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Abstract

This paper uses a modelling framework which includes two singularities (or poles) in the spectral density function, one corresponding to the long-run (zero) frequency and the other to the cyclical (non-zero) frequency. The adopted specification is very general, since it allows for fractional integration with stochastic patterns at the zero and cyclical frequencies and includes both long- and short- memory components. The cyclical patterns are modelled using Gegenbauer processes. This model is estimated using monthly data for five European stock market indices (DAX30, FTSE100, CAC40, FTSE MIB40, IBEX35) from January 2009 to January 2019. The results indicate that the series are highly persistent at the long-run frequency, but they are not supportive of the existence of cyclical stochastic structures in the European financial markets. The only clear evidence of a stochastic cycle is obtained in the case of France under the assumption of white noise disturbances; in all other cases, there is no evidence of cycles.

JEL-Codes: C220, C580.

Keywords: European stock markets, long run behavior, cycles, persistence.

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1. Introduction

Understanding the behaviour of asset prices is crucial for both investors and monetary authorities to design effective portfolio management strategies and stabilisation policies respectively. However, there is still no agreement on the most appropriate modelling framework to use. Whilst the early literature used specifications based on the classical dichotomy between I(0) and I(1), more recently the possibility of fractional integration and long-memory behaviour has also been taken into account. For instance, a long-memory specification was adopted by Caporale and Gil-Alana (2002) for US stock prices. In a subsequent paper, the same authors advocated an approach incorporating both long-run and cyclical components (see Caporale and Gil-Alana, 2014). The present study uses a similar modelling framework which includes two singularities (or poles) in the spectral density function, one corresponding to the long-run (zero) frequency and the other to the cyclical (non-zero) frequency. The adopted specification is very general, since it allows for fractional integration with stochastic patterns at the zero and cyclical frequencies and includes both long- and short- memory components. The cyclical patterns are modelled using Gegenbauer processes. A motivation for this type of specification is that it is sufficiently general to include as particular cases the Efficient Market Hypothesis, mean reversion with different speeds of adjustment towards the long-run equilibrium level, financial cycles, explosive patterns, etc. This model is then estimated in the case of five European stock market índices using monthly data for five European stock market indices (DAX30, FTSE100, CAC40, FTSE MIB40, IBEX35) from January 2009 to January 2019.

Therefore, our contribution is twofold: we incorporate trends in a general framework with both long- and short-memory processes at both zero and non-zero frequencies, and then provide new evidence on the behaviour of various European stock markets obtained by following this approach. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the modelling approach. Section 4 describes the data and presents the empirical results. Section 5 offers some concluding remarks.

2. Literature Review

According to Borio (2014), the term “financial cycle” refers to the self-reinforcing interactions among perceptions of value and risk, risk-taking, and financing constraints. Typically, rapid increases in credit boost property and asset prices, which in turn increases collateral values and the amount of credit the private sector can obtain, but the process subsequently tends to go into reverse. As highlighted by Borio et al. (2018), this mutually reinforcing interaction between financing constraints and perceptions of value and risks has historically been likely to generate severe macroeconomic imbalances.

The financial cycle can be approximated in different ways. The empirical literature suggests that a reasonable strategy is to capture it through fluctuations in credit and property prices, but also by means of the debt service ratio, defined as interest payments plus amortisation divided by GDP. Drehmann et al. (2018) find a robust relationship between debt accumulation and subsequent debt service (i.e., interest payments plus amortisation), which has a large negative effect on economic growth. All these series may be used individually or combined, as a composite financial cycle proxy similar to that constructed by Drehmann et al. (2012).

Borio et al. (2018) point out that previous literature has identified two important features of the financial cycle. First, its peaks generally coincide with banking crises or considerable financial stress. During expansions, the interaction between asset prices and risk-taking can overstretch balance sheets, making them more fragile and generating the consequent financial tightening. Second, financial cycles can be much longer than business cycles: most of the former have lasted around 15 to 20 years since the early 1980s, whilst the latter have typically lasted up to 8 years. Therefore, a financial cycle can span more than one business cycle, which is the reason why peaks in a financial cycle are generally followed by downturns, while not all recessions are preceded by one of those peaks.

A number of recent studies have provided more evidence on financial cycles. Specifically, Oman (2019), using a frequency-based filter, details the existence of a Eurozone financial cycle and high- and low-amplitude national financial cycles. Applying concordance and similarity analysis to business and financial cycles, he provides evidence of several empirical regularities: the aggregate Eurozone credit to-GDP ratio behaved pro-cyclically in the years preceding euro-area recessions; financial cycles are less synchronized than business cycles; business cycle synchronization has risen while financial cycle synchronization has decreased; financial cycle desynchronization was more pronounced between high-amplitude and low-amplitude countries; high-amplitude countries experienced divergent leverage dynamics after 2002. Filardo et al. (2018) explore financial conditions (120 years of data) over time in order to improve our understanding of financial cycles. They find that financial cycles are characterised by recurrent, endogenous swings in financial conditions, which result in booms and busts. Yet the recurrent nature of such swings may not appear so obvious when looking at conventionally plotted time-series data. Using the pioneering framework developed by Stock (1987), they offer a new statistical characterisation of the financial cycle based on a continuous-time autoregressive (AR) model subject to time deformation.

Iacoviello (2015), using Bayesian methods, estimates a DSGE model where a recession is initiated by losses suffered by banks and exacerbated by their inability to extend credit to the real sector. Claessens et al. (2011) provide a wide-ranging analysis of financial cycles using a large database covering 21 advanced countries over the period 1960:1-2007:4. They study cycles in credit, house prices and equity prices. The main results are the following: 1) financial cycles tend to be long and severe, especially those in housing and equity markets; 2) financial cycles are highly synchronized within countries, especially with credit and house price cycles, and 3) financial cycles magnify each other, especially when the downturns in credit and housing markets coincide. DePenya and Gil-Alana (2006) propose a method for testing nonstationary cycles in financial time series data. They develop a procedure that enables the researcher to test unit root cycles in raw time series. Their test has several distinguishing features compared with alternative ones. In particular, it has a standard null limit distribution and is the most efficient test against the fractional alternatives. In addition, it allows the researcher to test unit root cycles at each of the frequencies, and, thus, to approximate the number of periods per cycle. Finally, as already mentioned, Caporale and Gil-Alana (2014) propose a general framework including linear and segmented time trends, and stationary and nonstationary processes based on integer and/or fractional degrees of differentiation; moreover, the spectrum is allowed to contain more than a single pole or singularity, occurring at both zero but non-zero (cyclical) frequencies. They find that US dividends, earnings, interest rates and long-term government bond yields exhibit fractional integration with one or two poles in the spectrum; further, a model with a segmented trend and fractional integration outperforms rival specifications over long horizons in terms of its forecasting properties. A similar approach is taken in the present study (see the next section for details).

3. The Model

The adopted model is the following:

$$(1 - L)^{d_1}(1 - 2\cos w_r L + L^2)^{d_2} x_t = u_t, \quad t = 1, 2, ..., \qquad (1)$$

where x_t is the observed time series; d_1 and d_2 are the orders of integration corresponding to the long-run (zero) and the (cyclical) (non-zero) frequency respectively, and u_t is an I(0) process, defined as a covariance-stationary process with a spectral density function that is positive and finite at all frequencies in the spectrum. The first polynomial in equation (1) refers to the standard case of fractional integration or I(d) that basically imposes a singularity or pole in the spectrum at the long-run or zero frequency. The literature includes plenty of papers with such a specification and testing for unit or fractional degrees of differentiation (for the unit root case, see, e.g., Fama and French, 1988a,b; Poterba and Summers, 1988; for the fractional case see instead Baillie, 1996; Gil-Alana and Robinson, 1997; Abbritti et al., 2006; and others).

The second polynomial refers to the case of integration at a frequency away from zero and uses Gegenbauer processes, where $w_r = 2\pi r/T$, and $r = T/s$. Thus, s indicates the number of time periods per cycle, while r refers to the frequency with a pole or singularity in the spectrum of x_t. In this context, if r = 0 (s = 1), the second polynomial in (2) becomes $(1 - L)^{2d2}$, and therefore the whole process corresponds to the classical fractional integration model widely studied in the literature. Andel (1986) introduced this process for values of r different from 0 and fractional values of d_2, and Gray et al. (1989, 1994) showed that, by denoting $\mu = \cos w_r$, one can express the polynomial in terms of the orthogonal Gegenbauer polynomial $C_{j,d_2}(\mu)$, so that, for all $d_2 \neq 0$,

$$(1 - 2\mu L + L^2)^{-d_2} = \sum_{j=0}^{\infty} C_{j,d_2}(\mu) L^j,$$

where we can define $C_{j,d_2}(\mu)$ recursively as follows:

$$C_{0,d_2}(\mu) = 1, \quad C_{1,d_2}(\mu) = 2\mu d_2,$$

and

$$C_{j,d_2} = 2\mu\left(\frac{d_2-1}{j}+1\right)C_{j-1,d_2}(\mu) - \left(2\frac{d_2-1}{j}+1\right)C_{j-2d_2}(\mu),\ j = 2,3,\ldots\ .$$

Authors such as Giraitis and Leipus (1995), Chung (1996a,b), Gil-Alana (2001) and Dalla and Hidalgo (2005), among others, subsequently examined these processes; a recent empirical application using UK inflation can be found in Gil-Alana and Trani (2019).

In this paper we combine these two approaches in a single framework testing simultaneously for the orders of integration at both the zero and a non-zero frequency. This type of model has been already employed to analyse US inflation by Canarella et al. (2019), but to date there have been no applications to stock prices.

4. Data Description and Empirical Results

We use closing prices of the following five European stock market indices: DAX30 (Germany), FTSE100 (UK), CAC40 (France), FTSE MIB40 (Italy) and IBEX35 (Spain). The frequency is monthly, and the sample period goes from January 2009 to January 2019. The data source is Thomson Reuters Eikon. Plots of the series are shown in Figure 1. Visual inspection suggests that DAX30, FTSE100 and CAC40 exhibit an upward trend, whilst FTSE MIB40 and IBEX35 fluctuate around their mean.

INSERT FIGURE 1 ABOUT HERE

As a first step we compute the periodogram for the five series under examination. This is an asymptotically unbiased estimator of the spectral density function and can be used to obtain some preliminary evidence about the peaks in the spectrum of the series.

INSERT TABLE 1 ABOUT HERE

Table 1 displays the first five values of the periodogram for each series. It can be seen that for the stock markets of France, Germany and UK, the highest value corresponds to the smallest frequency, following by frequency 3; however, for France and Spain, it occurs at frequency 2, followed by frequency 1 and frequency 3 respectively.

In order to avoid deterministic terms, we use the demeaned series and estimate the model given by equation (1), testing the null hypothesis:

$$H_0 : d = d_0, \qquad (2)$$

where d = $(d_1, d_2)^T$, with both values ranging from -2.00 to 2.00 with 0.01 increments. Thus, the estimated model under the null is:

$$(1 - L)^{d_{1o}} (1 - 2\cos w_r L + L^2)^{d_{2o}} x_t = u_t, \quad t = 1, 2, \ldots, \qquad (3)$$

where u_t is assumed to be in turn an uncorrelated (white noise) process and an autocorrelated one, for the latter the exponential spectral approach of Bloomfield (1977) being used for the disturbances u_t; this is a non-parametric method that only requires specifying the spectral density function, which is given by:

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2 \sum_{r=1}^{m} \tau_r \cos(\lambda r) \right), \qquad (4)$$

where σ^2 is the variance of the error term and m indicates the short-run dynamic components. Bloomfield (1973) showed that this function approximates fairly well the behaviour of highly parameterized ARMA models and performs well in the context of fractional integration (Gil-Alana, 2004).

For the sake of generality, we do not restrict the first polynomial to be constrained at the zero frequency, and therefore consider initially a model with 2-factors of the Gegenbauer polynomial of the form:

$$\prod_{j=1}^{2}(1-2\cos w_r^{(j)}L + L^2)^{d_o^{(j)}} x_t = u_t, \quad t = 1, 2, \ldots, \tag{5}$$

where $d_o^{(1)}$ becomes $d_{1o}/2$ if $w_r^{(1)} = 0$ (or $j_1 = 1$). The estimated value of j is equal to 1 in all cases, which supports the existence of a pole or singularity in the spectrum at the zero frequency. Thus, in what follows we focus exclusively on the model given (3), estimating simultaneously d_{1o} (the order of integration at the long-run or zero frequency, d_{2o} (the order of integration at the cyclical frequency) and j_2 (the frequency in the spectrum that goes to infinity and that is related to the number of periods per cycle in the cyclical structure, i.e., $r_2 = j_2/T$).

Table 2 focuses on the case of white noise errors. It can be seen that that the frequency j_2 is equal to 2 for France, Italy and Spain, and to 3 for the UK and Germany. This implies that the number of periods per cycle is approximately 60 (5 years) for the stock markets in the former three countries and 49 (T = 121)/3 ≈ 40 months (3.3 years) for the latter two. Concerning the estimates of the differencing parameters, d_1 is smaller than 1 in the case of France, though the unit root null hypothesis cannot be rejected, while for the other countries the I(1) hypothesis is rejected in favor of values of d_1 above 1. As for the estimates of d_2, the highest is for France (0.33) and only for this country and Germany (0.08) the values are significantly positive. In the other three cases, they are positive but very close to zero and the I(0) null cannot be rejected.

INSERT TABLES 2 AND 3 ABOUT HERE

Table 3 displays the results for the case of weak autocorrelation using the model of Bloomfield (1973). The values of j_2 are now 2 for Italy and Spain and 3 for the other three countries; d_1 is substantially smaller than in the previous table, its estimates ranging between 0.58 (UK) and 0.71 (Spain), and evidence of mean reversion with respect to this frequency is only obtained in the UK case. In all other cases, the intervals indicate that the unit root null cannot be rejected. Finally, the estimates of d_2 are all positive but the null $d_2 = 0$ cannot be rejected in any country.

On the whole, our results indicate high persistence at the long-run frequency but they are not very supportive of the existence of cyclical stochastic structures in the European financial markets. The only clear evidence of a stochastic cycle is obtained in the case of France under the assumption of white noise disturbances; in all other cases, although d_2 is found to be positive, the confidence intervals are such that the null $d_2 = 0$ cannot be rejected, and therefore there is no evidence of cycles.

5. Conclusions

In this paper we have examined the possible presence of stochastic cycles in financial series. For this purpose, we have proposed a model that allows simultaneously for both long-run and cyclical patterns in the data using a method based on long-memory processes. For the zero frequency the standard I(d) approach is followed, whilst for the cyclical structure a Gegenbauer polynomial is used which also allows for fractional degrees of differentiation. Therefore, the chosen specification contains two singularities in the spectrum corresponding to the long-run (zero) and the cyclical (non-zero) frequencies respectively.

Using monthly data for five European stock market indices (namely, DAX30 (Germany), FTSE100 (UK), CAC40 (France), FTSE MIB40 (Italy) and IBEX35 (Spain)) over the period from January 2009 to January 2019 we find that the order of integration at the long-run or zero frequency is significantly higher than the one at the cyclical frequency, the latter being insignificantly different from zero in the majority of cases. The cycles seem to have a periodicity between 3 and 5 years.

However, these results should be taken with a degree of caution given the relatively short sample period. Specifically, with 121 monthly observations as in our case the smallest possible frequency apart from $j_1 = 1$ (that corresponds to the long-run frequency) is 2, which implies cycles of T/ 2 at most, i.e. 60 months or 5 years. Analysing much longer series, possibly spanning decades, would be much more informative about the possible existence of stochastic cycles. This is left for further research.

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Figure 1. Closing prices of five European stock market indices

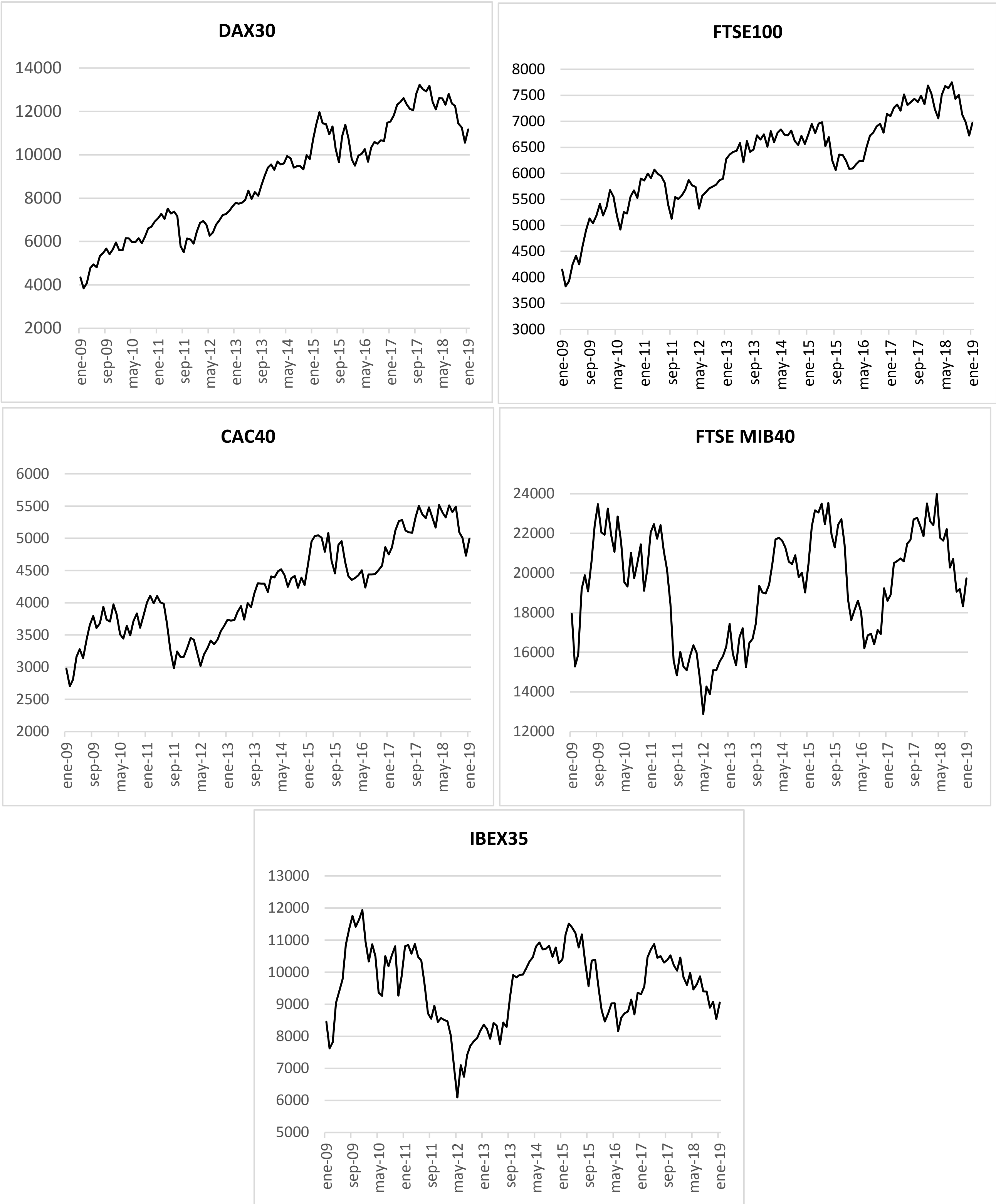

Table 1: First five values in the periodogram of the series

Country	1	2	3	4	5
FRANCE	**0.17205***	0.00407	**0.04472**	0.02301	0.00021
GERMANY	**0.55260***	0.06697	**0.10928**	0.04837	0.00627
ITALY	**0.04423**	**0.04806***	0.04228	0.01590	0.00905
SPAIN	0.01546	**0.05215***	**0.04449**	0.00507	0.01091
U.K.	**0.08426***	0.02807	**0.04186**	0.01064	0.00331

* refers to the largest value and in bold the largest two values.

Table 2: Estimates of d based on a model with white noise disturbances

Country	j_1	j_2	d_1	d_2
FRANCE	1	2	0.89 (0.73, 0.96)	0.33 (0.17, 0.65)
GERMANY	1	3	1.36 (1.11, 1.44)	0.08 (0.01, 0.25)
ITALY	1	2	1.24 (1.01, 1.39)	0.02 (-0.08, 0.14)
SPAIN	1	2	1.38 (1.14, 1.52)	0.08 (-0.03, 022)
U.K.	1	3	1.34 (1.10, 1.53)	-0.05 (-0.17, 0.15)

Table 3: Estimates of d based on a model with autocorrelated disturbances

Country	j_1	j_2	d_1	d_2
FRANCE	1	3	0.65 (0.27, 1.09)	0.05 (-0.27, 0.11)
GERMANY	1	3	0.66 (0.49, 1.18)	0.04 (-0.09, 0.18
ITALY	1	2	0.64 (0.45, 1.03)	0.01 (-0.18, 0.20)
SPAIN	1	2	0.71 (0.56, 1.24)	0.05 (-0.14, 0.26)
U.K.	1	3	0.58 (0.31, 0.99)	0.02 (-0.11, 0.21)