP growth. The results show the stochastic approaches are better than deterministic alternatives, even though the unit root analysis finds that the DGP could be rendered stationary using a deterministic trend. However, the selection of a specific methodology depends on the preference of the practitioner, in terms of the level of volatility (where the Baxter and King filter imposes with the lowest of it), the extent of co-movement with other approaches (where the Hodrick-Prescott filter sets as the one with highest co-movement with the different methodologies), or the correlation with the GDP growth (where the Baxter-King filter highlights).

More recently, the article by Pomenková and Maršálek (2015) analyses the theoretical[v] and empirical performance of three filters—Baxter-King, Christiano-Fitzgerlad (CF), and the Hamming window (HW)—applied to the extraction of six EU countries' GDP quarterly series (Greece, Ireland, Portugal, Spain, Italy, and Austria). In terms of the theoretical evaluation, the authors numerically estimate the undesired gains and attenuations of the three filters within the BCs frequencies and the undesired leakage outside those frequencies, finding that CF and HW perform better than BK. Similar conclusions arise in the latter part of the article when they apply the filters to actual EU data. Then, the authors compare the obtained cycles with the evolution of German's GDP as a benchmark country, finding that CF and HW show a high correlation with German's BCs; however, the results are dependent on the sample span. Finally, the authors point out that the CF filter is suitable even for small sample sizes.

III. DATA AND METHODOLOGY
III.1 ARGENTINA'S QUARTERLY GDP SERIES

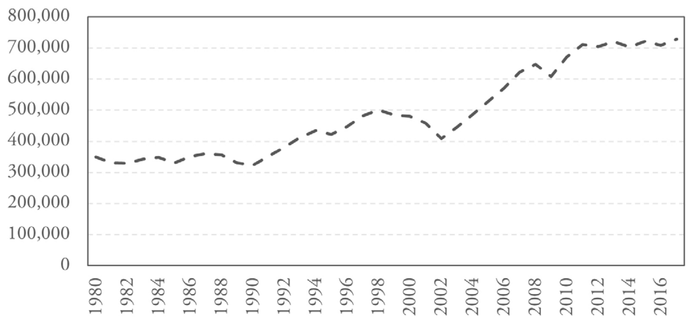
To perform accurate analysis and characterization of BCs in general, and of the GDP in particular, it is preferred to use high-frequency series (i.e., monthly or quarterly data). However, finding a consistent long-term GDP series with quarterly frequency is a difficult task in developing countries, where Argentina is not an exception. Argentina's National Institute of Statistics and Censuses (INDEC) currently has two national accounts data sets that offer quarterly and annual historical figures. One series is at constant prices of 1993 and runs from 1980q1 to2005q4. The other—at constant 2004 prices—begins at 2004q1, ending at 2018q2.[4]

The first issue to be solved with the data set is related to the series' concatenation to make a unique long-term series. Several problems arise when chaining series valuated at different prices and with methodological changes. To reduce these obstacles, it was followed the method proposed by Denton[5], which consists of interpolating a high-frequency series from an original low-frequency series using as a benchmark an associated high-frequency indicator series, ensuring that the new high-frequency series matches the values of the original low-frequency series.

To apply Denton's method, the two Argentina's GDP annual series were linked in the year 2004 to create a new annual GDP series for the period 1980-2004 at 2004 constant prices. Then, Denton's method allows obtaining quarterly GDP series at constant prices of 2004 for the whole period 1980q1 to 2004q4. For doing this, the linked annual GDP was used as the low-frequency series and the quarterly GDP at constant prices of 1993 as the high-frequency indicator, ensuring consistency of the interpolated quarterly GDP series at constant prices of 2004 with the annual GDP series at same prices. Then, linking the period 1980q1-2004q4 with INDEC's latest series, it was obtained a quarterly GDP series at constant prices of 2004 that runs from 1980q1 to 2018q2.

The next step consisted of the SA of the quarterly GDP series.[6] This process is necessary since the applied approaches to extract cycles do not contemplate high-frequency noises (i.e., seasonality) as constitutive of the observed series. The Argentina's quarterly GDP SA series is depicted in Figure 1.

Figure 1: Argentina SA quarterly GDP (constant 2004 prices)



Source: author's elaboration with data from INDEC.

[4] At the moment of writing this paper this was the last value released by the INDEC.

[5] For details of this method see Denton's Denton (1971).

[6] The SA process was carried out using the automatic parameter and model's specification of the Tramo-Seats program. See Gomez and Maravall Gomez and Maravall (1996) and Caporello and Maravall Caporello et al. (2004) for details.

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The following section describes the dating algorithm implemented for the detection of the turning points.

III.2 DATING ALGORITHM

As mentioned before, a key decision of BCs analysis consists in the selection of the dating algorithm. This document followed the algorithm described in Harding and Pagan (2002)[7], which defines a local peak (trough) occurring at (monthly) time *t* whenever:

$$y_t > (<) y_{t\pm k} \quad (1)$$

with k=1,2,…,K

In the case of quarterly data, the definition of a local peak is set to K=2 (censoring rule), implying:

$$\Delta_2 y_t > 0, \Delta y_t > 0, \Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0 \quad (2)$$

which ensures that y_t is a local maximum relative to two quarters on either side of y_t.

For a quarterly local trough, the censoring rule implies:

$$\Delta_2 y_t < 0, \Delta y_t < 0, \Delta y_{t+1} > 0, \Delta_2 y_{t+2} > 0 \quad (3)$$

which ensures that y_t is a local minimum relative to two quarters on either side of y_t.

The computational implementation of this algorithm requires setting up the minimum duration of phases and cycles. This paper follows Pater's insights that cycles last from 1.5 years to 8 years, from which results in a minimum value of 6 quarters for a complete cycle. The minimum length of each phase was set according to the rule of thumb that two consecutive quarters are—at least—required in order to identify an expansion or contraction.

The cycles' extraction in the classic approach emerges directly from the above algorithm. In contrast, the growth cycle approach requires the introduction of filters' methodologies, presented in the next section.

III.3 SELECTED UNIVARIATE FILTERS

The four following univariate filters: Hodrick-Prescott, Baxter-King, Christiano and Fitzgerald; and, Butterworth (BW), that approximate desirable characteristics of the ideal filter—which is presented in conjunction with basic concepts on spectral analysis and the four filters in Annex A—are applied to extract Argentina's GDP cycles.

III.4 UNIT ROOT TESTS

As can be inferred from the previous section, the DGP plays a key role in the selection and properties of the filter's methodologies. In particular, the presence of a unit root in the series is of utmost importance for it. This section begins with a review of the literature on Argentina's GDP integration testing, ending with the empirical application of several tests that favor the non-rejection of the null hypothesis of a unit root process in Argentina's GDP data.

[7] At this point it is important to note that the Bry and Boschan (monthly) algorithm Bry and Boschan (1971), updated later for dealing with quarterly data by Harding and Pagan Harding and Pagan (2002), was initially intended to be used with series in levels and not with long-run trend's deviations as those obtained by applying the growth cycle approach. However, several papers (i.e., Zarnowitz and Ozyildirim Zarnowitz and Ozyildirim (2006), Canova Canova (1999); and Musso Musso (2003)) dated cycles turning points using it; this paper follows this practice.

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III.4.1 BRIEF REVIEW ON UNIT ROOT TESTING ON ARGENTINA'S GDP

Starting with the work by Sturzenegger (1989), who studies Argentina's GDP fluctuations within a structural VAR approach decomposing the original series as a compound of transitory and permanent shocks. The identification problem in this methodology is resolved using restrictions over one additional variable (inflation). He finds that most of the behavior of Argentina's GDP (between 1952q1-1988q1) is due to supply side shocks, which are long memory shocks in contrast with those from the demand side. Before proceeding modeling with a structural VAR, the methodology requires testing for the potential presence of a unit root. The tests (Augmented Dickey-Fuller and Phillips-Perron) do not reject the null hypothesis of a unit root in Argentina's quarterly GDP series.

The work, by Sosa Escudero (1997) tests for the presence of a unit root in Argentina's GDP for the annual period between 1900 and 1993. He considers different alternatives for the potential non-stationarity of the GDP series, including trend stationary, difference stationary, time break models, and methodologies that account for the full sample, recursive, rolling, and sequential tests. The findings are in favor of not rejecting the unit root null in the GDP. Moreover, after eliminating the pre-test bias, the author cannot reject the unit-root hypothesis, even accounting for time breaks. The economic implication that emerges from Sosa Escudero's findings is that *"any shock suffered by the Argentine economy had and will have a permanent effect."*

In the same article, Sosa Escudero tested Argentina's GDP with higher frequency data, using quarterly data from 1970q1 to 1994q2, with similar results as those of the annual sample. However, the author advocates to re-elaborate the analysis reconsidering more extended quarterly time series since *"stochastic properties of GDP series are better characterized by processes with high explanatory power at low frequencies"* (Sosa Escudero,1997).

Similar results are reached by Carrera et al. (2000), who study the integration properties of several macroeconomic series of Argentina from 1980q1 to 1998q4. As in the previous case, these authors consider the possibility of time breaks in the series (including the alternatives of exogenous and endogenous selection of breaks). They perform a battery of tests (parametrics and non–parametrics) that account for different DGP integration properties (including persistence). Among the findings, the authors highlight that Argentina's GDP appears to be integrated of order one, non rejecting the unit root hypothesis. Moreover, based on their results, they appeal for the use of stochastic trends when dealing with cyclical extraction of Argentina's GDP.

In contrast with previous literature, Utrera (2001) finds trend stationarity in Argentina's GDP series, for both the annual period 1913-1999 and the quarterly period 1970q1 to 2000q3, when accounting for structural breaks. To reach this conclusion, the author follows resampling techniques (to obtain small sample distributions of the t statistics used to test the unit root null hypothesis) and endogenous selection of multiple structural breaks. According to the article, Argentina's GDP series seems to be stationary around a trend with one or more structural breaks.

The graduate thesis by Luttini (2008) studies the behavior of the GDP series of Argentina, for the annual period 1900-2000, which is split into two terms 1900-1969 and 1970-2000 according to an exogenous identification of one structural break. The results show that the first subsample is compatible with the trend stationarity hypothesis (with short-term shocks prevailing in total volatility). The later period shows the non-rejection of a unit root process (with long terms shocks explaining most of the volatility of the GDP). The author applies the methodology by Cochrane (1988), studying the relative composition of the variance between a random walk process (the stochastic or long-term component) and a white noise process (the stationary or short-term component) in Argentina's GDP.

In Rabanal and Baronio (2010) work, the authors test for unit root in Argentina's GDP, with annual data for the period 1880-2009, accounting for one structural break (1880-1969 and 1970-2009). They

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find for the whole period and for the first subsample stationarity of the GDP around a deterministic trend. However, for the second period they cannot reject the hypothesis of the presence of a unit root. According to the authors, the whole period's outcome could be influenced by the results obtained from the first and largest subsample.

Guaita's article (Guaita, 2016) performs six-unit root tests for the largest annual sample of Argentina's GDP: 1810 to 2004. The results are in line with most of the previous literature, showing the non-rejection of a unit root in the GDP series for the whole period. The author also tests for structural breaks, finding similar results to those in the entire sample. However, he finds mixed results for one specific sub-period between the Great Depression (1929) and the beginning of the Oil shock (1972), with individual tests that favored non-stationarity becoming weaker or disappearing.

Summing up, the literature is mostly in favor of the non-rejection of the presence of a unit root process in Argentina's GDP series. However, there is some reserve regarding the potential existence of structural breaks that could turn the series trend-stationary in the period before the 1970s. For the latter period, there is almost unanimity about the presence of a unit root process. A summary of literature's results is presented in Table 1.

III.4.2 TESTING ARGENTINA GDP FOR A UNIT ROOT

Considering previous literature results and the fact that this paper examines Argentina's GDP quarterly series starting at 1980q1, all the efforts were focused on testing for the null of a unit root without accounting for possible structural breaks in the series.[8]

The unit root tests applied are: the Augmented Dickey-Fuller, the Phillips-Perron, and the Dickey-Fuller–Generalized Least Squares (DF–GLS). According to the results, presented in Annex B and in line with the literature, it cannot be rejected the presence of a unit root process in Argentina's quarterly GDP series. In this regard, it is important to remind that in the growth cycle approach the four methods are suitable for dealing with stochastic trends from integrated processes.

Table 1: Unit root in Argentina's GDP series: literature main results

	Period	Frequency	Main Results
Sturzenegger (1989)	1952q1-1988q1	quarterly	I(1)
Sosa Escudero (1997)	1900-1993; 1970q1-1994q2	annual and quarterly	I(1), even after testing for structural breaks.
Carrera et al. (1999)	1980-1998	quarterly	I(1), even after testing for (endogenous and exogenous) structural breaks.
Utrera (2001)	1913-1999; 1970q1-2000q3	annual and quarterly	I(0): stationary over a deterministic trend (dt).
Luttini (2008)	1900-2000	annual	1900-1969: I(0) over dt. 1970-2000: I(1).
Rabanal and Baronio (2010)	1880-2009	annual	1880-2009: I(0) over dt. 1880-1969: I(0) over dt. 1970-2009: I(1)
Guaita (2015)	1810-2004	annual	1810-2004: I(1). 1929-1972: compatible with I(1) or I(0) over dt.

Source: author's elaboration.

III.4.3 VARIANCE RATIO ANALYSIS

In addition to above tests, it is applied the variance ratio test by Cochrane (1988) and Lo and MacKinlay (1989) to evaluate the magnitude of the random walk component in Argentina's quarterly GDP series.

[8] Nevertheless, as an academic exercise it was performed the unit root testing procedure suggested by Perron, with results that did not reject the null of integrated process without structural breaks.

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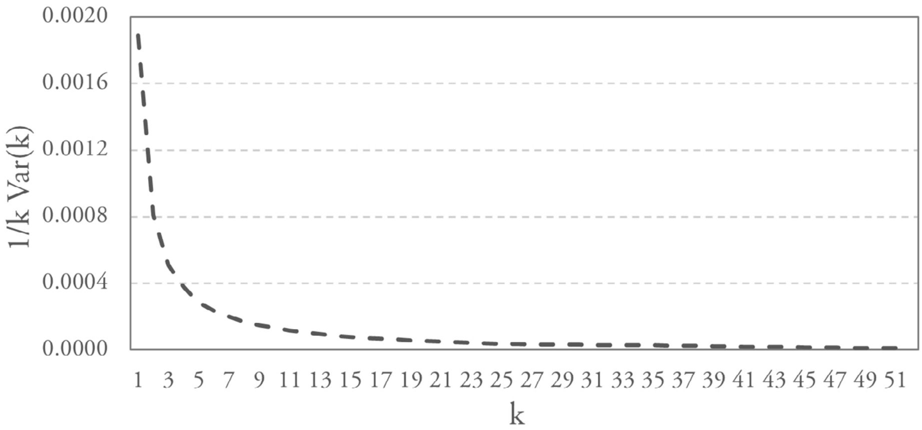
The methodology is detailed in the Annex C.

Applying the methodology to the natural logarithm of Argentina's quarterly GDP series—also in Annex C—shows the non rejection (including treatment for potential heteroscedasticity) for selected variance ratios of the presence—even after 20 years—of a random walk component in the GDP series.

Moreover, in Figure 2 it could be seen the presence of this random walk structure in the variance where *1/kVAR(k)* declines smoothly with the increase of *k*.

Figure 2: *1/k* times the variance of the *k*-differences of log of Argentina's GDP



Source: author's elaboration.

III.5 FILTERS' CALIBRATION

The selection criteria for the final parameters of each filter, except the HP filter, is based on the closest approximation of the filters' gain function to the ideal filter, which was reached by an iteration process. The figures with the final gains of the filters are presented in Annex D. In the HP filter was followed the parameter selection method proposed by Ravn and Uhlig (2002) that assigns to the parameter lambda a value of 1600 and 6.25 for quarterly and annual frequencies, respectively. Table 2 resumes the final parameters used on each filter.[9]

Table 2: Parameters' calibration

Filter	Parameter	Value
HP	Lambda	1,600
CF	SMA	10
BW	SMA	5
BK	Order	12

Source: author's estimations.

IV FINDINGS

IV.1 CLASSIC APPROACH

The number of complete cycles observed in the classic approach accounts 9 measured from peak to peak (PP) and 8 from trough to trough (TT). On average, a complete cycle is observed around 4 years, with expansions of 2.5 years and contractions of almost 1.5 years. The most extended cycles from PP corresponds to 2000q4-2008q2 (30 quarters), and 1987q3-1994q4 (29 quarters); while 2002q1-2009q2 (29 quarters) for TT cycles. The largest expansion is 2002q1-2008q2 (25 quarters), and 1987q3-1990q1 (10 quarters)

[9] For the CF filter; it was applied the drifted version based on the results of the unit root tests.

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the largest contraction. Regarding amplitudes[10], stand out the expansions of 2002q1-2008q2 (63.3%) and 1990q1-1994q4 (44.2%); and the contractions of 1987q3-1990q1 (-16.8%) and 2000q4-2002q1 (-16.5%). On average, the ratio of contractions to expansions duration is 0.5. Details are presented in Table 3.

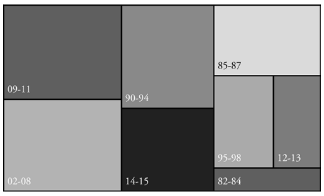
Table 3: Classic Approach

	Turning Points		Cycle Duration		Phase Duration			Amplitude	
	Peak	Troughs	P-P	T-T	Exp.	Cont.	C/E	Exp.	Cont.
1	1980q3	1982q2				7			-8.7%
2	1984q2	1985q3	15	13	8	5	0.6	9.9%	-9.5%
3	1987q3	1990q1	13	18	8	10	1.3	16.2%	-16.8%
4	1994q4	1995q2	29	21	19	2	0.1	44.2%	-5.3%
5	1998q2	2000q2	14	20	12	8	0.7	20.5%	-6.0%
6	2000q4	2002q1	10	7	2	5	2.5	1.7%	-16.5%
7	2008q2	2009q2	30	29	25	4	0.2	63.3%	-11.1%
8	2011q3	2012q2	13	12	9	3	0.3	23.2%	-5.7%
9	2013q2	2014q3	7	9	4	5	1.3	6.1%	-4.2%
10	2015q2		8		3			6.1%	
	Mean		15.4	16.1	10.0	5.4	0.5	21.2%	-9.3%
	Stand. Dev.		8.4	7.3	7.6	2.5	0.8	20.3%	4.7%

Source: author's estimations.

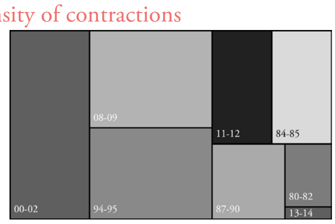
In terms of intensity of expansions highlight 2009-2011 and 2002-2008 (as seen in Figure 3), and the contractions of 2000-2002, 2008-2009, and 1994-1995 (Figure 4).

Figure 3: Classic approach: intensity of expansions



Source: author's elaboration.

Figure 4: Classic approach: intensity of contractions



Source: author's elaboration.

IV.2 GROWTH CYCLE APPROACH

IV.2.1 MAIN FINDINGS

The number of complete cycles—presented in Table 4—from the different methods is quite similar. The BW methodology has the most (11 PP and 10 TT), while the BK with (8) shows the least (due to estimations' constraints). The HP and CF filters present similar number of cycles.

Table 4: Number of cycles

Methodology	Peak to Peak	Trough to Trough
Classic	9	8
HP	10	9
CF	9	9
BW	11	10
BK	8	8

Source: author's estimations.

[10] In the classic approach, amplitudes of expansions (contractions) are measured as the percentual variation in Argentina's GDP between troughs (peaks) and peaks (troughs).

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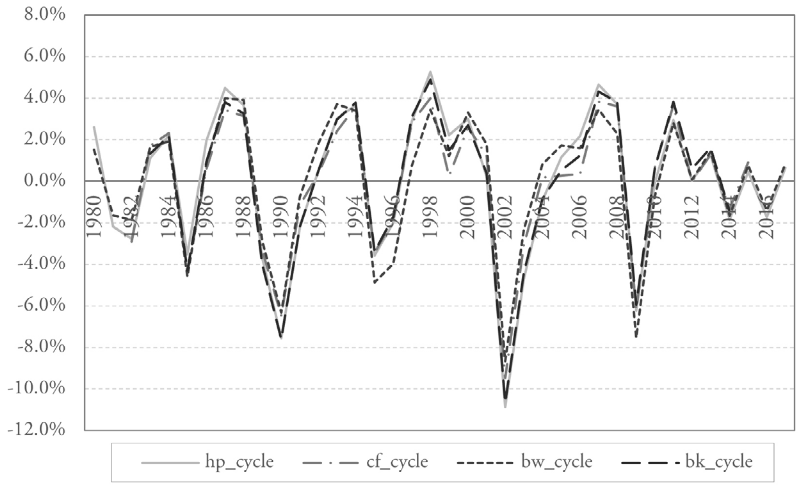
The dating comparison is performed by using the Classic approach as the benchmark.[11] The results presented in Table 5, show that—on average—turning points for both peaks and troughs are closely connected across the four methods. However, highlights that the CF and the BK filters show the lowest combined (peaks and troughs) mean and volatility.

The correspondence observed in the turning points is extended to the general behavior of the cycles, showing high values of cross-correlation, as can be visually observed in Figure 5 and numerically in Table 6.

Figure 5: Argentina's quarterly GDP cycle by filtering methodology



Source: author's elaboration.

Regarding duration, the different methods estimate cycles that are accomplished between three and three and a half years, with the BK filter showing the largest duration. Disaggregation by phases shows that in all filters expansions present longer duration than contractions, with an average slightly below to 2 years, and contractions averaging almost 1.5 years. The most significant expansion is observed in the BK (9.1 quarters), while the shortest in the BW (6.8 quarters). Concerning contractions, all methods show similar results (between 5 and 6 quarters), with the HP filter (6.1 quarters) being the largest and the BK the least (5.3 quarters).

On average, the ratio of contractions to expansions is 0.7. Table 7 accounts for these results.

Table 5: Dating: leads (-) and lags (+) relative to peaks and troughs from the turning points of the classic approach

	Reference T-PS	HP		CF		BW		BK	
	Peaks-Troughs	P	T	P	T	P	T	P	T
1	1980q3-1982q2	0	0	X	X	1	0	X	X
2	1984q2-1985q3	0	0	0	0	-3	0	0	0
3	1987q3-1990q1	0	0	2	0	-4	0	2	0
4	1994q4-1995q2	-5	2	-2	2	-5	2	-2	2
5	1998q2-2000q2	0	-4	-1	-4	0	-4	-1	-4
6	2000q4-2002q1	-4	0	1	1	0	0	0	2
7	2008q2-2009q2	0	0	-1	0	-4	0	-1	0
8	2011q3-2012q2	0	0	-1	1	0	0	0	1
9	2013q2-2014q3	0	0	0	0	0	0	0	0
10	2015q2-	0	X	X	X	0	X	X	X
	Mean	-0.9	-0.2	-0.3	0.0	-1.5	-0.2	-0.3	0.1
	Std. Dev.	1.9	1.5	1.3	1.8	2.2	1.6	1.2	1.9

[11] Those cycles not presented in the classic approach were dropped in Table 5.

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Table 6: Cross-correlation matrix

	Cycle Duration		Phase Duration		
	P-P	T-T	Exp.	Cont.	C/E
HP	13.9	14.3	7.8	6.1	0.8
CF	12.9	12.9	7.4	5.4	0.7
BW	12.5	12.9	6.8	5.7	0.8
BK	14.5	14.5	9.1	5.3	0.6
Average	13.5	13.7	7.8	5.6	0.7

Source: author's estimations.

Table 7: Average cycle and phases lengths in Argentina's GDP by type of filter

	Cycle Duration		Phase Duration		
	P-P	T-T	Exp.	Cont.	C/E
HP	13.9	14.3	7.8	6.1	0.8
CF	12.9	12.9	7.4	5.4	0.7
BW	12.5	12.9	6.8	5.7	0.8
BK	14.5	14.5	9.1	5.3	0.6
Average	13.5	13.7	7.8	5.6	0.7

Source: author's estimations.

Table 8 presents the results of the coefficients of variation (CV) of amplitude and duration.[12] The average results of the CV of *amplitude* show that contractions have higher variability than expansions (0.59 vs. 0.49). Likewise, contractions show more dispersion of the CV than expansions. Besides, CV of *duration* indicates greater variability in expansive stages to contractive ones (0.43 vs. 0.31), with significant dispersion between each method. Summing up, the four filters have similar results and strong correlation. Details of each filter are presented in Annex E.

IV.2.2 FILTER SELECTION

The four filters are—ex ante—theoretically appropriate for dealing with the unit root process presented in Argentina's quarterly GDP series. Moreover, they produce a similar characterization of the GDP cycles. The following paragraphs introduce some criteria for the selection of the most suitable filter for the Argentina's series.

First, and despite that the four filters can deal with integrated processes, some authors have rejected the empirical application of the HP filter. In this regard, although the findings by King and Rebelo (1993) and Ladiray et al. (2003a), Cogley and Nason (1995) point out that the HP filter is only suitable for data without a unit root (or a near unit root), in the sense that if the original series is first-order integrated, the application of the HP filter may result in BCs that do not exist in the raw data (creation of artificial BCs). Moreover, Park (1996) states that the increase of the degree of integration in the raw series deepens the artificial BCs effect of the HP filter. Accounting for the number of cycles, the two filters that are closer to the classic approach are the CF and BK, meanwhile the HP and BW reflect additional—potentially artificial—cycles.[13]

[12] These coefficients measure the diversity of expansions and contractions in terms of amplitude and duration. For details and formulas see Plessis du Plessis (2006).

[13] However, it should be noted that the parameters' selection, based on the approximation to the ideal filter's gain, generates data constraints - according to the methodology - to the BK and CF filters, a situation that could influence the total number of cycles for these methods.

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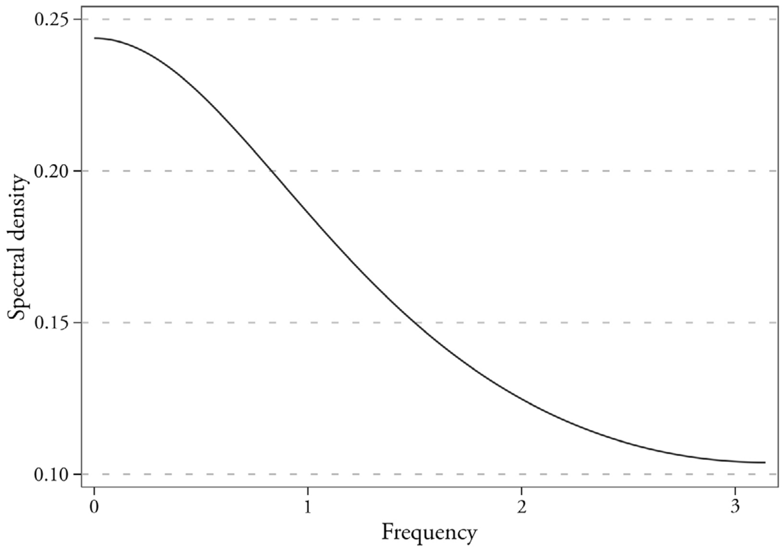
Table 8: Coefficient of variation

	Amplitude		Duration	
	Exp.	Cont.	Exp.	Cont.
HP	0.49	0.52	0.49	0.38
CF	0.42	0.67	0.25	0.24
BW	0.50	0.58	0.56	0.38
BK	0.53	0.61	0.42	0.25
Average	0.49	0.59	0.43	0.31

Source: author's estimations.

Second, according to Guay and St.-Amant (2005) if the spectra has Granger's shape the HP and BK filters introduce spurious dynamic properties of the cycles. A parametric estimation of the spectra density of Argentina's GDP shows Granger's shape.[14]

Figure 6: Spectral density of Argentina's quarterly GDP



Source: author's elaboration

Moreover, the sample spectral density function of the filters' cycles shows interesting results. These graphs—introduced in Annex F—are depicted with two straight ordinates lines reflecting the upper and lower cycles' bounds (6 and 32 quarters, respectively). Before and after these lines, it is expected—ideally—that a band-pass filter does not show ordinates with values over the minimum; and high-pass filters for those frequencies before the lower bound. The gaphs shows the CF and BK filters as the closest to the ideal.

Third, another criteria utilized in the literature is related with the rolling standard deviation of the cycles (see for example Rabanal and Baronio (2010)). In this case, the rolling standard deviation shows similar behavior between all filters; however, the CF highlights with the lowest deviation among them.

[14] Not included in the article, but also estimated, a raw periodogram of detrended Argentina's quarterly GDP series likewise reflects Granger's shape.

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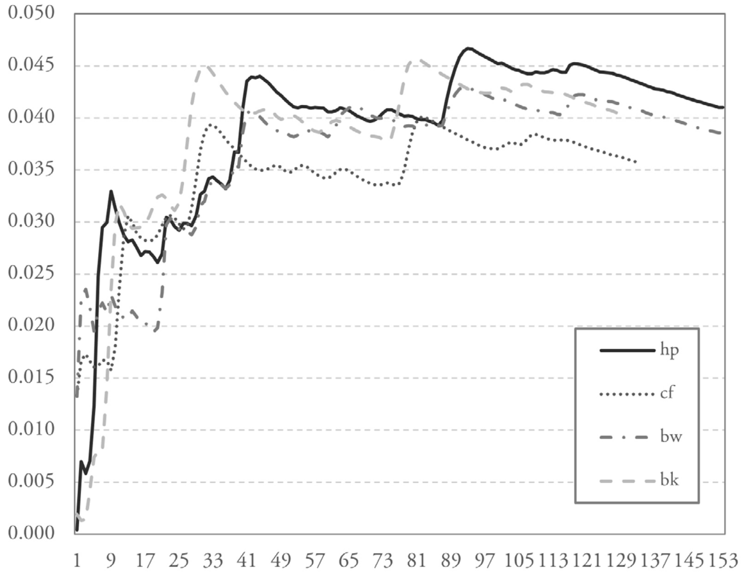
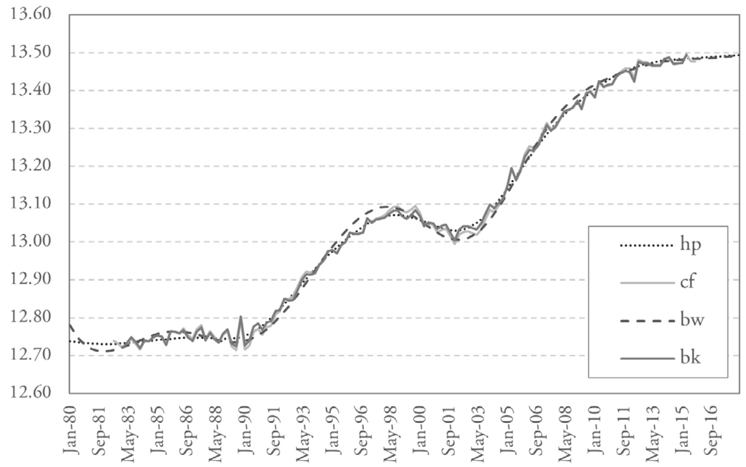
Figure 7: Rolling standard deviation of the cycles



Source: author's elaboration.

Figure 8: Trends from different methods



Source: author's elaboration

Fourth, Table 9 presents high statistical moments extracted from the cycles of the filters and the classic approach. All the methods show normality in kurtosis but reject the null of simmetry.

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Table 9: Description of cycles' moments

	Std. Dev.	Skewness	p-value*	Kurtosis	p-value**
Classic	6.2%	-0.41	0.040	2.76	0.649
HP	4.1%	-0.93	0.000	3.63	0.108
CF	3.6%	-0.97	0.000	3.54	0.163
BK	4.0%	-1.00	0.000	3.53	0.173
BW	3.9%	-0.88	0.000	3.19	0.457

*H_0: symmetry.
**H0: normal distributed of kurtosis.
Source: author's estimations.

Fifth, the correlation between the cycles from the classic approach and those from the filters are pretty similar, being BK cycle (0.54) the lowest. A graph of the rolling correlation of each filter's cycle with the classic shows practically no distinction on the convergence phase of the different methods. However, the HP and the CF filters register the fastest correlation convergence[15] of the four filters.

Sixth, the cycles' turning points derived from the CF and BK filters are the closer in time to those of the classic cycle, as presented in Table 5.

Seventh, as highlighted by Canova (1998b,a, 1999) the cycles are also sensitive to changes in the dating algorithm. In Table 10 and Table 11, are presented the result of an exercise that modifies the minimum duration of phases and cycles.

The results of changing the minimum cycle duration from the traditional use of 6 cycles to 7 and 8 is presented in Table 10. The CF method is the only one that keeps the same number of cycles in all the scenarios. The HP and the BK show slight variations. The BW filter is the one with most sensitivity to the changes in the cycle duration.

Table 10: Total cycles and algorithm parameter's change (minimum phase duration fixed at 2 quarters)

	Number of Peaks			Number of Troughs		
	Minimum Cycle Duration			Minimum Cycle Duration		
	#6	#7	#8	#6	#7	#8
HP	11	11	10	10	10	9
CF	10	10	10	10	10	10
BW	12	10	9	11	9	8
BK	9	9	8	9	9	8

Source: author's estimations.

Table 11 presents a similar exercise where varies the minimum cycle duration and the minimum phase is set at three quarters. The results are similar to those of the previous exercise, however with less variability in all the methods. In brief, marginal variations in phase or cycle's minimum duration do not significantly modify the number of peaks and troughs of the different methods. However, the CF method—in this particularly bounded exercise—is the only one that looks robust to these changes.

Finally, the cumulative spectral distribution—with graphs presented in Annex G—reflects within the BCs frequencies, that the CF filter is the one that accounts for almost the same variability (107%) as that of the classic filter. The HP (112%) follows in the same comparison.

Based on the results from above criteria, the filter method of the growth cycle approach that appears to be suitable for the best characterization of Argentina's GDP cycle is the CF.[16]

[15] In terms of absolute changes in the desviations of the rolling correlations

[16] The BK filter has also presented favorable results. However, the advice by Guay and St.-Amant (2005) , about avoiding the use of the HP and BK filters in Granger's shape spectra (as the case with Argentina's GDP series) was considered for favoring - among others criteria - in the selection of the CF filter.

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Table 11: Total cycles and algorithm parameter's change (minimum phase duration fixed at 3 quarters)

	Number of Peaks			Number of Troughs		
	Minimum Cycle Duration			Minimum Cycle Duration		
	#6	#7	#8	#6	#7	#8
HP	11	11	10	10	10	9
CF	10	10	10	10	10	8
BW	10	10	9	9	9	8
BK	9	9	8	9	9	8

Source: author's estimations.

IV.3 CLASSIC AND CF CYCLES COMPARISON

Taking into account the previous section, this section compares the main results from the classic approach and the growth approach using the CF cycles. This comparison yields interesting results. In first place, both approaches report similar number of cycles: the classic 9 PP and 8 TT, and the CF 9 for both measures.

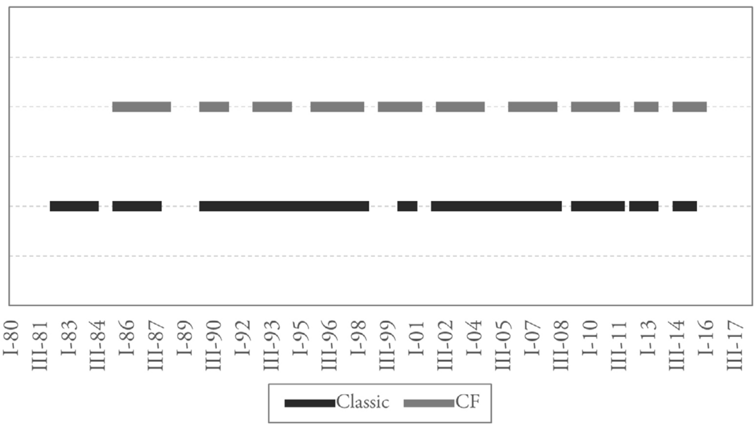
The classic approach shows the longest cycles' length, with an average duration of expansions of 2.5 years and contractions of 1.5 years; meanwhile the CF cycle shows averages of 2.0 years for expansions and 1.3 years for contractions. The ratio between contractions to expansions is pretty similar, with 0.5 for the classic approach and 0.7 for the CF.

In terms of intensity, the average intensity of expansions in the classic approach is 1.9%, which is almost two times that of CF (1.0%). The average intensity of contractions in the classic approach is -1.9%, and 1.4% in the CF cycle.

Moreover, the classic approach has more variabilitly both in complete cycles and in phases (particularly in expansions).

A visual inspection of the timing of the expansions—presented in Figure 9—reflects a high level of synchronization between both approaches. However, there are two expansions not captured by each method.

Figure 9: Periods of expansions



Source: author's elaboration.

Similarly, the timing of contractions is presented in Figure 10 where, again the synchronization is high. Besides, in the classic approach contraction's duration are larger in the middle of the sample, compared with those of the CF filter.

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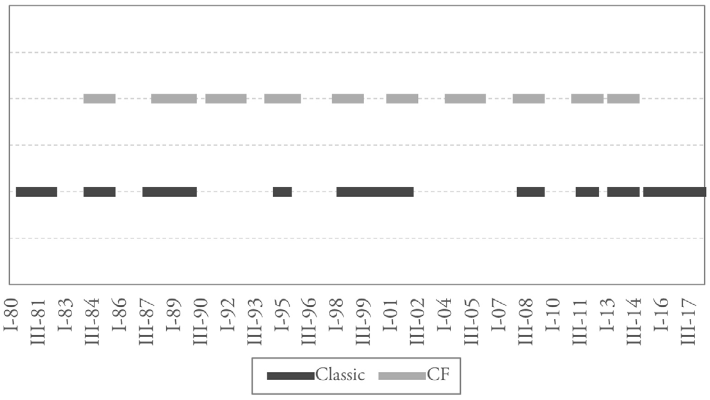
Figure 10: Periods of contractions



Source: author's elaboration.

Top-five ranking of event's intensity is presented in Table 12 where stands out that the two approaches have four common periods in both contractions and expansions. Of particular interest is the fact that the two top period of contractions are the same in both approaches. A similar situation arises in expansions, however with crossed values for the first two places.

Table 12: Intensity ranking: top five phases

	Expansions		Contractions	
	Classic Approach	CF	Classic Approach	CF
1st	09-11	02-04	00-02	01-02
2nd	02-08	09-11	08-09	08-09
3rd	90-94	95-98	94-95	84-85
4th	14-15	90-92	11-12	88-90
5th	85-87	85-88	84-85	94-95

Source: author's estimations.

V. LITERATURE COMPARISON

Comparing the turning points on this paper and those of Jorrat (2005) and Cerro (1999) exhibit an important degree of correspondence. For instance, in the common period with Jorrat's (1980q1-2005q1) its highlights a correspondence of 85%, with greater synchronicity in peaks (90%). In the common period with Cerro's (1980q1-1998q4), the results show a correspondence of 88%, with 75% for the peaks and 100% for the troughs.

The comparison with Jorrat's paper was made using the following rule:

For each turning point i:

$$|\text{Quarter}(m_i) - q_i| \leq 1 \Rightarrow v_i = 1$$

$$1 < |\text{Quarter}(m_i) - q_i| \leq 4 \Rightarrow v_i = 0.5$$

$$|\text{Quarter}(m_i) - q_i| > 4 \text{ or } |\text{Quarter}(m_i) - q_i| = \emptyset \Rightarrow v_i = 0$$

where: Quarter(m_i) is the turning point's quarter of the Jorrat's monthly series m_i; q_i is the turning point's quarter of quarterly Argentina's GDP series; v_i is the value assigned to individual realizations.

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To analyze the similarities between Cerro's findings of turning points and that of the CF, it was used the following rule:

For each turning point *i*:

$$|Q_i - q_i| \leq 1 \Rightarrow v_i = 1$$

$$1 < |Q_i - q_i| \leq 4 \Rightarrow v_i = 0.5$$

$$|Q_\mathrm{i} - q_i| > 4 \text{ or } |\mathrm{Quarter}(m_i) - q_i| = \emptyset \Rightarrow v_i = 0$$

VI. CONCLUDING REMARKS

The cycles of the quarterly series of Argentina's GDP were extracted by applying two approaches (classic and growth cycle). Within the growth cycle approach, four alternative univariate filters were considered. The selection criteria used in the literature allowed the CF filter to stand out with desirable characteristics for Argentina's GDP series over the rest of the alternatives considered in the analysis.

Despite the methodological differences between the two approaches, both reached a quite similar characterization of the GDP's BCs. In particular, in terms of: a) the number of cycles (9 PP and 8 TT for the classic approach; and 9 PP and 9 TT for the CF filter); b) the duration of the cycles (between three and a half and four years); c) the prevalence of expansions to contractions' duration; d) the dating of the cycles; and, e) the ranking of the intensities of phases. In addition, comparing the extracted cycles with common periods of previous works displayed high correspondence ratios for both approaches.

Looking forward, the next step clearly promotes the inclusion of multivariate filters that could enrich the characterization of the BCs and its analysis. Moreover, the inclusion of economic models to extract the cycles could be another important future improvement.

Besides, the application of the filters to simulated data can yield significant results for selection's criteria.

Finally, a methodology that contemplates cycle extraction with explicit account for potential structural breaks in a more extended series, particularly with an endogenous dating of the breaks (as in Perron and Wada (2016)) would be another desirable avenue of inquiry.

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ANNEX A: BASIC CONCEPTS ON SPECTRAL ANALYSIS[17]

ANNEX A.1 INTRODUCTION

A stationary process y_t with autocovariance function $\gamma(t)$, t ε {-∞,…,∞}, can be converted from the time domain to the frequency domain (or spectral representation) with the use of the *Fourier transform* resulting in the following *power spectrum or spectral density* function[18]:

$$S_y(\omega) = \frac{1}{2\pi}\left\{\gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j \cos(\omega_j)\right\} \qquad (A.1)$$

with cycles occurring at frequencies ω ε $[-\pi, \pi]$. The power spectrum shows the contribution of the stochastic cycles at frequencies ω, relative to the variance of y_t:

$$\int_{-\pi}^{\pi} S_y(\omega)\partial w = \gamma_0 \qquad (A.2)$$

Because the true autocovariance function is unknown in practice, the following *sample spectral density function* is estimated instead:

$$\widehat{S_y}(\omega) = \frac{1}{2\pi}\sum_{t=-K}^{K} w_t \hat{\gamma}_t e^{-i\omega t} \qquad (A.3)$$

where w_t for t=0,±1,±2,…±K are weights called a forming lag window, and K is a truncation lag, which describes the length of the lag window. The sample spectral density function reflects, in a similar manner to the power spectrum, the contribution of the stochastic cycles at frequencies ω, relative to the estimated variance of y_t.

[17] This section on spectral analysis is mainly based on: Priestley Priestley (1981), Ruth et al. van Ruth et al. (2005), Ladiray et al. Ladiray et al. (2003b), Harvey and Trimbur Harvey and Trimbur (2003); and, Hamilton Hamilton (1994).

[18] The spectral density function is normalized by the variance compared with the power spectrum.

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Because of the stationarity conditions assumed for y_t the autocovariances have the following property: $\gamma(i)=\gamma(-i)$, and the sample spectral density function reduces to:

$$\widehat{S_y}(\omega) = \frac{1}{2\pi}\left[w_0\hat{\gamma}_0 + 2\sum_{t=1}^{K}\omega_t\hat{\gamma}_t\cos(\omega_t)\right] \qquad (A.4)$$

In addition, it is possible to demonstrate that the autocovariance function can be expressed in relation to the sample spectral density function as:

$$\gamma(t) = \int_{-\infty}^{\infty} e^{i\omega t}\cdot\widehat{S_y}(\omega)\partial w \qquad (A.5)$$

ANNEX A.2 LINEAR FILTERS

The Crámer decomposition states that a stationary process y_t can be decomposed into an infinite sum of uncorrelated random components, each associated with a particular frequency:

$$y_t = \int_{-\pi}^{\pi} e^{i\omega t}\partial z(\omega) \qquad (A.6)$$

where $\partial z(\omega)$ are complex orthogonal increments that satisfy:

$$\begin{aligned} &\mathrm{E}\left[\partial z(\omega_1)\overline{\partial z}(\omega_2)\right] = 0, \qquad \forall\omega_1 \neq \omega_2 \\ &\mathrm{E}\left[\partial z(\omega)\overline{\partial z}(\omega)\right] = S_y(\omega)\partial\omega, \qquad \forall\omega \end{aligned} \qquad (A.7)$$

Let us consider a second process x_t related to the original time series as follows:

$$x_t = \sum_{j=-\infty}^{\infty} h_j y_{t-j} \qquad (A.8)$$

Since the lag polynomial—H(L)—is defined as:

$$\mathrm{H(L)} = \sum_{j=-\infty}^{\infty} h_j L^j \qquad (A.9)$$

where $L^j=y_{t-j}$ we can re-express the process x_t as follows:

$$x_t = \sum_{j=-\infty}^{\infty} h_j L^j y_t = \mathrm{H(L)}y_t \qquad (A.10)$$

where H(L) is known as the *linear filter* and x_t is the *filtered process* of the original y_t series.
If we assume that represents the *Fourier transform* of the H(L) filter such that:

$$\overline{\mathrm{H}}(\omega) = h_0 + 2\sum_{j=-\infty}^{\infty} h_j e^{i\omega t} \qquad (A.11)$$

and nothing that if the filter is symmetric ($h_j=h_{-j}$, $\forall j$) the reduces to:

$$\overline{\mathrm{H}}(\omega) = h_0 + 2\sum_{j=-\infty}^{\infty} h_j\cos(\omega) \qquad (A.12)$$

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Then, using the Crámer decomposition implies:

$$x_t = \int_{-\pi}^{\pi} \overline{\mathrm{H}}(\omega) e^{i\omega t} \partial z(\omega) \qquad (A.13)$$

Because $\overline{\mathrm{H}}(\omega)$ is complex it is possible to rewrite the filter in polar coordinates:

$$\overline{\mathrm{H}}(\omega) = G(\omega) e^{-i\Psi(\omega)} \qquad (A.14)$$

where:

$G(\omega)$: is known as the *gain of the filter* at frequency ω. The gain measures the amplification induced by the filter on the components with frequency in the original series.

$\Psi(\omega)$: is known as the *phase of the filter*, which measures the time displacement induced by the filter on the components with frequency ω in the original series.

The relation stated in can be re-expressed in terms of the spectral density function as Wei (2006):

$$S_y(\omega) = \left|G\left(e^{i\omega}\right)\right|^2 \cdot S_y(\omega) \qquad (A.15)$$

where the term $|G(e^{i\omega})|$ is the gain of the filter as defined in (13).

ANNEX A.3 IDEAL FILTER

The *ideal filter*, named $H^*(L)$, is the filter that once applied to extracts components in the frequencies specified in the subset Ω^* in the range $[0, \pi]$, from which follows these optimal conditions:

$$\begin{aligned} G^*(\omega) &= 1, \qquad \forall\omega \;/\; |\omega| \in \Omega^* \\ G^*(\omega) &= 0, \qquad \forall\omega \;/\; |\omega| \notin \Omega^* \\ \Psi(\omega) &= 0, \qquad \forall\omega \end{aligned} \qquad (A.16)$$

According to the specific frequency spectrum to be extracted the ideal filter can be classified in one of these categories:

Ideal low-pass filter: if $\Omega^*=[0,\omega^*]\omega \;/\; 0 \le \omega^* \le \pi$

Ideal high-pass filter: if $\Omega^*=[\omega^*,\pi]\omega \;/\; 0 \le \omega^* \le \pi$

Ideal band-pass filter: if $\Omega^*=[\omega_1^*,\omega_2^*]\omega$ \/ 0 ≤ω1*≤ω_2* ≤ π

In the ideal band-pass filter, the cut-off frequencies are defined by $\omega_1=2\pi/p_1$ and where p_l and p_u are the same cut-offs but in the time domain.

Nevertheless, one important drawback of the ideal filter is that it cannot be applied to empirical analysis because it would require an infinite time series to be estimated. In practice, the filter is applied to the spectral density function by transforming the original stochastic series y_t into a *filtered* series for which:

$$\begin{aligned} S_{y^*}(\omega) &= 0 \\ S_{y^*}(\omega) &= S_y(\omega) \end{aligned} \qquad (A.17)$$

according to the wanted frequencies defined in Ω^*.

The following univariate filters, that approximate desirable characteristics of the ideal filter—which is presented in conjunction with basic concepts on spectral analysis in Annex A—are applied to extract Argentina's GDP cycles.

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ANNEX A.4 FILTERS USED IN THE ANALYSIS

ANNEX A.4.1 THE HODRICK-PRESCOTT FILTER

The Hodrick-Prescott (HP) filter is not a filter in a strict sense because it does not have a cut-off frequency to be extracted. However, King and Rebelo (1993) show how the HP filter could be represented in the frequency domain equivalently to a high-pass filter. This filter is the most used techniques for cycles' extraction (van Ruth et al., 2005).

The HP filter assumes that a series is composed by a trend or growth component τ_t and a cycle component c_t:

$$y_t = \tau_t + c_t \qquad (A.18)$$

This filter also assumes that the long-term average of the cyclical component is zero and extracts the cycle from observed time series by minimizing the sum of squares of the distance between the trend and the original series plus a trade-off or penalty related with the smoothness of the trend, which is achieved by minimizing its curvature:

$$\min_{\tau} \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=1}^{T} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \qquad (A.19)$$

where λ is the parameter that reflects the penalty related to the smoothness of the estimated trend; its value depends on the data time-frequency and is usually set to 100, 1600, and 14400 for annual, quarterly, and monthly data, respectively, as suggested by Hodrick and Prescott (1997).
The first order conditions of (19) are:

$$\tau_t = \frac{y_t}{\lambda L^{-2}(1-L)^4 + 1}$$
$$c_t(L) = \frac{\lambda L^{-2}(1-L)^4}{\lambda L^{-2}(1-L)^4 + 1} \qquad (A.20)$$

From the FOC it could be shown that the ratio of the variance of τ_t and c_t is assumed to be equal to the chosen value of λ. Moreover, as λ tends to infinite, turns to a linear trend. If the cycle component and the second difference of the trend are normally and independently distributed, the HP filter is optimal. Finally, another important characteristic of the HP filter is that, as shown by Ladiray et al. (2003b), it could render a stationary time series containing up to four-unit roots.

ANNEX A.4.2 THE BAXTER AND KING FILTER

The Baxter and King univariate filter (BK) is a band-pass filter that approximates the ideal filter for series that are integrated up to order two and contain a deterministic trend (van Ruth et al., 2005). To estimate the cycle the BK filter minimizes the expected quadratic deviation between the ideal filter and the finite series approximation, by estimating a band-pass filter that only extracts those components with frequencies lying in the range . The cyclical component c_t is extracted by applying to y_t the following—centered—moving average process:

$$c_t = H_{BK}^{k}(L) y_t = \sum_{j=-K}^{K} h_j'' y_{t-j} \qquad (A.21)$$

where the coefficient $h_j^{*}=h_{2j}-h_{1j}+\theta_2-\theta_1$ and; h_{1j} and h_{2j} are the jth weights of the low pass filters with cut-off frequencies and ; θ_1 and θ_2 are the correction terms.
The weights of the BK filter are given by:

$$\begin{cases} \dfrac{\sin\left(\frac{2\pi k}{p_l}\right)-\sin\left(\frac{2\pi k}{p_u}\right)}{\pi k}-\dfrac{C}{1+2K}, & for\ 1\leq k\leq K \\ \dfrac{2}{p_l}-\dfrac{2}{p_u}-\dfrac{C}{1+2K}, & for\ k=0 \end{cases} \qquad (A.22)$$

where:

$$C=\frac{2}{p_l}-\frac{2}{p_u}+2\sum_{k=1}^{K}\left[\sin\left(\frac{2\pi k}{p_l}\right)-\sin\left(\frac{2\pi k}{p_u}\right)\right] \qquad (A.23)$$

and, p_l and p_u are—respectively—the lower and upper boundaries of the wavelength.

ANNEX A.4.3 THE CHRISTIANO AND FITZGERALD FILTER

The Christiano and Fitzgerald (CF) filter is a band-pass filter that assumes the time series follows a random walk structure (possible with drift):

$$y_t=y_{t-1}+\varepsilon_t, \qquad where\ \varepsilon_t\sim \text{iid} \qquad (A.24)$$

The process of cycle extraction in the CF filter is done by minimizing the expected square deviations from the ideal weights, where final observation receives the weights of all the missing (futures) observations.

$$\begin{aligned} &c_t = \\ &h_o y_t + h_1 y_t + 4 + \cdots + \\ &h_{T-1} y_{T-1} + \tilde{h}_1 y_{t-1} + \cdots + \\ &h_{t-2} y_{t-2} + \tilde{h}_{t-1} y_1 \end{aligned} \qquad (A.25)$$

$$\text{where } h_j=\frac{\sin(jb)-\sin(ja)}{\pi j}, \text{with } j\geq 1$$
$$\text{and } h_0=\frac{b-a}{\pi}, \text{with } a=\frac{2\pi}{p_u}, \text{and } b=\frac{2\pi}{p_l}$$
$$\text{and } \tilde{h}_k=-\frac{1}{2}h_0\sum_{j=1}^{k-1}h_j$$

The cut-off cycle length of the cyclical component is defined by p_u and p_l.
This filter is similar to the BK filter in the sense that both are band-pass filters trying to replicate the ideal filter. However, each filter has a specific assumption for the DGP that assures its optimality. Moreover, the CF is an asymmetric filter comparing with the symmetry of the BK.

ANNEX A.4.4 THE BUTTERWORTH FILTER

The Butterworth filter (BW) was initially used in electrical engineering as a symmetric low-pass filter with phase neutrality. It is defined with a positive parameter q and a positive integer index m.

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In the time domain the BW low-pass filter can be expressed as:

$$BW_m^{lp}(L) = \frac{1}{1 + q[(1-L)(1-L)^{-1}]^m} \qquad (A.26)$$

with m=1, 2, 3, …

$$BW_m^{lp}(L)y_t = \sum_j w_j \cdot y_{t+j} \qquad (A.27)$$

$$w_j = \frac{1-\theta}{1+\theta} \cdot \theta^{|j|} \qquad (A.28)$$

with j=0, ±1, ±2, …
where:

$$\theta = \frac{q + 2 - \sqrt{q^2 + 4q}}{2} \qquad (A.29)$$

and

$$\sum_j w_j = 1 \qquad (A.30)$$

which implies that L=1 in Equation (A.26).

$$BW_m^{lp}(\omega) = \left[1 + \left(\frac{\sin(\omega/2)}{\sin(\omega_{lp}/2)}\right)^{2m}\right]^{-1} \qquad (A.31)$$

where $\omega_{lp}=\omega/G(\omega)=$ ½, with $0 \leq \omega_{lp} \leq \pi$; and ω is the frequency in radians with $0 \leq \omega \leq \pi$. This filter cuts out frequencies above ω_{lp}.
Similarly, the gain of the BW high-pass filter (the type of BW filter that is used later in this study) can be expressed as:

$$BW_m^{hp}(\omega) = \left[1 + \left(\frac{\sin(\omega_{hp}/2)}{\sin(\omega/2)}\right)^{2m}\right]^{-1} \qquad (A.32)$$

In this case with $\omega_{hp}=\omega/G(\omega)=$ ½. This filter retains frequencies above ω_{hp}.
The BW band-pass filter can be obtained by subtracting the weights from two low-passes or two high-passes BW filters. For example, using two BW low-pass filters, and keeping the following frequencies relations:

$$\begin{array}{c} \text{1st: } \omega_{lp} = \omega_1 \\ \text{2nd: } \omega_2 \geq \omega_1 \end{array} \qquad (A.33)$$

The gain of the BW band-pass filter is then defined as:

$$BW_n^{bp}(\omega;\omega_1) = \left[1 + \left(\frac{\sin(\omega/2)}{\sin(\omega_{lp}/2)}\right)^{2n}\right]^{-1} - \left[1 + \left(\frac{\sin(\omega/2)}{\sin(\omega_{lp}/2)}\right)^{2n}\right]^{-1} \qquad (A.34)$$

Moreover, the sum of the weights of the BW band-pass filter is zero, resulting from subtracting two BW low-pass filters.

ANNEX B: UNIT ROOT TESTS RESULTS

The following tables show the results of the unit root tests. The ADF and the PP tests were performed with up to three lags. The DF-GLS was done with up to twelve lags (final results by the Ng-Perron criteria includes eight lags).

Table 13: Augmented Dickey-Fuller Unit Root Test

Model specification	PP-statistic			Critical Values		
	1 Lag	2 Lags	3 Lags	1%	5%	10%
det. tren	2.037	1.936	1.841	-2.593	-1.950	-1.613
Intercept	-0.295	-0.342	-0.389	-3.493	-2.887	-2.577
Intercept & tren	-2.434	-2.526	-2.621	-4.023	-3.443	-3.143

Source: author's estimations.
H_0: unit root in Argentina's GDP.
* denotes statistical significance at 10% level.
** denotes statistical significance at 5% level.
*** denotes statistical significance at 1% level.

Table 14: Phillips-Perron Unit Root Test

Model specification	PP-statistic			Critical Values		
	1 Lag	2 Lags	3 Lags	1%	5%	10%
det. tren	2.037	1.936	1.841	-2.593	-1.950	-1.613
Intercept	-0.295	-0.342	-0.389	-3.493	-2.887	-2.577
Intercept & tren	-2.434	-2.526	-2.621	-4.023	-3.443	-3.143

Source: author's estimations.
H_0: unit root in Argentina's GDP.
denotes statistical significance at 10% level.
** denotes statistical significance at 5% level.
*** denotes statistical significance at 1% level.
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Table 15: DF-GSL Unit Root Test

Model specification	DF-GLS-statistic	Critical Values		
	8 Lags	1%	5%	10%
Intercept & trend	-1.696	-3.515	-2.875	-2.593
Intercept	0.579	-2.593	-2.010	-1.703

Source: author's estimations.
H0: unit root in Argentina's GDP.
* denotes statistical significance at 10% level.
** denotes statistical significance at 5% level.
*** denotes statistical significance at 1% level.

ANNEX C: VARIANCE RATIO METHODOLOGY

The variance ratio test is due to Cochrane (1988) and Lo and MacKinlay (1989). The application of this test serves to evaluate the magnitude of the random walk component in Argentina's quarterly GDP series. The methodology assumptions are:

1- If the natural logarithm of Argentina's GDP series (y_t) follows a pure random walk:

$$y_t = \mu + y_{t-1} + \varepsilon_t \qquad (C.1)$$

It follows that the variance of the k-difference should grow linearly with k, such that:

$$VAR(y_t - y_{t-k}) = k \cdot \sigma_\varepsilon^2 \qquad (C.2)$$

2- In the assumption that y_t follows a stationary process around a trend:

$$y_t = bt + \sum_{j=0}^{\infty} a_l \varepsilon_{t-j} \qquad (C.3)$$

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It follows that the variance of the k-difference approaches the constant of twice the unconditional variance of the series:

$$VAR(y_t - y_{t-k}) = 2 \cdot \sigma_y^2 \qquad (C.4)$$

Interesting results arise from a situation of a time series with partly permanent and partly temporary process. For these cases, Cochrane suggests applying the multiplication of the variance times (1/k) such that:
a) If the process is a pure random walk, the ratio will be constant at the variance of the shock of the random walk process:

$$\frac{1}{k} \cdot VAR(y_t - y_{t-k}) = \sigma_\varepsilon^2 \qquad (C.5)$$

b) if the process is trend-stationary, the ratio should decline toward zero with the gradual increase of the k-difference:

$$\frac{1}{k} \cdot VAR(y_t - y_{t-k}) = \frac{2 \cdot \sigma_y^2}{k} \qquad (C.6)$$

The ratio should settle down to the shock's variance to the random walk component in a mixed situation (with a partly random walk and partly stationary series).
In this context, the following ratio accounts for an estimate of the measure of the random walk component of the series:

$$\text{random walk component:} \frac{\left(\frac{1}{k}\right) \cdot VAR(y_t - y_{t-k})}{VAR(y_t - y_{t-k})} \qquad (C.7)$$

The unbiased variance estimator is defined as:

$$\sigma_{(k)}^2 = \frac{1}{m} \sum_{t=k}^{T} (y_t - y_{t-k} - k\hat{\mu})^2 \qquad (C.8)$$

$$\sigma_{(1)}^2 = \frac{1}{T-1} \sum_{t=k}^{T} (y_t - y_{t-1} - \hat{\mu})^2 \qquad (C.9)$$

where:

$$m = k(T - k + 1)(1 - k/T) \qquad (C.10)$$

The variance ratio test is given by:

$$VR(k) = \frac{1}{k} \frac{\sigma_{(k)}^2}{\sigma_{(1)}^2} \qquad (C.12)$$

The homoscedasticity variance of the variance ratio is given by:

$$\phi(k) = \frac{2(2k-1)(k-1)}{3kT} \qquad (C.13)$$

with the following test statistic:

$$M_1(k) = \frac{VR(k) - 1}{\phi(k)^{1/2}} \sim N(0,1) \qquad (C.14)$$

For its part, the heteroscedasticity-consistent asymptotic variance of the variance ratio is:

$$\dot{\phi}(k) = \sum_{j=1}^{k-1} \left[\frac{2(k-j)}{k}\right]^2 \hat{\delta}(j) \qquad (C.15)$$

where:

$$\hat{\delta}(j) = \frac{\sum_{t=j+1}^{T}(y_t - y_{t-1} - \hat{\mu})^2 (y_{t-j} - y_{t-j-1} - \hat{\mu})^2}{[\sum_{t=1}^{T}(y_t - y_{t-1} - \hat{\mu})^2]^2} \qquad (C.16)$$

The heteroscedasticity-consistent standard normal test statistic is given by:

$$M_2(k) = \frac{VR(k) - 1}{\dot{\phi}(k)^{1/2}} \sim N(0,1) \qquad (C.17)$$

The following table shows the results of the variance ration test:

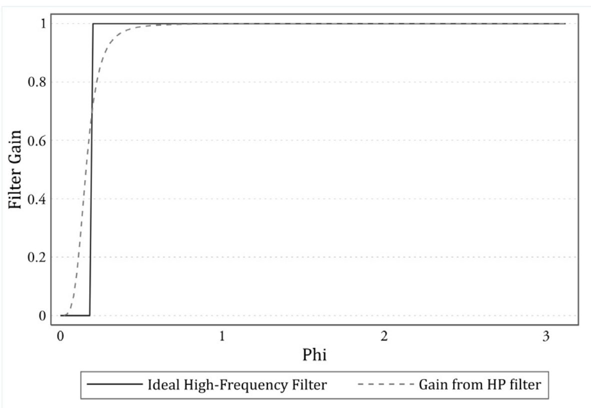
Table 16: Variance ratio test for selected k-differences

k-diff	Var. ratio	M_1	M_2
2	0.429	-1.980**	-1.723*
8	0.089	-1.324	-1.186
20	0.029	-1.116	-1.046
40	0.012	-0.990	-0.930
80	0.006	-0.683	-0.626

Source: author's estimations.
Note: M_2 are heteroscedasticity-consistent standard statistics.
H_0: variance ratio statistically equal to one.
* denotes statistical significance at 10% level.
** denotes statistical significance at 5% level.
*** denotes statistical significance at 1% level.

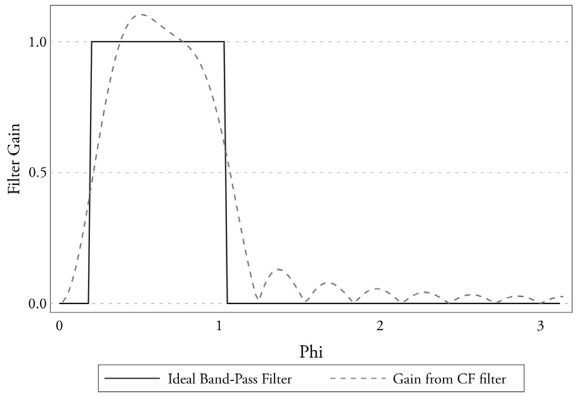
ANNEX D: FILTERS' GAINS

Figure 11: Gain of the Hodrick-Prescott filter



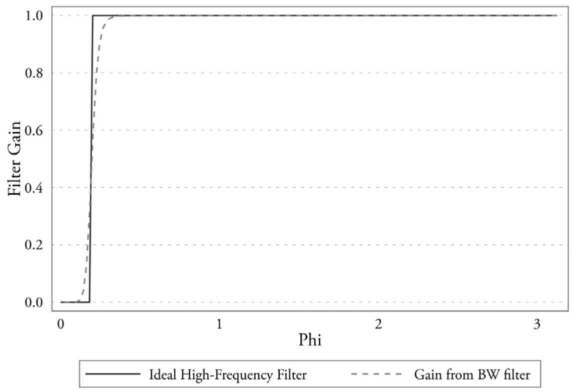
Source: author's elaboration.

Figure 12: Gain of the Christiano-Fitzgerald filter



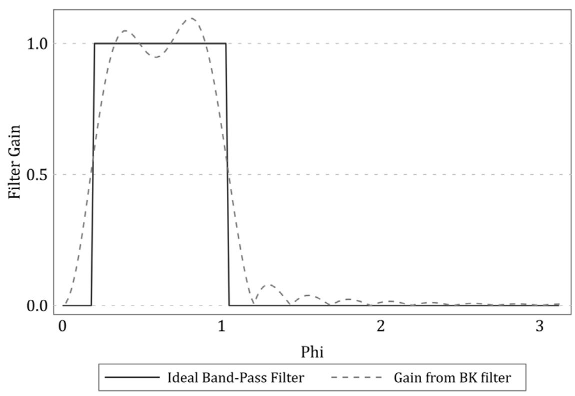
Source: author's elaboration.

Figure 13: Gain of the Butterworth filter



Source: author's elaboration.

Figure 14: Gain of the Baxter-King filter



Source: author's elaboration.

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ANNEX E: CYCLES' DATA BY FILTER

Table 17: Hodrick-Prescott Filter

	Turning Points		Cycle Duration		Phase Duration			Amplitude	
	Peak	Troughs	P-P	T-T	Exp.	Cont.	C/E	Exp.	Cont.
1	1980q3	1982q2				7			-8.6%
2	1984q2	1985q3	15	13	8	5	0.6	8.7%	-10.5%
3	1987q3	1990q1	13	18	8	10	1.3	14.5%	-18.9%
4	1993q3	1995q4	24	23	14	9	0.6	16.1%	-10.0%
5	1998q2	1999q2	19	14	10	4	0.4	11.9%	-5.2%
6	1999q4	2002q1	6	11	2	9	4.5	3.5%	-16.8%
7	2005q2	2006q3	22	18	13	5	0.4	16.7%	-2.5%
8	2008q2	2009q2	12	11	7	4	0.6	4.3%	-15.8%
9	2011q3	2012q2	13	12	9	3	0.3	13.8%	-7.3%
10	2013q2	2014q3	7	9	4	5	1.3	4.7%	-5.1%
11	2015q2		8		3			5.7%	
	Mean		13.9	14.3	7.8	6.1	0.8	10.0%	-10.1%
	Stand. Dev.		6.2	4.5	4.0	2.5	1.3	5.2%	5.5%

Source: author's estimations.

Table 18: Christiano-Fitzgerald Filter

	Turning Points		Cycle Duration		Phase Duration			Amplitude	
	Peak	Troughs	P-P	T-T	Exp.	Cont.	C/E	Exp.	Cont.
1	1984q2	1985q3				5			-8.8%
2	1988q1	1990q1	15	18	10	8	0.8	10.8%	-13.1%
3	1992q1	1992q4	16	11	8	3	0.4	8.8%	-0.2%
4	1994q2	1995q4	9	12	6	6	1.0	3.9%	-9.5%
5	1998q1	1999q2	15	14	9	5	0.6	10.3%	-5.0%
6	2001q1	2002q2	12	12	7	5	0.7	4.4%	-15.3%
7	2004q2	2006q1	13	15	8	7	0.9	11.4%	-1.1%
8	2008q1	2009q2	15	13	8	5	0.6	6.3%	-13.1%
9	2011q2	2012q3	13	13	8	5	0.6	11.1%	-4.5%
10	2013q2	2014q3	8	8	3	5	1.7	2.6%	-4.2%
	Mean		12.9	12.9	7.4	5.4	0.7	7.7%	-7.5%
	Stand. Dev.		2.8	2.8	2.0	1.3	0.4	3.5%	5.3%

Source: author's estimations.

Table 19: Butterworth Filter

	Turning Points		Cycle Duration		Phase Duration			Amplitude	
	Peak	Troughs	P-P	T-T	Exp.	Cont.	C/E	Exp.	Cont.
1	1980q4	1982q2				6			-5.8%
2	1983q3	1985q3	11	13	5	8	1.6	6.6%	-12.1%
3	1986q3	1987q1	12	6	4	2	0.5	11.7%	-1.4%
4	1988q1	1990q1	6	12	4	8	2.0	5.5%	-17.1%
5	1993q3	1995q4	22	23	14	9	0.6	15.8%	-13.3%
6	1998q2	1999q2	19	14	10	4	0.4	11.9%	-3.9%
7	2000q4	2002q1	10	11	6	5	0.8	5.4%	-15.4%
8	2005q2	2006q3	18	18	13	5	0.4	15.2%	-4.2%
9	2007q2	2009q2	8	11	3	8	2.7	3.4%	-15.9%
10	2011q3	2012q2	17	12	9	3	0.3	15.6%	-7.0%
11	2013q2	2014q3	7	9	4	5	1.3	4.7%	-5.3%
12	2015q2		8		3			5.6%	
	Mean		12.5	12.9	6.8	5.7	0.8	9.2%	-9.2%
	Stand. Dev.		5.5	4.7	4.0	2.3	0.8	4.9%	5.6%

Table 20: Baxter-King Filter

	Turning Points		Cycle Duration		Phase Duration			Amplitude	
	Peak	Troughs	P-P	T-T	Exp.	Cont.	C/E	Exp.	Cont.
1	1984q2	1985q3				5			-8.8%
2	1988q1	1990q1	15	18	10	8	0.8	10.2%	-14.6%
3	1994q2	1995q4	25	23	17	6	0.4	13.0%	-9.8%
4	1998q1	1999q2	15	14	9	5	0.6	10.3%	-4.1%
5	2000q4	2002q3	11	13	6	7	1.2	1.8%	-16.2%
6	2005q2	2006q1	18	14	11	3	0.3	12.7%	-0.3%
7	2008q1	2009q2	11	13	8	5	0.6	5.6%	-13.0%
8	2011q3	2012q3	14	13	9	4	0.4	9.2%	-4.3%
9	2013q2	2014q3	7	8	3	5	1.7	1.7%	-4.7%
	Mean		14.5	14.5	9.1	5.3	0.6	8.1%	-8.4%
	Stand. Dev.		5.4	4.4	4.1	1.5	0.5	4.5%	-5.4%

Source: author's estimations.

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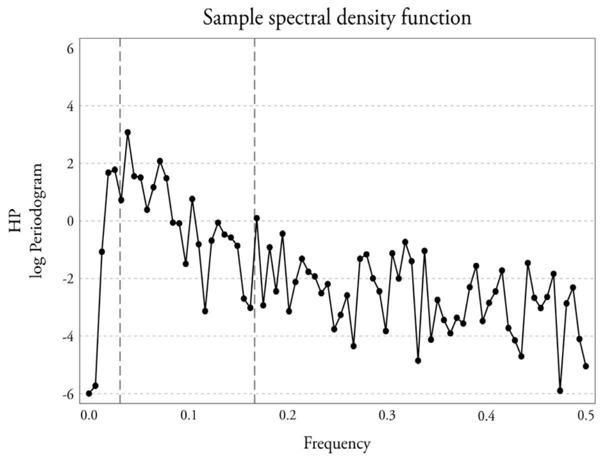
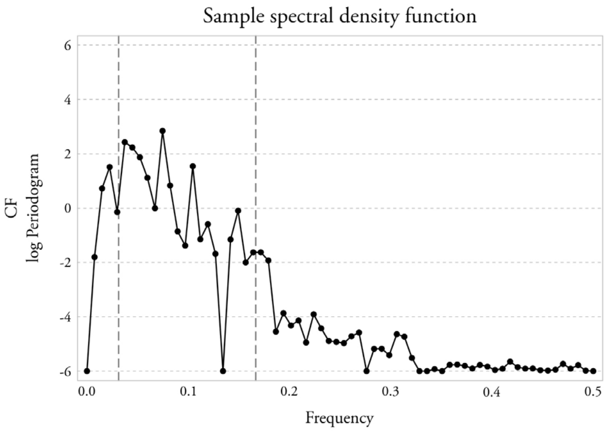
ANNEX F: SAMPLE SPECTRAL DENSITY FUNCTIONS

Figure 15: Sample spectral density of HP cycle



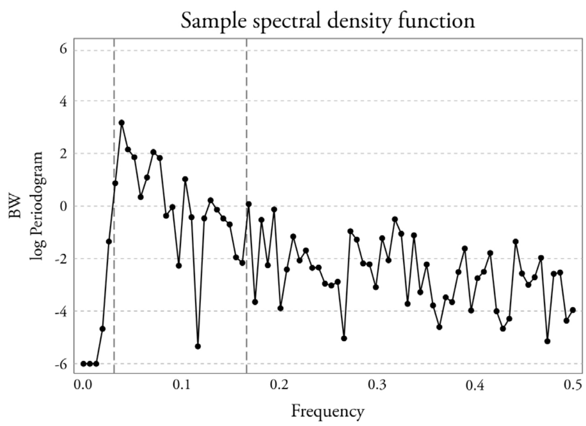
Source: author's elaboration.

Figure 16: Sample spectral density of CF cycle



Source: author's elaboration.

Figure 17: Sample spectral density of BW cycle



Source: author's elaboration.

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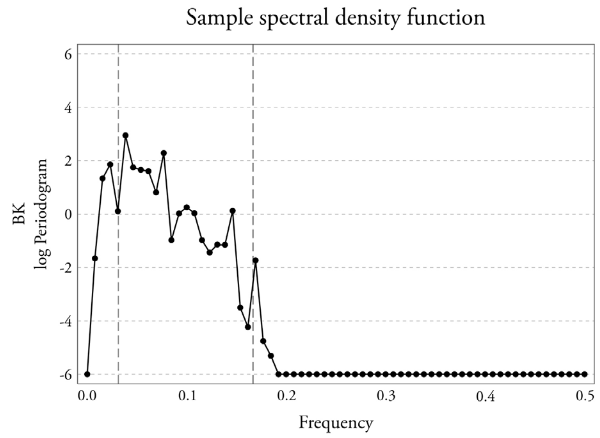
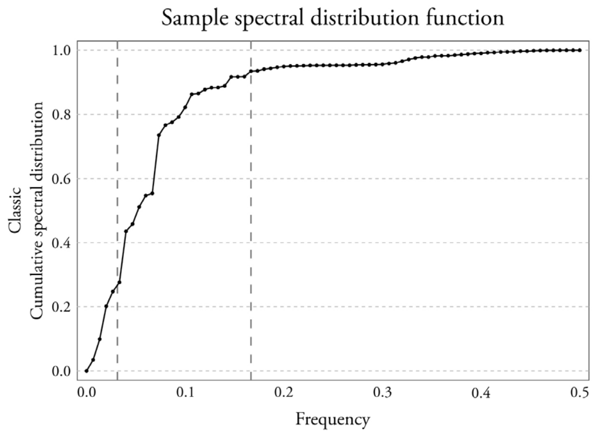
Figure 18: Sample spectral density of BK cycle.



Source: author's elaboration.

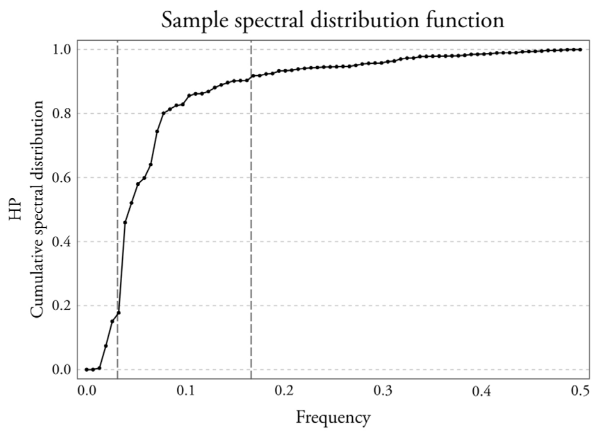
ANNEX G: CUMULATIVE SPECTRAL DISTRIBUTION

Figure 19: Cumulative spectral distribution — Classic Cycle



Source: author's elaboration.

Figure 20: Cumulative spectral distribution – HP



Source: author's elaboration.

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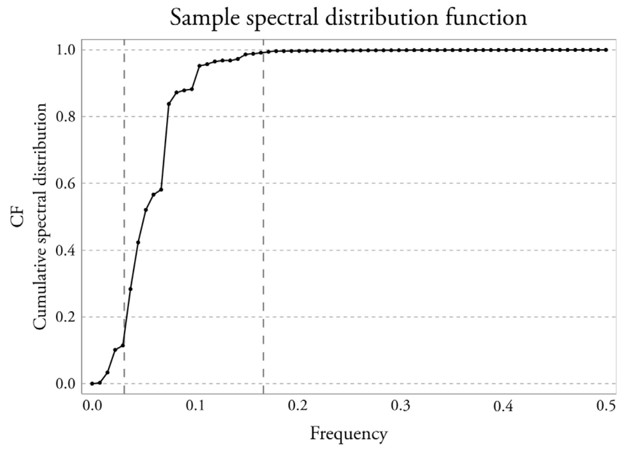
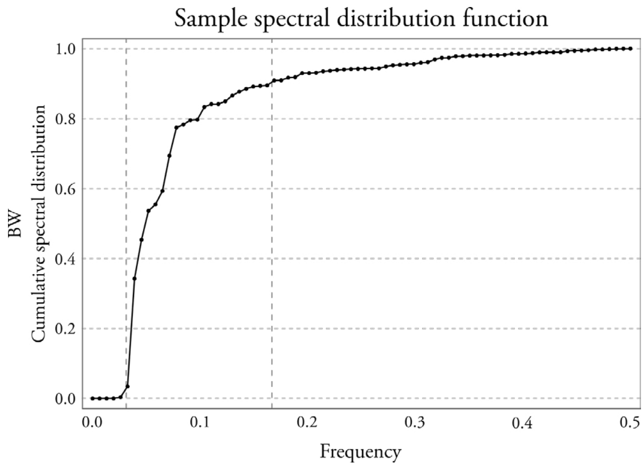
Figure 21: Cumulative spectral distribution – CF



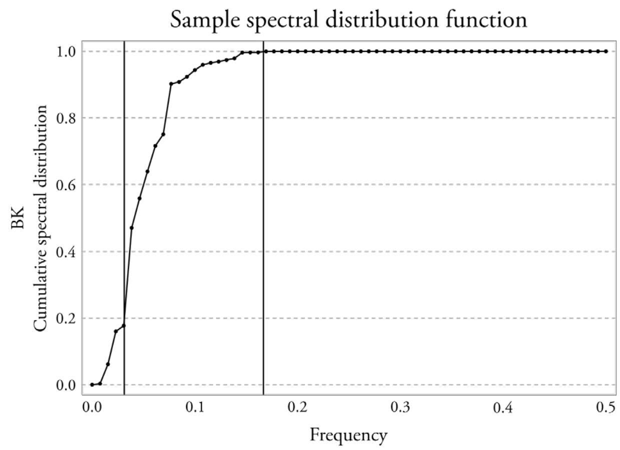
Source: author's elaboration.

Figure 22: Cumulative spectral distribution — BW



Source: author's elaboration.

Figure 23: Cumulative spectral distribution — BK



Source: author's elaboration.