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Abstract

We present new short, medium, and long-run indicators to date and characterise expansions and contractions in financial and economic time series. These Bull-Bear Indicators (BBIs) measure the risk-adjusted excess return with respect to average, to different time horizons, expressed in standard deviations. We illustrate the benefits of this measure by describing the boom-bust cycle in the UK stock market between 1922 and 2015. We compare our results with those obtained from frequently used methodologies in the literature and find that our measures contain substantially more information than the usual binary sequences that describe expansions and contractions and allow for a more granular and nuanced description of time series.

JEL classification: C1, C43, E32, G01, G1, N14

Keywords: Boom-bust cycle; Bull and bear markets; Stock market; Time series analysis; Severity measures; Dating rules.

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1. Introduction

Since the works of Schumpeter and Kondratieff waves of varying frequency have been both theorised and evidenced in economic data giving origin to a field of research devoted to identifying the secular trend and the underlying cycles in economic and financial time series (Metz, 2011). The literature on financial crises has profited from these developments in series decomposition to expand on the study of booms and busts in asset and credit markets. Regardless of the technique used, results in this search for expansions and contractions usually take one of two forms.

A first usual result is a sequence of dates for peaks and troughs that allow studying booms and busts according to their rate of change (amplitude), length (duration) and severity. These dates are unidimensional in the sense that they do not allow researchers to analyse whether a boom or a bust had any effect on medium or long-run returns after its ending date. The relevance of the notion of persistence, as stated by Borio and Lowe (2002, p.12) is that it "focuses on cumulative processes, rather than growth rates over just one year. Vulnerabilities are generally built up over an extended period, rather than in a single year". Unfortunately, persistence, as defined here, is unobservable with the current methodological toolkit.

The second type of result, a series of ones and zeros that indicates the presence of either booms or busts, challenges researchers in several ways. A first issue is a "lack of consensus on the mechanics of measurement, such as the choice of indicators and the method used to construct them" (Schüler, Hiebert, and Peltonen, 2015, p. 2; see also Sarferaz and Uebele, 2009). Secondly, these dummy series result from financial data, which in its original state show features such as strong and changing variability, and other properties that make them distinctive (Pagan and Sossounov, 2003). Summarizing their evolution in a yes / no sequence implies a loss of information and the assumption that the transition from a calm period to a crisis period is an instantaneous change, not a process that occurs over time. A final issue is that in a series where ones represent crises and zeros represent calm periods, researchers treat all crises as identical events. As indicated by Romer and Romer (2015, p. 2) "This binary classification surely obscures some important information about the variation in the severity of crises. It also means that errors in classification are likely very consequential".

We believe that these methodological limitations have restricted the depth of the analysis of financial data to focus excessively on the short-run

drivers and effects. We argue that the current methodological toolkit offers a myopic perspective of the behaviour of booms and busts which does not allow for differences in persistence across time or for a nuanced characterisation based on their characteristics.

Consequently, this paper aims to present a new methodological approach for the characterisation of expansions and contractions in time series: the Bull-Bear Indicator (BBI). These series, which we calculate globally or locally, measure the direction and intensity of bull and bear markets, in standard deviations, to different time horizons: short, medium and long-run. These continuous indicators tend to the issues mentioned above without significant statistical assumptions about the underlying data generating process. Finally, BBIs allow us to perform the usual analysis of amplitude, duration, and severity while providing insight on the evolution of the underlying time series to different horizons.

We apply this methodology to the case of the UK stock market, from January 1922 until September 2015, to illustrate its use. This case is of interest because of the relevance of a well-functioning stock market in supporting economic growth in modern economies. Moreover, long-run price series of high quality are available, which facilitate comparing results with other studies, and there exists plenty literature on the economic history of the UK during the twentieth century to frame our analysis.

The paper is structured as follows. The second section takes stock of the current methodological toolbox that is usually employed in the financial literature to motivate the need for another measure. A third section discusses the Bull-Bear Indicator methodology which offers global and local measures of expansions and contractions to different time horizons. The fourth section presents a case study using the BBIs to perform a detailed exploration of the evolution of the British stock market for the period 1922-2015. The fifth section compares the results obtained using the BBIs with those coming from the current methodological toolkit. Section 6 concludes.

2. The Current Methodological Toolkit for Identifying Bull and Bear Markets

The techniques available for the study of the boom-bust cycle in time series are diverse (Harding and Pagan, 2002b). For our purposes, we can distinguish between non-parametric techniques in the time domain, such as the turning point algorithm (TP) (Bry and Boschan, 1971 and Pagan and Sossounov, 2003) and the severity index (Harding and Pagan, 2002b and Agnello and

Schuknecht, 2011), and parametric time series decomposition methods in the time and frequency domains, such as the Hodrick and Prescott (1997) filter (HP), and the band-pass filter (BP) of in Christiano and Fitzgerald (2003). Let us briefly describe their most salient features.

2.1. Turning Point Algorithm (TP)

The TP algorithm describes local maxima and minima of a time series under a pre-set group of conditions. The result is a series of dates for peaks and troughs with intermediate sections classified as contractions (bears) or expansions (bulls) (Harding and Pagan, 2005). One of the most frequently used algorithms in business cycle literature is the one developed by Bry and Boschan (1971) to mimic the recession dates found by National Bureau of Economic Research (NBER). Three decades later, Pagan and Sossounov (2003) implement these instructions for a long-run monthly index for the US stock market from January 1835 until May 1997 and offer a summary of the rules (pp. 44-45):

I. Determination of initial turning points in data.
   I.A. Choice of peaks and troughs in symmetric windows of X months around each price observation.
   I.B. Enforcing of alternation.
II. Censoring operations
   II.A. Elimination of turns within six months of beginning and end of series
   II.B. Elimination of peaks (troughs) at both ends of series which are lower (higher) than values closer to the end
   II.C. Elimination of cycles with a shorter duration than Y months both for peak-to-peak and trough-to-trough.
   II.D. Elimination of phases (peak-to-trough or trough-to-peak) with a shorter duration than Z months (unless fall/rise exceeds 20%)
III. Statement of final turning points

This simple algorithm produces results that are robust to changes in sample size, although not to window size (Harding and Pagan, 2002a). However, it leaves several choices for researchers allowing for different results using the same inputs. Additionally, the method lacks statistical foundation, making inference and hypothesis testing difficult (Harding and Pagan, 2002b).

2.2. Severity Index

Harding and Pagan (2002b) use the TP algorithm to identify boom and bust periods and then develop measures for the duration and amplitude of the phases. The duration (D_i) of a phase is the distance in months between a peak (trough) and the next trough (peak). The amplitude (A_i) is the percentage change during the period. Agnello and Schuknecht (2011) construct a severity index which corresponds to Harding and Pagan's (2002b) "triangle approximation" to cumulative movements. The base of the triangle is the duration, and the height of the triangle is the amplitude of the cycle. The severity index for phase i is obtained as

$$S_i = \frac{1}{2}(D_i \times A_i) \qquad (1)$$

The main caveat to the use of the triangular methodology is that severity indices for booms may be more significant, in absolute value than those for busts because the value of A_i has a lower bound of -100% (prices cannot take negative values).

2.3. Time Series Decomposition: Filtering

While the turning point algorithm and the severity index use the original data, filtering techniques work under the assumption that any time series can be decomposed into various orthogonal components: trend, one or several cyclical components, and an error term. These decompositions can be performed on the time or the frequency domain. Overall, models in the time domain rest on the idea that the current value of a variable is a function of its previous observations or previous observations of other time series. On the other hand, the frequency domain approach is interested in systematic or sinusoidal variations within the data which is attractive as it involves only a small set of primary oscillations, the so-called Fourier transforms (see Shumway and Stoffer, 2017).

2.3.1. The HP Filter

The Hodrick and Prescott (1997) filter (HP) is a one-sided high-pass filter designed to decompose a time series in a trend component assumed to vary smoothly over time with a stable second difference, and an independent cyclical component. The HP filter is a parametric approach which depends on the

choice of a smoothing parameter, often called λ, which penalises the growth component over the cyclical component. Lower values of λ yield models that adapt faster to changes in the data.

The filter extracts a trend from an observed time series with a weighted moving average and returns high-frequency component (usually frequencies higher than 40 quarters for quarterly data). It does so with the added benefit that it can be performed on nonstationary time series although the literature has shown that the filter produces artificial long-term cycles if the series is non-stationary (Metz, 2011). Additionally, even if the filter does not have a cycle, as it is based on trend extraction, there are some distortions in the cyclical component due to leakage (low frequencies that are not filtered out) and compression of cycles (Cendejas, Muñoz, and Fernandez-de-Pinedo, 2017). Finally, Hamilton (2017) indicates that even for martingale series (or for series that are close to being martingales), the HP filter generates, by construction, a serial dependence within the cyclical component of the series. This added structure is not a feature of the data but the filtering process.

2.3.2. The Band-Pass Filter

The band-pass filter is a two-sided, symmetric filter designed to minimise the adjustment error of a cycle between a pre-set bandwidth. The central assumption underlying the band-pass filter, as presented by Stock and Watson (1999) and Christiano and Fitzgerald (2003), is that of a minimum and maximum cycle length. Any cycles or information of shorter (longer) frequency than the lower (upper) bound of the bandwidth will be smoothed-out of the time series. A useful characteristic of this method is that it can be used to decompose a time series into as many orthogonal cyclical components as the researcher might need by using different bandwidths. For example, in a study of the long-run behaviour of the financial cycle for seven countries, Drehmann, Borio, and Tsatsaronis (2012) use the band-pass filter to extract the medium term component of credit and asset prices to explain its determinants. This method is not exempt of caveats. First, since the various cyclical components are orthogonal, the underlying assumption is that the determinants of their behaviour should be different. Moreover, according to Gallegati, Gallegati, Ramsey, and Semmler, (2015), filters in the frequency domain require time series to be stationary. It is shown that the decomposition can produce non-existent cycles if the series are nonstationary. Finally, results are not robust to outliers and structural breaks (Metz, 2010).

3. A New Approach: The Bull-Bear Indicator

Let **R** be an n-period linear return matrix in which rows will represent time and column vectors $\mathbf{r_n}$ will hold the return from period t-n until t; that is, $r_{t,n} = (P_t/P_{t-n}) - 1$, where P_t corresponds to the value of the asset at time t.

The index n represents the different time horizons to which we calculate returns. Following the traditional financial literature (Bodie et al., 2017), short-run returns cover up to one year (1 to 12 months in a monthly series), medium-run returns up to three years (18, 24, 30, 36 months for a monthly series) and long-run returns up to five years (42, 48, 54 and 60 months). For annual or quarterly series, a different set of values for n should be considered.

To highlight some traits of the information contained in **R**, in Figure 1 we draw a heat map for the monthly returns of the UK stock market (left), and of the rolling twelve-month standard deviations estimates for the vector of returns (right). We follow a vector by vector colouring rule. In the case of returns, observations farther away to the left (right) of the distribution will be coloured in red (green), as they represent the worst (best) returns in the full sample. The shading becomes darker as returns move closer to the tails of the distribution. We distinguish four different shades of red (green) for percentiles 1 (99), 5 (95), 10 (90) and 25 (75). In the case of rolling standard deviations, we use the inverse colouring rule, where lower (higher) standard deviations are coloured green (red) as they denote the less (more) risky events. In both cases, returns in the interquartile range are not coloured.

Figure 1: Heat maps for UK monthly stock market index (selected decades)

Fig 1a: Of returns for different time horizons.

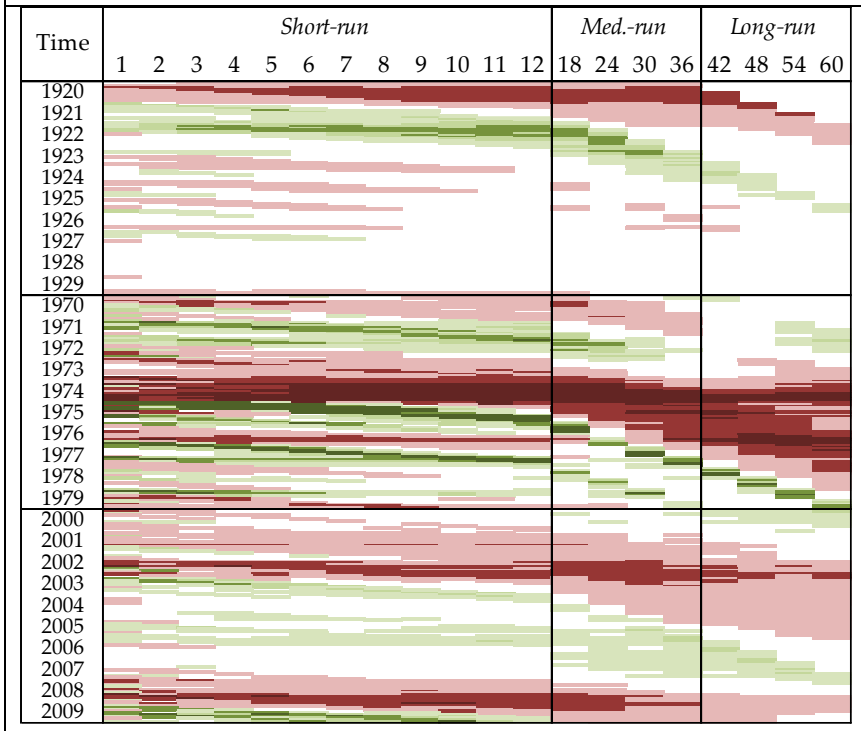
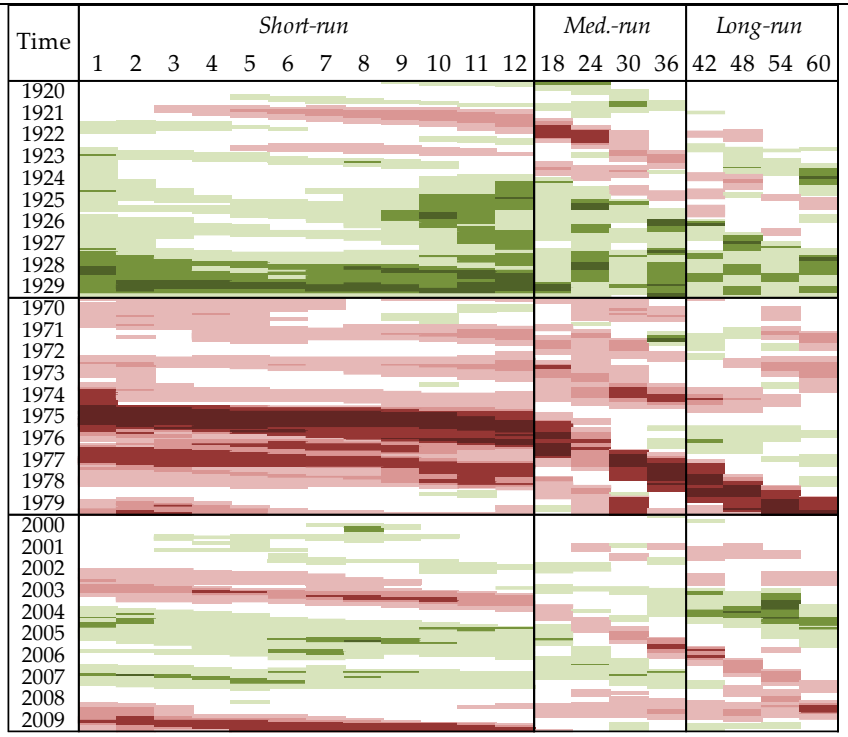


Fig 1b: of the 12-month rolling stand. dev. of returns in 1a.



Note: Colouring rule followed a vector-by-vector basis using the full sample. Only selected results presented for the 1920s, 1970s, and 2000s. Each coloured box represents a month. Only observations falling in percentiles 1 (99), 5 (95), 10 (90), and 25 (75), are shaded Short-run panels show return or rolling standard deviation vectors for n=1, 2, 3,…, 11, 12. Medium-run panels show return or rolling standard deviation vectors for n=18, 24, 30, and 36. Long-run panels show return or rolling standard deviation vectors for n=42, 48, 54, and 60. **Figure 1a**. Darker shades of red (green) represent returns that are farther to the left (right) of the distribution. **Figure 1b.** Darker shades of green (red) represent lower (higher) standard deviations.

Several remarkable features emerge from Figure 1a. First, on a vector-by-vector basis, there are clusters of positive and negative returns which can be understood as persistence from a time series perspective. Second, moving from left to right, it is evident that some phases of expansion (in green) and some phases of contraction (in red) affect only short-run returns, while others affect the medium-run, and even the long-run as well. This can be thought of as persistence from a cross-sectional perspective. For example, the bear phase occurring by the end of 1926 only affects the returns up to 8 months but does not show up either in the medium or long-run panels. Conversely, the bear phase that occurs in 1973, and the recovery that follows, affects returns to every time horizon, indicating strong persistence. The heat map on the right (Figure 1b) reveals volatility clustering both from a time series and cross-sectional perspective (Campbell et al., 1997). We identify a period of protracted stability in returns during the second half of the 1920s that affects all time horizons and, similarly, there is a period of pervasively high volatility during the second half of the 1970s which coincides with corresponding bulls and bears in the series of returns in the same period.

The heat maps tell us that not all bulls and bears are created equal and that a significant amount of underlying information in a financial series is not adequately reflected by any of the current approaches, as discussed in the previous section. This is the purpose of the new measure introduced below. Before going into details, let us propose a thought experiment to highlight what BBIs contribute to the current state-of-art.

One can think of the data generating process for a time series as throwing a stone in the centre of a pond, producing waves that move outward towards the shore. The TP algorithm identifies the peaks and troughs of the waves. The severity index identifies waves with high amplitude (substantial differences in height between peaks and troughs) and low frequency (large distances between peaks and troughs) and omits weaker or higher frequency ripples. The HP filter compares the observed wave to a recursive prediction of how it should behave and highlights only significant deviations. The band-pass filter decomposes the ripples and observes only those that conform to pre-set frequencies. None of these methodologies cares whether the ripple is close to or far away from the centre of the lake. The BBIs look at the waves differently, separating those that disappear closer to the centre (short-run impact), those that move farther away and those that reach the shore (long-run impact).

3.1. The Global Bull-Bear Indicators (GBBIs)

By construction, vectors $\mathbf{r_n}$ and $\mathbf{r_m}$ in $\mathbf{R}$ have different measures since they express n and m period returns respectively. A solution to keep comparability

and other desirable properties, is to standardize matrix **R**. By doing so we generate a new matrix **Z** such that:

$$z_{t,n} = \frac{(r_{t,n} - \mu_n)}{\sigma_n} = \left[\frac{r_{t,n}}{\sigma_n} - \frac{\mu_n}{\sigma_n}\right] \quad (2)$$

The values obtained from (2) refer to the number of sample standard deviations σ_n that a given observation $r_{t,n}$ is away from the sample mean μ_n of vector $\mathbf{r_n}$. The right part of expression (2) allows to treat $z_{t,n}$ as the risk-adjusted above-trend return for vector n at time t.

Matrix Z, in the case of a monthly series, consists of 20 vectors (in a Txn matrix), which are too many to be efficient, so a natural next step is to aggregate that information into simple indicators. Thus, we will define Global BBIs (GBBIs) as,

$$\text{GBBI} = \omega'\mathbf{Z} \quad (3)$$

Where ω is a vector of weights that add to 1. To be more specific, we define three different indicators: a short-run GBBI with the returns from one month up to one year, $\mathbf{Z_{short}}$, a medium-run GBBI with returns from 18 months up to three years, $\mathbf{Z_{medium}}$, and a long-run GBBI with returns from 42 months up to five years, $\mathbf{Z_{long}}$.

The corresponding vectors of weights ω for each **Z** (short, medium or long) are obtained through factor analysis as proposed by Tsay (2002). For each specification, we obtain only one factor, **f**, such that

$$\mathbf{Z} = \mathbf{f}\boldsymbol{\lambda}' + \boldsymbol{\epsilon} \quad (4)$$

$\boldsymbol{\lambda}$ is an ($mx1$) vector of scalars, being m the number of return series included in **Z**; $\boldsymbol{\epsilon}$ is a (Txn) matrix of error terms. Written in a linear form:

$$z_{t,n} = \lambda_n f_t + \epsilon_{t,n}; n = 1, \dots, N \quad (5)$$

Once the factor **f** has been extracted from **Z**, using maximum-likelihood methods, and assuming white noise errors in $\boldsymbol{\epsilon}$, is inmediate to estimate the optimal weight corresponding to every vector $\mathbf{z_m}$. As a final step, the set of factor loadings are rescaled in order to add to one, so:

$$\omega_n = \frac{1/\widehat{\lambda_n}}{\sum_{i=1}^{n}\left(1/\widehat{\lambda_n}\right)} \quad (6)$$

The construction of ω in (5) guarantees that GBBIs mimic the most relevant factor for the matrix **Z** while still being interpretable as standard deviations. We can rewrite (3) using (5) as follows:

$$\text{GBBI}_t=\omega_n z_{t,n}=\frac{\widehat{f_t}}{\sum_{i=1}^{n}\left(1/\widehat{\lambda_n}\right)};\ n=\left\{\begin{array}{c}1,2,\ldots,12 \text{ if GBBI}_{\text{short}}\\ 18,\ 24,\ 30,\ 36 \text{ if GBBI}_{\text{medium}}\\ 42,48,54,60 \text{ if GBBI}_{\text{long}}\end{array}\right\} \quad (7)$$

3.2. The Local Bull-Bear Indicators (LBBIs)

One of the caveats in the calculation of the GBBI has to do with using the full sample mean and standard deviation in the standardisation of (2), which implies that all expansions and contractions are measured relative to the full sample risk-adjusted average return, the second term in (2). However, we know from Figure 1 that there are substantial runs of positive or negative returns and clear signs of clustered volatility.

Moreover, using the GBBIs to compare expansions and contractions during different time periods may omit *contextual characteristics*: i.e., a particular increase when the annual standard deviation is 5% has a different meaning when it occurs when the annual standard deviation is 10%. To take into account the context, we adjust the indicator to include time-varying means and dispersion measures, so we rewrite (2) as:

$$d_{t,n}=\frac{\left(r_{t,n}-\mu_{t,n}\right)}{\sigma_{t,n}} \quad (8)$$

Where $\mu_{t,n}$ and $\sigma_{t,n}$ are local measures of mean and dispersion in period t.[1] Note that we change the notation from $z_{t,n}$ to $d_{t,n}$. The collection of locally standardized series forms the (*Txn*) **D** matrix.

To obtain a time-varying mean, we use an exponentially weighted five-year moving average (EWMA), such as:

[1] This idea resembles the one presented in expression (5) in Le Bris (2017) where he proposes analyzing crashes in the context of market volatility at the time. Our measure differs in several ways. First, we use time-varying means and volatilities that account for clustering. Second, we use the whole series rather than just the observations that correspond to crashes. Third, as described ahead, we offer a full dating and characterization of expansions and contractions for the period. Finally, Le Bris employs the time-varying means and standard deviations at time *t-1* to calculate the value of his measure at time t. Contrarily, we employ the contemporaneous means and volatilities calculated for each observation at time *t*.

$$\mu_{t,n} = \frac{\sum_{t=0}^{59} \alpha(1-\alpha)^t r_{t,n}}{\sum_{t=0}^{59} \alpha(1-\alpha)^t} \quad (9)$$

Where, as usual, $\alpha = \frac{2}{\text{obs}+1}$.[2] It is well-known that this measure gives more weight to the more recent observations while as we go back in time, they are assigned decreasing weights.

For the time-varying measure of dispersion, we use the forecasted standard deviation obtained from a GARCH(1,1) model such as:

$$h_t = \gamma + \alpha(r_{t-1} - \mu_{t-1})^2 + \beta h_{t-1} \quad (10)$$

Where γ is a strictly positive parameter and α and β satisfy stability conditions: they are non-negative and it is expected that $\alpha + \beta < 1$, (Engle and Bollerslev, 1986; Engle, 2001). The order of the GARCH may be seen as an unnecessary restriction but, in this sense, we follow Hansen and Lunde (2005) when they show that choosing the GARCH specification that maximizes goodness-of-fit for each series adds little value with respect to the standard of a GARCH(1,1) equation for every return series.

In continuation we solve the factor analysis described above, but using matrix **D**, from which the corresponding series of the Local Bull-Bear Indicator (LBBI) can be obtained:

$$\text{LBBI}_t = \omega_n d_{t,n} = \frac{\widehat{f_t}}{\sum_{i=1}^{n}\left(1/\widehat{\lambda_n}\right)};\ n = \begin{Bmatrix} 1,2,\ldots,12 \text{ if } \text{LBBI}_{\text{short}} \\ 18, 24, 30, 36 \text{ if } \text{LBBI}_{\text{medium}} \\ 42,48,54,60 \text{ if } \text{LBBI}_{\text{long}} \end{Bmatrix} \quad (11)$$

4. Empirical Results: What BBIs Tell Us about the cycles

This section aims to illustrate the benefits derived from using our proposal with the purpose of dating bull and bear phases in financial, economic series. To this end, we are going to study the UK FTSE stock market monthly index for the period January 1922 to September 2015. Let us begin with a brief introduction of our data; the second part of the section discusses main results

[2] In our case obs = 60

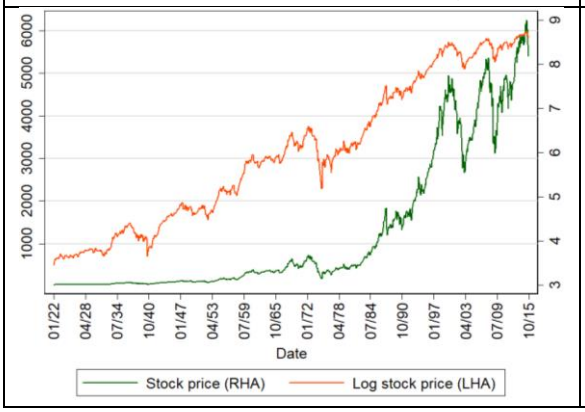
4.1. Sources and description of data

The UK FTSE All-Share Return Index has been obtained from Global Financial Data (GFD). This is a monthly series from August 1694 until December 1964, and daily frequency from December 1964 until September 2015. For the case of daily data, we chose the observation for the last trading day available each month. According to GFD, the index corresponds exclusively to Bank of England shares from 1874 to 1922. Thus, we use the UK Banker's Magazine All Securities as a secondary source. The sample period for our research, based on considerations of relevance and historical background, covers from January 1922 to September 2015. We reset the index to take a value of 100 in January 1950. Moreover, the final series has been deflated using the corresponding CPI for the UK on base January 1987. Finally, we have a series of 1,185 observations.

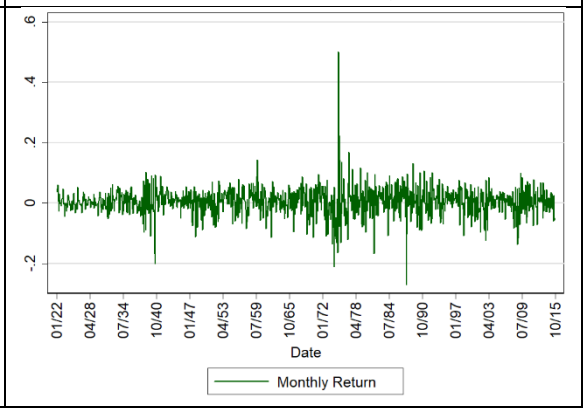
Figure 2 shows the time series evolution of the UK stock market, index in levels and logarithms, and its monthly return.

Figure 2: Time series evolution of the UK FTSE index

2.a. FTSE index (levels and logs)



2.b. FTSE index (monthly return)



In Figure 2 we observe substantial price decreases in the series at the end of the 1920s, during the Second World War, during the oil shocks of the 1970s, during the emerging market crisis that began in the late 1990s, and during the Great Financial Crisis 2007-2010 (GFC). We evidence significant price increases during the period before the Second World War, during the golden age of capitalism in 1950-70 (Middleton, 2014), during the 1980s, and in the period between the dot.com crash and the GFC. Table 1 presents descriptive statistics for the series in levels and its monthly and yearly returns.

Table 1: Descriptive statistics for stock market indices			
	Level	Monthly return	Yearly return
Number of observations	1185	1184	97
Mean	1,197.6	0.52%	7.40%
Median	342.5	0.73%	7.80%
Standard Deviation	1,680.1	4.59%	20.52%
Coefficient of variation	0.7125	0.1133	0.3606
Skewness	1.42	0.4883	0.6609
Kurtosis	3.58	13.7456	4.4164
Minimum	21.6	-26.87%	-59.54%
Maximum	6,253	50.05%	101.69%

The three series are positively skewed and have fat tails, pointing to the presence of abnormally high/low prices and returns. More formally, the null hypotheses of the absence of asymmetry and a kurtosis equal to three are strongly rejected. As expected, the monthly series of returns is more volatile than the other two, with a coefficient of variation of 0.11.

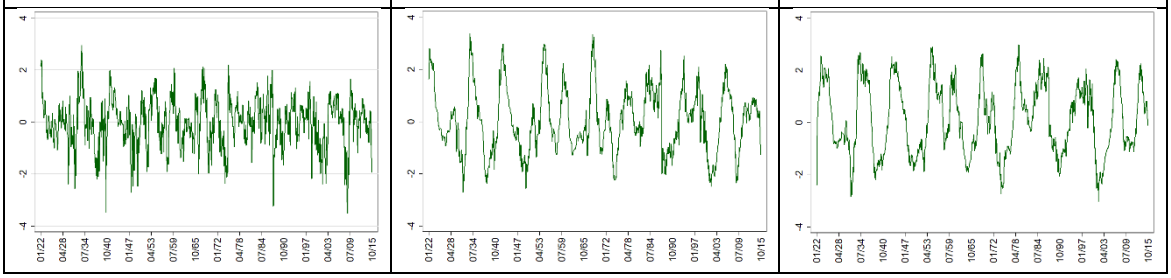
Using this information, we construct BBIs to different time horizons as described in section 3. For the sake of simplicity (another relevant reason is that we do prefer the contextual approach offered by these series), in the following section, we focus only in the case of the Local BBIs.

4.2. Bull-Bear Indicators for the case of the UK stock market

Figure 3 presents the three indicators corresponding to the FTSE index. Let us recall that the short run indicator contains information for the series of monthly returns up to 12 months, the medium-run indicator proceeds from the series of returns from 18 months up to three years and the long run indicators combines the information contained in the series of returns from 42 months up to five years.

Figure 3: Local Bull-Bear Indicators for the UK stock market

Short-run indicator (LBBIS)	Medium-run indicator (LBBIM)	Long-run indicator (LBBIL)



A first issue to highlight from Figure 3 is the apparent noisiness of the short run indicator (however, the series is not a random term; to the contrary, it is stationary and has a very strong autoregressive structure). The high frequency of the data compounded with its high variability creates this impression. The medium-term indicator, again stationary, is less noisy and allows us to observe that booms and busts are not all created equal, but that there are substantial differences in their amplitude, duration and in the speed with which they occur. The evolution of the long run LBBI is sharper and allows, upon direct observation, to find boom and bust phases. Interestingly, not all booms are followed by busts, if booms are understood as periods where the indicator remains above zero and busts are defined conversely. An event of a double-peaked boom, with no bust, appears at the end of the 1970s running until the late 1980s, which may be thought of as a prolonged boom that occurs in two distinct phases.

Table 2 below completes the information with a brief statistical summary of the three Local BBIs

Table 2: Descriptive statistics for Local BBIs

	LBBIS	LBBIM	LBBIL
Number of observations	1125	1125	1125
Mean	-0,0246	0,0430	0,1278
Median	0,0419	-0,0215	0,0210
Standard Deviation	0,9222	1,2205	1,3350
Coefficient of variation	-0,0267	0,0353	0,0957
Skewness	-0,3181	0,2943	0,0565
Kurtosis	3,5448	2.6264	1.9204
Minimum	-3,5155	-2,7056	-3,0167
Maximum	2,9576	3,3768	2,9827
Dickey-Fuller test	-9.1137 [(0,000]	-6.2584 [0,000]	-6.1659 [0,000]

Note: The equation for the Dickey-Fuller tests contains a linear trend and a constant. The p-values appear in brackets. The null hypothesis is that the series has a unit root.

Only the mean of the LBBIL is statistically different from zero, but the three means are statistically equal to the corresponding Median. In no case, we can accept a unitary variance, which tends to grow with the horizon of the LBBI. The short-run indicator is negatively skewed, but the skew is positive for the medium term LBBI; that corresponding to the long-run indicator is not

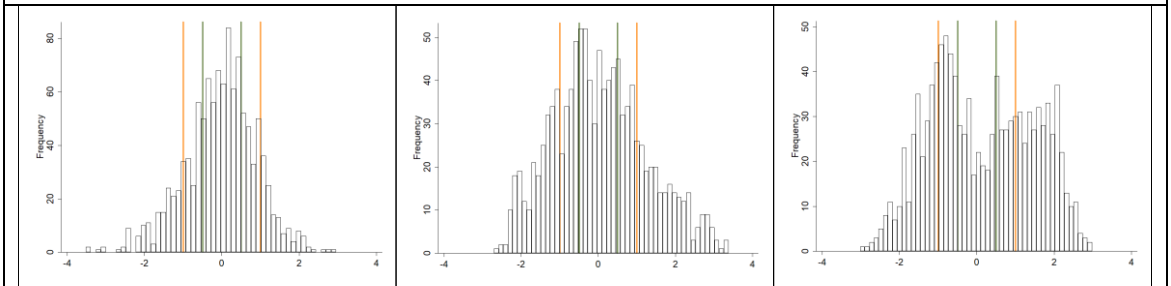
statistically different from zero. Positive skewness indicates that there is a larger probability mass to the right of the median, which indicates a more substantial presence of above average risk-adjusted returns. Negative skewness is defined conversely. In sum, this is an indication that while there may be a higher prevalence of short-run busts, medium-run risk-adjusted returns tend to be above average.

The LBBIS presents strong evidence of fat tails, indicating that the indicator has a propensity to take extreme values beyond what would be predicted by a normal distribution. However, the density of the tails diminishes when we move towards medium and long-run horizons. The distribution of the LBBIs become platykurtic and fewer outliers are standing in the extremes, which corroborates the greater regularity that we observe, for these cases, in Figure 3.

4.3. Dating Bears and Bulls: Duration, Amplitude, and Severity

After constructing the LBBI series, we face the issue of characterising them according to phases of expansion and contraction. To define such phases, we follow a simple approach. If the indicator takes a value above a certain threshold of X standard deviations, we consider the observation to make part of a bull period, and if it has a value below a threshold -X, we consider the observation to make part of a bear period. Figure 4 shows the histograms of the three specifications of LBBIs using a lax threshold of X=0.5 (green vertical lines) and a restrictive threshold of X=1.0 (orange vertical lines). The data in the table summarises the percentage of observations in each bin (bulls in green and bears in red).

Figure 4: Identifying bull and bear phases in LBBIs



Short-run LBBI			Medium-run LBBI			Long-run LBBI		
<–0.5σ	–0.5σ< X <0.5σ	> 0.5σ	<–0.5σ	–0.5σ< X <0.5σ	> 0.5σ	<–0.5σ	–0.5σ< X <0.5σ	> 0.5σ
27.10%	45.40%	27.50%	34.70%	31.40%	33.90%	39.50%	18.70%	41.80%
<–1σ	–1σ< X <1σ	> 1σ	<–1σ	–1σ< X <1σ	> 1σ	<–1σ	–1σ< X <1σ	> 1σ
14.20%	73.80%	12.00%	21.50%	57.60%	20.90%	23.50%	45.30%	31.20%

In the figure, we find that for short-run LBBIs a significant amount of information falls within the thresholds; more so than for medium and long-run LBBIs. Additionally, in the less stringent specification, we find a slight asymmetry as a more significant percentage of observations is classified as expansions rather than contraction for all time horizons. In any case, the most relevant difference across panels is the amount of information that is omitted from classification. While in the lax specification (top panel) less than 45% of the information falls between the two thresholds, in the restrictive specification (bottom panel) over 50% of the information, in most cases, falls in the middle bin. In what follows, we choose to work with the less restrictive threshold of ±0.5 standard deviations.

As said, to date expansions and contractions we follow a simple rule. An expansion (contraction) will begin the first time, and LBBI takes a value above (below) (-)0.5, and the phase will end the first time that the indicator takes a value below (above) (-)0.5. We will not enforce alternation between expansions and contractions, contrary to what is done by Pagan and Sossounov (2003). However, if two expansions (contractions) are separated by less than three months and the indicator never changes sign, we treat it as a single phase. Additionally, we do not allow expansions or contractions that last for a single month, unless the indicator takes an absolute value of at least 1.0 standard deviations.

After dating the beginning and end of each phase, we obtain several descriptive measures, such as:

- *Duration*, which we obtain as the number of months between the start and end date.
- *Amplitude,* for which we use two different measures. One is the compounded annual growth rate, CAGR, between the level of the series at starting and ending dates; the second is the difference between the 60-observation rolling 1, 3 and 5-year CAGR for the short, medium and long-run BBIs respectively between starting and ending date.
- *Severity*, for which we use an approximation to the Riemann integral of the LBBI function between two dates. In fact, the severity indicator of a given phase is obtained as the accumulated value of the indicator during the phase. The severity of booms will be positive and negative in case of contractions

The detailed characterisation of bull and bear phases for the UK stock market appears in Table 3.

Table 3: Dating, duration, amplitude, and severity of bull and bear phases in the UK stock market

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Short-run LBBI						
Bull	01/22	09/22	9	31.60%	33.00%	14.50
Bear	11/23	01/24	3	-18.68%	-6.06%	-1.90
Bear	07/25	12/25	6	-10.60%	-1.65%	-4.55
Bear	09/26	11/26	3	-16.05%	-2.04%	-2.52
Bull	03/27	05/27	3	22.98%	3.45%	2.04
Bull	02/28	04/28	3	15.62%	-1.27%	1.91
Bear	09/29	01/30	5	-9.64%	-7.12%	-6.95
Bull	03/30	04/30	2	41.17%	3.30%	1.68
Bear	06/30	02/31	9	-6.83%	-1.60%	-5.87
Bear	04/31	01/32	10	-13.65%	-7.93%	-12.28
Bull	07/32	05/34	23	28.35%	37.54%	35.14
Bear	07/34	08/34	2	-26.98%	-18.26%	-1.43
Bear	10/35	10/35	1	-37.73%	-5.99%	-1.02
Bull	02/36	03/36	2	53.17%	6.61%	1.83
Bear	03/37	10/38	20	-20.98%	-29.42%	-28.31
Bear	09/39	10/39	2	-55.24%	-0.44%	-2.81
Bear	06/40	10/40	5	-45.60%	-14.02%	-8.88
Bull	05/41	08/43	28	30%	52.58%	28.07
Bear	05/45	08/45	4	-11.03%	-12.27%	-2.87
Bull	11/46	12/46	2	57.40%	11.81%	1.70
Bear	07/47	09/48	15	-11.07%	-18.56%	-18.94
Bear	03/49	11/49	9	-18.96%	-23.18%	-10.85
Bull	08/50	06/51	11	16.48%	7.48%	7.40
Bear	11/51	06/52	8	-37.96%	-34.52%	-11.33
Bull	11/52	11/54	25	29.28%	55.82%	27.09
Bear	08/55	03/56	8	-24.37%	-30.47%	-6.72
Bear	11/56	11/56	1	-56.73%	-7.15%	-1.15
Bull	04/57	05/57	2	50.46%	2.76%	1.37
Bear	09/57	03/58	7	-22.98%	-20.40%	-9.66
Bull	08/58	03/60	20	43.99%	51.25%	21.34
Bear	11/60	12/60	2	-19.97%	-13.13%	-1.39
Bear	06/61	07/62	14	-22.05%	-32.25%	-14.29
Bear	11/64	08/65	10	-13.06%	-13.66%	-7.63
Bull	10/65	02/66	5	24.40%	17.63%	4.48
Bull	05/66	06/66	2	41.71%	12.72%	1.84
Bear	07/66	11/66	5	-35.38%	-33.00%	-6.20
Bull	04/67	01/69	22	39.20%	41.46%	27.47
Bear	02/69	10/69	9	-33.22%	-55.57%	-10.33
Bear	04/70	06/70	3	-44.20%	0.22%	-3.95

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Short-run LBBI						
Bull	04/71	04/72	13	46.89%	43.10%	10.42
Bear	09/72	10/72	2	-41.90%	-8.15%	-1.81
Bear	01/73	12/74	24	-48.91%	-67.62%	-32.20
Bull	01/75	01/76	13	105.57%	105.02%	13.75
Bear	09/76	10/76	2	-70.03%	-21.19%	-1.57
Bull	01/77	10/77	10	45.07%	81.22%	6.90
Bull	03/79	04/79	2	141.09%	10.19%	1.28
Bear	10/79	05/80	8	-16.63%	-19.65%	-4.94
Bull	10/80	11/80	2	36.76%	17.92%	1.38
Bear	09/81	10/81	2	-61.70%	-23.90%	-2.62
Bull	09/82	07/83	11	33.83%	34.06%	11.73
Bull	03/84	04/84	2	54.52%	-1.89%	1.74
Bull	11/84	02/85	4	39.94%	-1.96%	3.17
Bull	02/86	04/86	3	84.70%	20.55%	4.06
Bull	01/87	09/87	9	63.66%	33.58%	11.51
Bear	10/87	12/88	15	-20.39%	-51.99%	-18.15
Bear	02/90	12/90	11	-15.56%	-25.10%	-9.40
Bull	07/91	08/91	2	80.07%	22.78%	1.31
Bear	07/92	08/92	2	-42.43%	-18.34%	-1.64
Bull	11/92	01/94	15	34.10%	27.10%	11.97
Bear	05/94	06/94	2	-35.85%	-11.79%	-2.00
Bear	12/94	02/95	3	-11.52%	-10.01%	-1.83
Bull	07/95	08/95	2	46.11%	-5.40%	1.17
Bull	09/97	09/97	1	139.74%	7.20%	1.18
Bull	01/98	05/98	5	35.79%	4.63%	5.25
Bear	08/98	10/98	3	-29.96%	-8.67%	-5.05
Bull	03/99	04/99	2	51%	3.72%	1.57
Bear	01/00	07/00	7	-10.30%	-18.39%	-6.50
Bear	09/00	03/03	31	-20.56%	-40.25%	-35.75
Bull	05/03	04/04	12	19.27%	43.66%	10.72
Bull	09/04	04/06	20	22.06%	21.88%	16.39
Bear	11/07	03/09	17	-30.15%	-38.06%	-31.89
Bull	07/09	03/10	9	45.99%	65.04%	9.83
Bull	09/10	10/10	2	64.15%	6.78%	1.07
Bear	08/11	09/11	2	-55.85%	-18.93%	-2.08
Bull	01/13	05/13	5	33.33%	17.51%	3.65
Bear	09/14	10/14	2	-20.24%	-9.00%	-1.55
Bear	08/15	09/15	2	-48.29%	-9.63%	-3.30

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Medium-run LBBI						
Bull	01/22	02/24	26	10.14%	16.29%	47.46
Bear	09/25	02/27	18	4.59%	2.19%	-11.87
Bull	04/29	05/29	2	-0.68%	-0.35%	1.07
Bear	11/29	07/32	33	-0.33%	-5.79%	-43.94
Bull	02/33	08/35	31	18.07%	14.33%	57.31
Bull	02/36	03/36	2	53.17%	1.50%	1.20
Bear	05/37	03/40	35	-7.89%	-14.03%	-53.93
Bear	05/40	05/41	13	-18.08%	-0.84%	-12.86
Bull	10/41	10/44	37	17.51%	19.33%	61.94
Bear	02/46	10/46	9	15.97%	1.04%	-5.01
Bear	07/47	08/50	38	-5.08%	-12.06%	-56.79
Bull	06/51	10/51	5	-3.69%	-0.01%	2.11
Bear	01/52	08/52	8	-10.81%	2.12%	-7.01
Bull	08/53	12/55	29	21.38%	18.37%	56.82
Bear	11/56	01/57	3	19.87%	-1.19%	-1.89
Bear	09/57	07/58	11	-3.13%	-6.26%	-11.12
Bull	04/59	05/61	26	26.46%	17.33%	34.10
Bear	10/61	06/64	33	3.29%	-16.55%	-29.31
Bear	11/64	09/65	11	-6.08%	-0.39%	-7.29
Bear	07/66	02/67	8	-19.43%	-6.88%	-7.03
Bull	06/67	05/69	24	20.17%	10.97%	50.63
Bear	04/70	06/71	15	7.43%	-13.14%	-15.00
Bull	04/72	08/72	5	0.80%	6.66%	3.56
Bear	07/73	10/75	28	-19.87%	-28.83%	-41.30
Bull	12/76	06/79	31	22.00%	27.43%	28.54
Bear	09/81	10/81	2	-61.70%	-3.89%	-1.73
Bull	11/82	09/87	59	27.15%	20.27%	74.21
Bear	10/87	01/92	52	-1.40%	-27.55%	-61.38
Bear	07/92	08/92	2	-42.43%	-6.21%	-1.57
Bull	12/92	08/94	21	15.26%	6.25%	26.14
Bull	11/96	07/98	21	20.60%	8.48%	23.31
Bull	02/99	04/99	3	56.95%	3.03%	2.12
Bear	01/00	11/03	47	-9.43%	-26.27%	-74.59
Bull	07/04	07/07	37	13.41%	20.06%	47.21
Bear	03/08	02/10	24	-2.42%	-9.80%	-33.92
Bull	12/10	07/11	8	6%	7.56%	4.88
Bull	01/12	02/12	2	50.22%	6.99%	1.22
Bull	01/13	06/14	18	11.78%	2.72%	13.50
Bear	08/15	09/15	2	-48.29%	-4.76%	-2.14

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Long-run LBBI						
Bear	01/22	03/22	3	64.12%	-2.62%	-4.05
Bull	07/22	02/26	44	3.02%	12.22%	69.11
Bear	10/26	12/28	27	5.09%	-3.50%	-20.30
Bear	10/29	01/30	4	-11.00%	-0.21%	-2.92
Bear	08/30	02/33	31	1.33%	-2.08%	-42.30
Bull	06/33	04/37	47	12.23%	11.39%	85.70
Bear	10/37	09/41	48	-5.64%	-16.09%	-69.13
Bull	07/42	06/46	48	15.65%	21.29%	79.18
Bear	08/47	01/53	66	-2.49%	-16.70%	-81.83
Bull	09/53	08/57	48	13.41%	13.04%	78.44
Bear	01/58	07/58	7	24.48%	1.61%	-5.33
Bull	10/59	12/61	27	8.62%	4.66%	37.19
Bear	06/62	07/62	2	-19.47%	-0.94%	-1.19
Bear	04/63	04/67	49	1.82%	-14.18%	-59.24
Bull	10/67	06/69	21	10.71%	0.44%	35.78
Bull	11/69	03/70	5	16.20%	2.85%	3.73
Bull	07/71	04/72	10	39.75%	7.41%	7.70
Bear	09/72	04/77	56	-13.44%	-25.35%	-80.54
Bull	11/77	05/81	43	3.30%	14.84%	57.00
Bull	04/83	09/87	54	26.59%	17.73%	82.70
Bear	03/88	10/92	56	5.62%	-11.76%	-64.03
Bull	12/93	04/94	5	3.03%	-2.70%	3.54
Bull	08/94	07/98	48	16.12%	8.66%	53.84
Bull	11/98	12/99	14	25.84%	6.40%	13.90
Bear	09/00	12/04	52	-5.92%	-19.30%	-86.30
Bull	11/05	05/08	31	4.99%	11.41%	52.54
Bear	10/08	01/12	40	5.95%	-5.46%	-31.60
Bull	09/12	08/14	24	11.37%	8.77%	34.85
Bull	01/15	05/15	5	22.64%	2.69%	3.53

Although we will provide in-depth analysis of the results from Table 3, it is noteworthy that the number of phases identified by the short-run LBBI doubles the number of phases identified by the medium and long-run indicators.

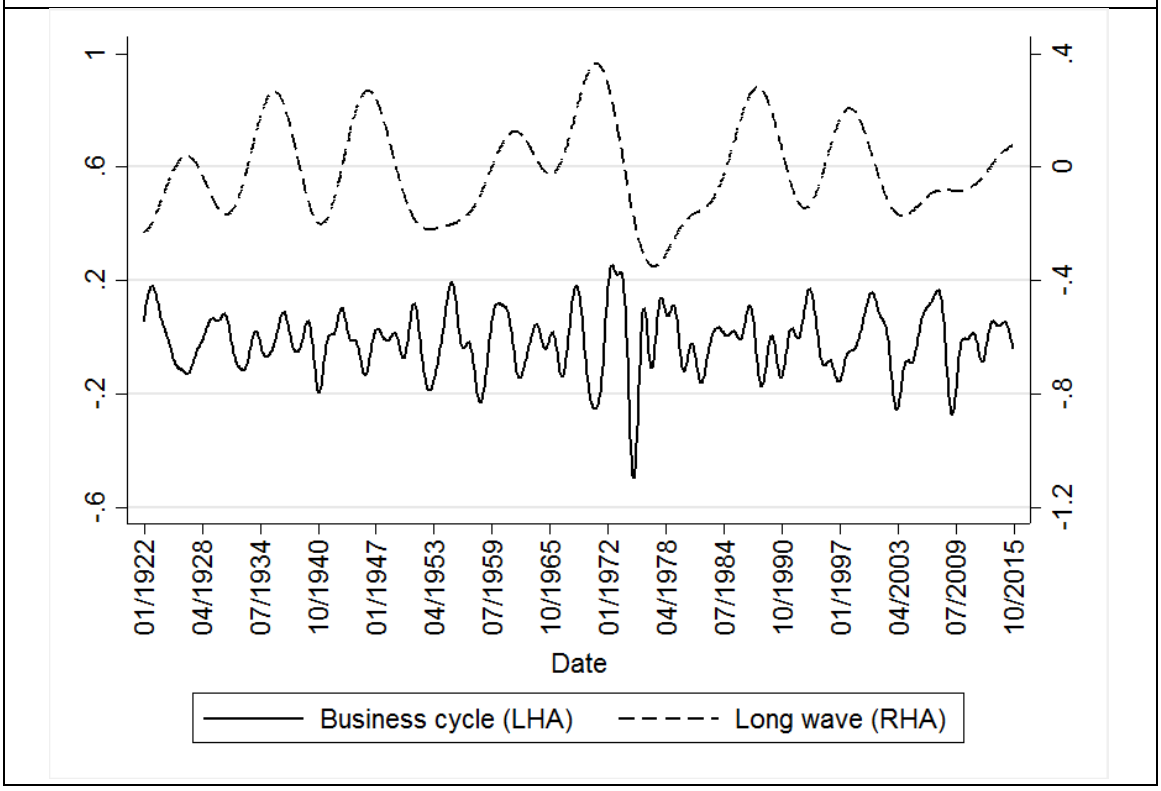
5. How BBIs Measure Up? Comparing Methodologies

In this section, we apply the different methodologies discussed in section 2 to the real stock market data for the United Kingdom.

For the TP algorithm, we perform two specifications to obtain starting and ending dates for expansion and contraction phases. First, one for the short-run with an observation window of 8 months, a minimum cycle length of 16 months and minimum phase duration of 4 months as in Pagan and Sossounov (2003). An alternative long-run specification uses an observation window of 12 months, a minimum cycle length of 24 months and minimum phase duration of 6 months as in Bordo and Wheelock (2009).

Subsequently, we follow Drehmann et al. (2012) and use the band-pass filter as in Christiano and Fitzgerald (2003) to extract a business cycle and a medium-term cycle from the logarithmic transformation of the index. The former has a duration between 18 and 96 months, and the latter a duration between 96 and 360 months. These two components, independent by construction, are presented in Figure 5.

Figure 5: Business and long-run cycles extracted using the band-pass filter

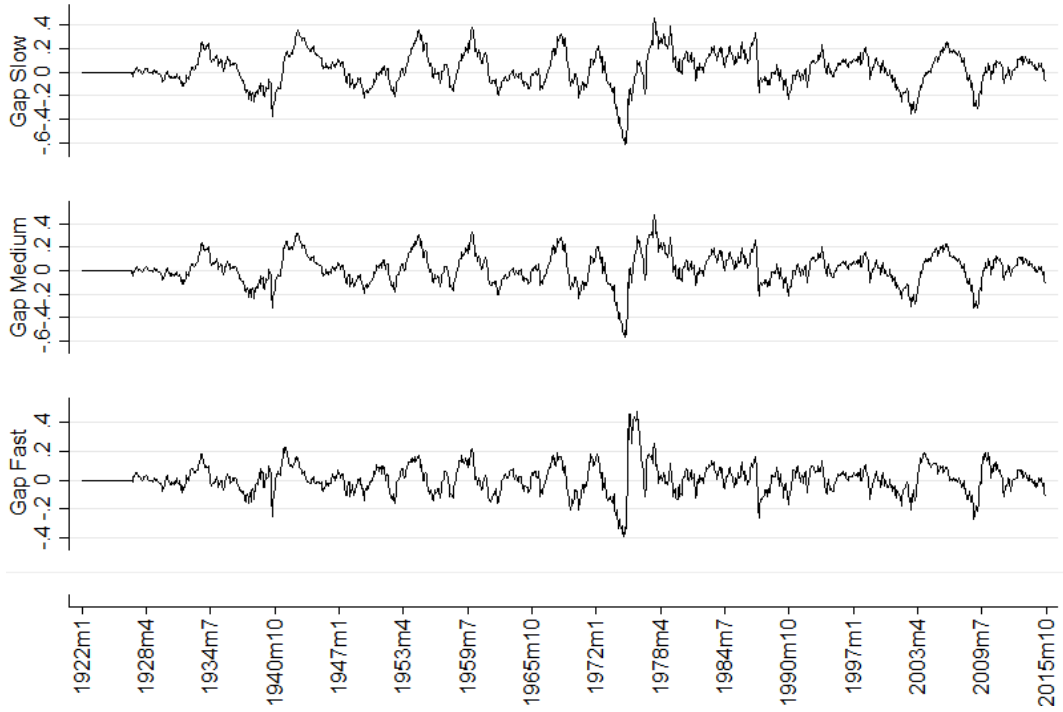


Authors like Bordo et al. (2001) use the business cycle series extracted through the band-pass filter to date booms and busts. By using a centred moving window of 25 observations, we find local maxima and minima in both filtered frequencies in a process reminiscent of the turning point algorithm.

An issue that arises from the decomposition of time series into orthogonal components is that, as Cendejas et al. (2017) indicate, there may be overlap between waves of different frequency. In that sense, using the various components (business cycle and long wave) to date booms and busts may yield turning points that do not necessarily coincide with maxima and minima in the original series. Due to this caveat, we choose to only present the results from the business cycle component.

A third approach consists in the Hodrick and Prescott (1997) filter to identify bulls and bears. Following what has been done traditionally in the literature we tested three different specifications of the filter by changing the values for the parameter λ. Hodrick and Prescott (1997) find that for quarterly data the optimal λ is 1,600 based on a 5% cyclical component and a quarterly change of 0.125% every quarter. Converting the quarterly growth rate change to a monthly frequency yields a λ of 14,411 which we round to 14,400 and use as the fast adapting λ. Secondly, we follow Ravn and Uhlig (2002) and use a medium-speed λ of 129,600. Finally, following Borio and Lowe (2004), we define a slow adapting λ of 400,000. The filter is applied to the stock market index directly, extracting the last observation for the trend on a rolling window of 120 observations (10 years). We then calculate the stock market growth gap as the percentage difference between the expected value of the series and the observed value for a given date. We present the resulting series Figure 6.

Figure 6: HP filter gaps for three different specifications



We find that neither the predicted trend nor the growth gap differ significantly between parameterisations and thus only discuss results for the intermediate lambda of 129,600. A remarkable result from Figure 6 is that any of the gap series can identify boom and bust periods, defined as above or below trend growth. However, the series mimic each other substantially, with a minimum correlation coefficient of 0.6 among them; thus, they roughly reflect same booms and busts.

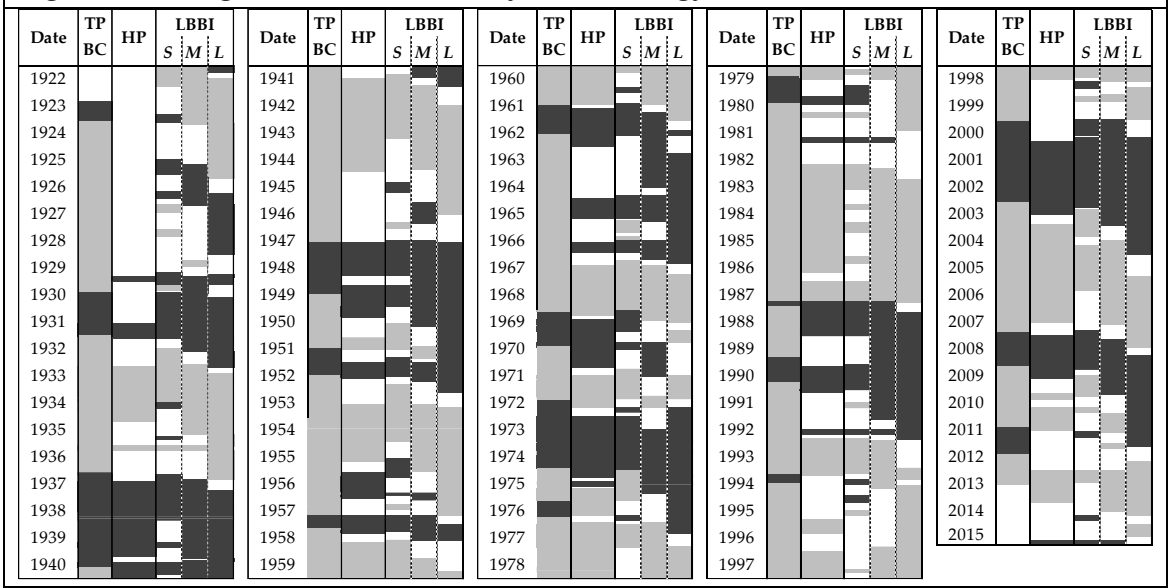
To compare the results from the three approaches, we establish starting and ending dates for booms and busts. The two versions of the turning point algorithm and the band-pass filter produce an output series. Since their results are quite similar, we summarise them in a single series by stating that any given month is a boom month if at least two out of the three coincide. Busts were defined similarly. We will refer to this series of dates as those from the Turning Point and Business Cycle consensus (TPBC).

To extract dates from the HP filter we needed to establish thresholds for what constitutes a bull or a bear. In this case, however arbitrary, we followed a similar rule to that of the LBBIs (bull and bears are observations beyond 0.5 standard deviations from the mean). The standard deviation for the HP gap series is 12.95%, thus as a threshold, we chose a value of 6.5%. When the value of the gap exceeds 6.5% upward, it indicates a boom and when it exceeds -6.5%

downward it indicates a bust. As in the case of LBBIs, if two booms (busts) were three or fewer months apart and the value of the gap never turned negative (positive), we treated it as a single boom (bust). Additionally, booms (busts) that lasted only one month were kept only if the value of the HP gap was at least (-)13%.

Figure 7 summarises the results graphically by identifying the differences in dating across methodologies. Expansion periods are shaded in light grey, and contraction phases are shaded in dark grey according to each methodology for the period between January 1922 and September 2015.

Figure 7: Dating of bulls and bears by methodology



Once the starting and ending dates are fixed for each methodology (TPBC and HP), we obtain the same measures of duration and amplitude as for the LBBIs. As a measure of severity, we calculated the severity index in (1) which follows the triangular approximation of Harding and Pagan (2002b) and Agnello and Suchknet (2011). The details appear in Table 4. We do not follow the same approach like the one employed for LBBIs for reasons of scale and interpretability. In the case of the TPBC, we would be adding values of the index for different phases which would be affected by the changes in level. In the case of the HP filter, we would be adding percentage deviations from trend without any correction for contextual conditions.

Table 4: Expansions and contractions in the UK stock market. Turning point algorithm, band-pass and HP filters

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Turning Point and Busines Cycle (TPBC)						
Bear	04/23	01/24	10	-7.54%	-16.29%	-31.61
Bull	02/24	04/30	75	4.02%	4.25%	1,048.57
Bear	05/30	12/31	20	-10.17%	-11.71%	-163.65
Bull	01/32	12/36	60	15.98%	25.22%	3,296.26
Bear	01/37	07/40	43	-18.72%	-51.91%	-1,127.11
Bull	08/40	06/47	83	19.14%	53.91%	9,787.39
Bear	07/47	06/49	24	-13.73%	-27.35%	-306.85
Bull	07/49	05/51	23	13.17%	27.62%	307.77
Bear	06/51	06/52	13	-26.52%	-45.51%	-184.52
Bull	07/52	07/57	61	16.62%	43.95%	3,614.67
Bear	08/57	02/58	7	-33.51%	-29.39%	-72.82
Bull	04/58	04/61	37	32.62%	31.31%	2,567.82
Bear	06/61	07/62	14	-22.05%	-32.25%	-176.56
Bull	08/62	01/69	78	13.40%	53.07%	4,931.74
Bear	02/69	05/70	16	-27.78%	-58.09%	-283.74
Bull	06/70	04/72	23	34.05%	59.77%	866.71
Bear	05/72	11/74	31	-42.06%	-101.25%	-1,171.61
Bull	12/74	01/76	14	95%	108.33%	828.06
Bear	02/76	09/76	8	-35.11%	-59.06%	-100.96
Bull	10/76	04/79	31	25.46%	42.14%	1,234.92
Bear	05/79	05/80	13	-22.45%	-47.10%	-156.47
Bull	06/80	09/87	88	23.22%	75.00%	15,940.07
Bear	10/87	11/87	2	-92.07%	-59.20%	-34.45
Bull	12/87	09/89	22	20.98%	22.98%	459.74
Bear	10/89	09/90	12	-21.86%	-42.10%	-131.16
Bull	10/90	01/94	40	21.77%	51.86%	1,855.79
Bear	02/94	06/94	5	-35.04%	-26.59%	-42.19
Bull	07/94	12/99	66	16.50%	18.63%	4,343.45
Bear	01/00	01/03	37	-18.19%	-52.96%	-853.75
Bull	02/03	10/07	57	15.82%	39.91%	2,883.09
Bear	11/07	02/09	16	-33.47%	-41.98%	-332.91
Bull	03/09	04/11	26	23.88%	41.03%	767.35
Bear	05/11	05/12	13	-11.02%	-18.99%	-77.21
Bull	06/12	06/13	13	18.59%	25.14%	131.85

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
HP Filter λ=129,600						
Bear	11/29	12/29	2	-18.78%	-3.37%	-3.41
Bear	08/31	01/32	6	-16.98%	-7.54%	-26.66
Bull	03/33	02/35	24	21.96%	-3.37%	581.43
Bull	02/36	03/36	2	53.17%	6.61%	7.62
Bear	06/37	02/40	33	-10.18%	-1.56%	-420.89
Bear	06/40	12/40	7	-28.29%	-15.25%	-61.71
Bull	07/41	11/44	41	21.81%	12.17%	1,973.12
Bear	08/47	09/48	14	-6.81%	-11.38%	-55.27
Bear	03/49	04/50	14	-10.70%	-16.09%	-86.54
Bull	02/51	06/51	5	15.85%	-1.58%	16.23
Bear	01/52	07/52	7	-20.97%	-13.56%	-44.90
Bull	08/53	08/55	25	26.77%	-5.35%	798.77
Bear	02/56	12/56	11	-2.28%	1.62%	-11.57
Bear	09/57	04/58	8	-15.51%	-22.02%	-42.52
Bull	09/58	05/61	33	27.69%	12.39%	1,581.37
Bear	08/61	12/62	17	-2.69%	-5.12%	-32.23
Bear	12/64	08/65	9	-8.29%	-7.47%	-28.27
Bear	08/66	11/66	4	-22%	-21.36%	-16.20
Bull	06/67	03/69	22	28.55%	19.56%	643.16
Bear	06/69	02/71	21	-8.57%	-9.52%	-151.47
Bull	07/71	08/72	14	23.86%	-7.39%	198.48
Bear	01/73	03/75	27	-30.39%	-18.29%	-752.48
Bear	06/75	07/75	2	-65.43%	-1.42%	-16.22
Bull	09/75	08/76	12	-5.03%	-41.50%	-30.19
Bull	12/76	06/79	31	22.00%	33.10%	1,040.58
Bear	03/80	05/80	3	-37.71%	-17.51%	-16.74
Bull	10/80	11/80	2	36.76%	17.92%	5.36
Bear	09/81	10/81	2	-61.70%	-23.90%	-14.78
Bull	09/82	08/86	48	24.35%	27.29%	3,337.97
Bull	01/87	09/87	9	63.66%	33.58%	201.13
Bear	10/87	12/88	15	-20.39%	-51.99%	-186.01
Bear	03/90	01/91	11	-11.41%	-18.96%	-57.81
Bear	07/92	08/92	2	-42.43%	-18.34%	-8.79
Bull	11/92	02/94	16	27.48%	19.24%	303.02
Bull	11/95	04/96	6	23.34%	9.69%	33.18
Bull	01/97	06/98	18	21.90%	10.10%	311.27
Bear	11/00	06/03	32	-14.62%	-17.38%	-550.39
Bull	12/03	06/07	43	13.39%	4.92%	1,223.23
Bear	01/08	06/09	18	-21.31%	-20.45%	-271.71
Bull	03/10	04/10	2	23.46%	-12.42%	3.57
Bull	09/10	06/11	10	15.09%	14.11%	62.15
Bull	01/13	02/14	14	16.72%	1.41%	137.00
Bear	08/15	09/15	2	-48.29%	-9.63%	-10.41

5.1. Differences in Dating

In Figure 7 we can observe there is a strong consensus across methodologies in the broad classification of bull and bear phases. This is particularly clear in the dating offered by the HP and the short-run local indicator (LBBIS). However, they are not the same. Let us summarise several noteworthy differences across methodologies.

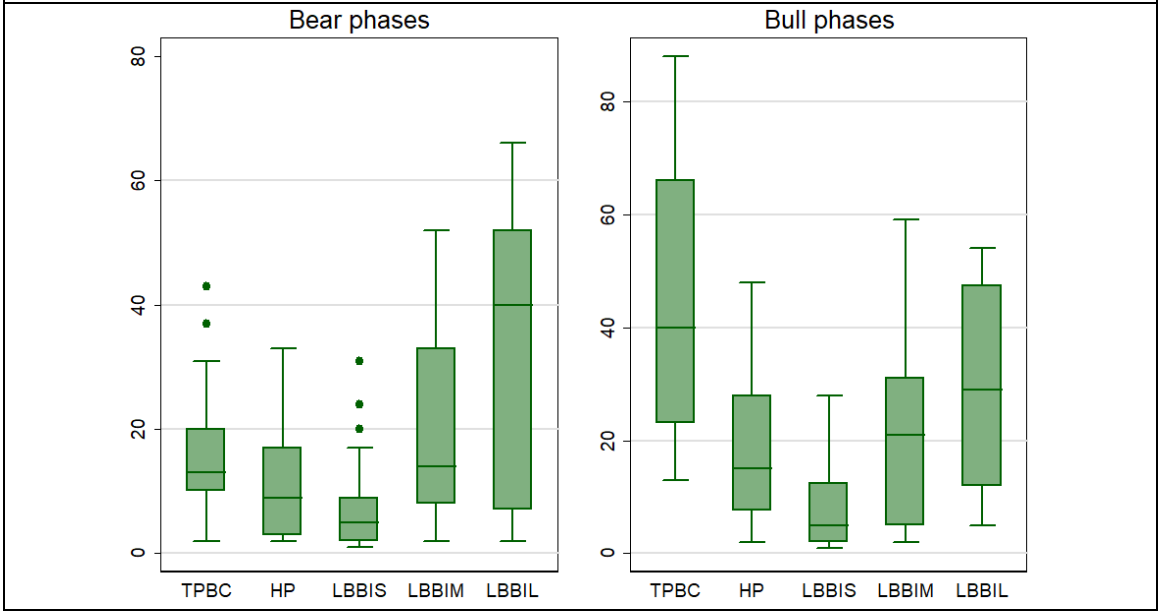
- Several phases are only reported by one or two of the methodologies (i.e., two bear phases in the 1940s, a bear phase in the early 1980s, or a short bull phase in the early-2010s).
- According to TPBC or HP, a phase may cover an extended period, but LBBIS nuance this result by breaking it into different shorter waves (i.e., the long bull phase in the early 1980s).
- While the dating from the short-run LBBI coincides roughly with the HP filter, the medium and long-run datings show that expansions and contractions are usually persistent events that affect long-run returns well beyond a shock. An example of this is the shock in the early 1970s, which seems to run until 1974-75 according to TPBC, HP, and the short-run LBBI, while the medium and long-run local indicators (LBBIM and LBBIL) show that its effects lasted until 1977.
- Interestingly, different LBBIs can show both an expansion and a contraction for the same period (i.e., 1965-66 and 1974-77). This apparent contradiction denotes that while the variable may be suffering a long-run contraction, short-run expansions may also take place which does not necessarily cause the long-run trend to revert. An excellent example of this has to do with the stock exchange after the oil shock of 1973, where it started a long-run contraction process. During 1975, there was a short-run expansion which, however, was not strong enough to cause a reversal of the long-run trend.

Additionally, the number of bull and bear phases changes significantly depending on the methodology as shown in Table 5. In most cases, the number of bull or bear phases by methodology is below 30, which makes them subject to small sample issues. This occurrence is usual in empirical applications in economic history, and the only alternative would be to prolong our study in time to allow for the inclusion of more phases. As this is impractical in the current context, we choose only to mention the caveat.

Table 5: Number of phases by methodology					
	TPBC	*HP*	*LBBIS*	*LBBIM*	*LBBIL*
Bull	17	20	36	19	16
Bear	17	23	41	20	13

Figures 8 to 10 show the boxplots for the three salient features of amplitude, duration and severity of the bull and bear phases according to the different approaches that we are comparing. It is clear, according to these Figures, that measures such as duration and severity are quite disperse for both bull and bear phases; an indication that each phase is a distinct event and that making generalisations about their behaviour is not an easy task.

Figure 8: Boxplot for the duration of phases by methodology



Of course, the high dispersion that we observe in the collection of boxplots is an argument in favour of extending the analysis of expansions and contractions beyond simple binary sequences and using the LBBIs proposed here as an additional measure for the identification and characterisation of phases.

Figure 9: Boxplot for the amplitude of phases by methodology

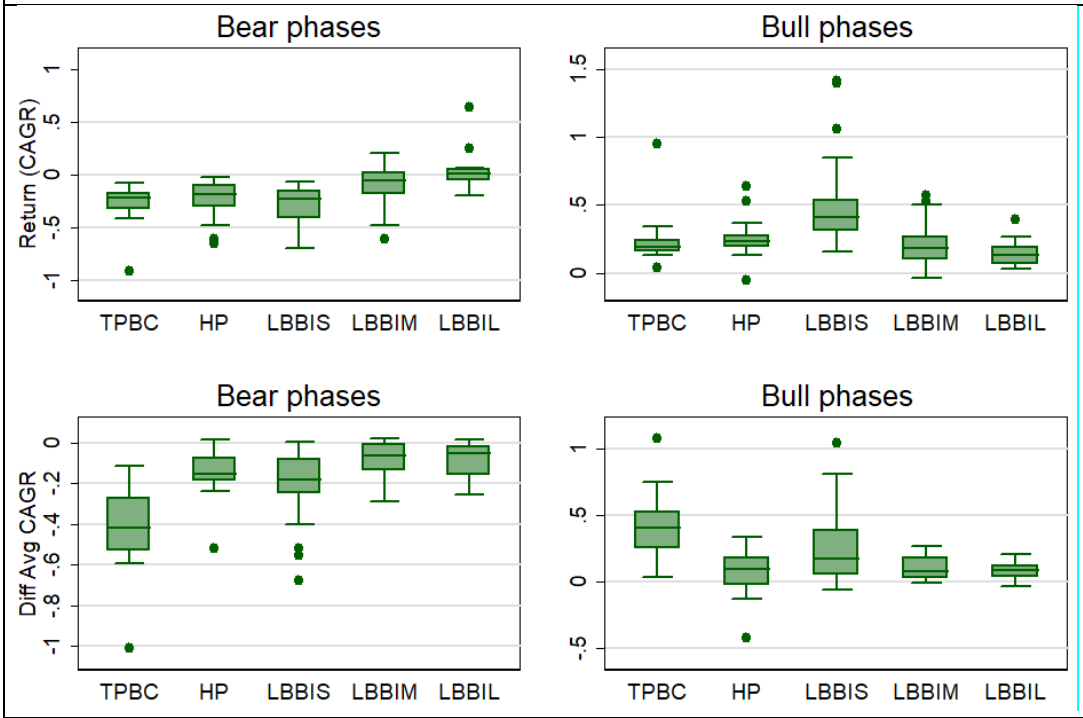
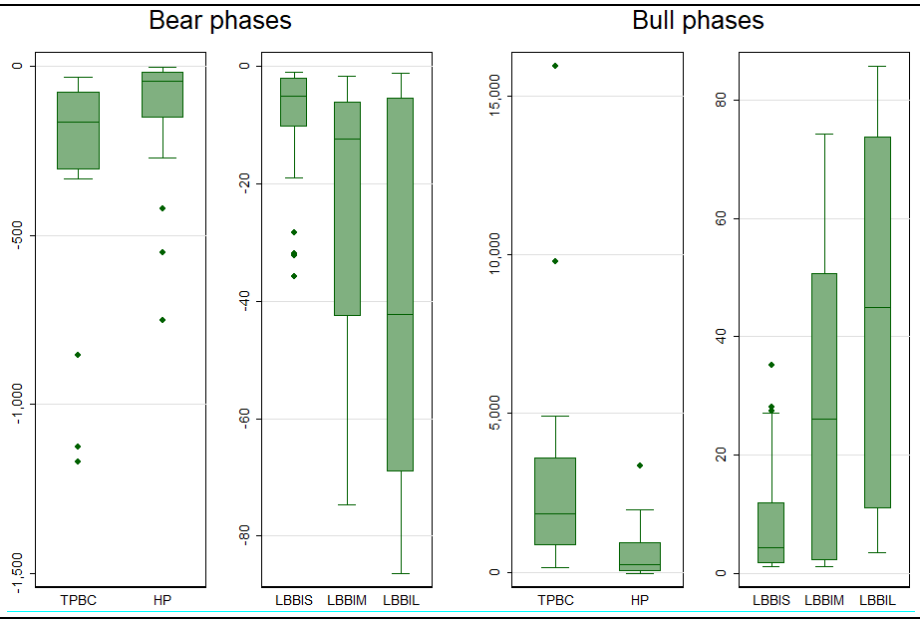


Figure 10: Boxplot for the severity of phases by methodology



To complete the picture, Table 6 presents a summary of the percentages of pairwise mean comparison tests that reject the null hypothesis of equality, by measure, for the five different methods discussed here (TPBC, HP, LBBIS, LBBIM, and LBBIL).

Table 6: Pairwise mean comparison tests. Percentage of rejections of the null by measure, confidence level and type of phase

		Bear phases			Bull phases		
Confidence level		*75%*	*90%*	*95%*	*75%*	*90%*	*95%*
Duration		90%	70%	70%	90%	90%	80%
Amplitude	*Period CAGR*	80%	70%	70%	60%	40%	40%
	Difference in return	80%	60%	60%	70%	70%	70%
Severity		100%	100%	100%	100%	100%	100%

The table shows that, even to the stricter confidence level, there are relevant differences across methodologies. The more critical differences, as expected, are found in the severity measures, while the smallest ones are apparent in the measures of amplitudes. These results hold for both bull and bear phases. We expect the number of differences to increase even more with a significant increase in sample size but prefer to leave this extension for further research.

To finish this part, let us add some details of interest by each measure that summarise our findings.

5.1.1. Duration

We identify that bear phases are shortest when measured by HP followed in ascending order by LBBIS, LBBIM, and LBBIL. Additionally, the duration of bear phases is similar when using TPBC or the LBBIM. Regarding bull phases, we find that they are shortest when measured by LBBIS, followed in ascending order by LBBIM, LBBIL, and TPBC. Moreover, it is indifferent to measure duration by HP or LBBIM.

The relevant takeaway with regards to the LBBI methodology is that as the time horizon increases the median duration of bull and bear phases also increases. This is indicative of persistence in expansions and contractions which this indicator, under its three distinct specifications, makes evident for researchers.

5.1.2. Amplitude

With regards to amplitude, we have two different measures. The first is the CAGR and the second is the difference between the 60-observation rolling 1, 3 and 5-year CAGR between starting and ending date. For TPBC, HP, and LBBIS

we employ the one-year average CAGR as this measure arises from the short-run evolution of the underlying series. For LBBIM we use the three-year average CAGR, and for LBBIL we use the five-year average CAGR, keeping consistency with the vectors in **D** from which the indicators originate.

For the first measure, we find that bear phases have similar negative amplitudes when identified through TPBC, HP, and LBBIS. The amplitude measures increase towards zero when measured by LBBIM and then by LBBIL. Regarding bull phases, the largest gains are evidenced in the phases measured by LBBIS. Amplitude is closer to zero when measured by either TPBC or HP. According to LBBIM and LBBIL, amplitude is both closest to zero and statistically indifferent across both methodologies.

The second amplitude measure employed, indicates that the most harmful bear phases are those identified by TPBC, followed by LBBIS, and HP. Measures of amplitude according to LBBIM and LBBIL are closest to zero and indistinguishable from each other. For bull phases, TPBC has the highest mean amplitude, followed by HP and LBBIS. As is the case for bear phases, amplitude according to LBBIM and LBBIL are closest to zero and indistinguishable from each other.

It is interesting that both measures of amplitude yield similar results and that the amplitude of bulls and bears as dated by both medium and long-run indicators is closer to zero than when identified by other methodologies. This may happen because the way in which medium or long-run expansions and contractions are dated may include the beginning of short-term recoveries. However, these results should not be discouraging: a very negative, or positive, CAGR that occurs which only shows up in the LBBIS, may affect general economic conditions far less than a small but persistent negative or positive trend in that shows up in the LBBIM or LBBIL.

5.1.3. Severity

As measures of severity, we employ the triangular approximation of Harding and Pagan (2002b) for bull and bear phases identified by TPBC and HP. Conversely, the severity of phases identified by LBBIs is measured as the accumulated value of the indicator between the starting and ending date of the phase. In sum, the measures of severity are not expressed in the same units, so we perform comparisons between HP and TPBC and among the different LBBIs separately.

We find that both bear and bull phases are more severe when using the TPBC dating than through the HP filter. When comparing the LBBIs, we find that both bull and bear phases are most severe when identified using the LBBIL, they are least severe when identified by LBBIS, with results for LBBIM being in the middle. The means for the three measures of severity are statistically different between them. The results for LBBIs are, as expected, consistent with the results for the measure of duration. Concurrently, we indicate that these two measures reflect well on the persistence of booms or busts in time, where a single shock can affect medium and long-run returns well after the short-term event has diluted.

6. Conclusions

From a methodological perspective, we contribute to the literature on the identification of trends and cycles in financial and economic time series. We have shown that the LBBI indicator, in its short, medium and long-run specifications provides as much information as alternative methodologies and allows for further nuance and detail in the analysis of amplitude, duration, and severity. These indicators are valuable as they require fewer statistical assumptions than alternative filtering techniques and aggregate in three measures sufficient information about the returns structure of the series to different time horizons. Finally, since LBBIs are continuous time series that adequately reflect the empirical distribution of the underlying data, they exceed by far the informational content of the binary sequences that are usually employed in the financial crises literature.

For researchers in economics and finance, the Local Bull-Bear Indicators offer a measure that is tractable and readily interpretable: the risk-adjusted deviation from the average expressed in standard deviations. The fact that it can be constructed to different time horizons is of added interest as it captures the persistence of phases in the series well beyond what is contained in the usual methodologies. Moreover, the measure of severity that can be derived by LBBIs resolves the issues of interpretation and bias in the triangular methodology discussed above. Finally, the fact that it uses both time-varying means and volatilities serves the purpose of analysing events in their respective historical context rather than observing them with respect to long-run measures of central tendency and dispersion.

The spread in the measures of amplitude, duration, and severity indicates that not all booms or busts are created equal. On the contrary, they

show that each phase is a unique event, with specific characteristics that need not be shared with other phases. In this sense, an added value of the measure we propose is that it allows researchers to identify and work with a higher level of granularity.

A final noteworthy issue has to do with the relationship among the different specifications of LBBIs. On the one hand, while the short-run indicator may be denoting a bull phase, the long-run indicator may signal a contraction. This apparent contradiction is moot since it merely reflects that while the variable may be suffering a long-run contraction, short-run expansions that do not cause the long-run trend to revert may also take place. On the other hand, it is noteworthy that according to measures of amplitude, both bull and bears are ampler when identified by the short-run indicator, than under the medium or long-run specification. This may happen because the dating of medium or long-run expansions and contractions may include the beginning of short-term recoveries. However, these results should not be discouraging: a very negative or positive amplitude that affects short-run returns for just a few months may affect investors and even general economic conditions far less than a small but persistent negative or positive trend in medium or long-run indicators.

There are several avenues for further research. First, an inquiry can be made into the nature of the more extreme events by restricting the ±0.5 standard deviation threshold to more stringent values. Second, further research can explore the determinants of the anatomical differences between bull and bear phases through time. Finally, we believe that this new indicator will be useful for an ample set of research questions related to financial crises, international macroeconomics, long-run economic growth and development, and international trade cycles and globalisation.

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