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PERSISTENCE IN EUROPEAN STOCK MARKET RETURNS AND VOLATILITY

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Abstract

This paper applies fractional integration techniques to analyze persistence in stock market returns and volatility at different frequencies in the case of various European indices, specifically the French CAC, the Spanish IBEX 35, the German DAX, the British FTSE 100, and the Euro Stoxx 50, over the period from January 2018 to January 2023.Returns are calculated as the first differences of the logged prices, while absolute and squared returns are used as volatility proxies. The method used yields estimates of the differencing parameter d, which is allowed to take any real value, including fractional ones, and represents a measure of persistence. This parameter provides information about whether the series of interest exhibit either long memory or mean reversion. Specifically, a value of d greater than 0 indicates the presence of long memory in the series, while a value less than 1 implies mean reversion, with the effects of shocks being transitory. The results vary depending on the data frequency. More precisely, evidence of long memory is found for returns at the daily frequency only and for volatility proxies at both the weekly and daily frequencies but not at the monthly frequency. In most cases our findings imply that stock prices are I(1) and thus follow a random walk, which is consistent with the efficiency markets hypothesis (EMH).

JEL Classification: C22, G12

Keywords: Stock market prices; volatility; fractional integration; persistence.

1. Introduction

Investors are interested in both stock market returns and volatility. The latter is a measure of the uncertainty or risk associated with the value of an investment and can be caused by a range of factors, including the overall economic environment, shifts in market sentiment, changes in interest rates, and unexpected events such as natural disasters, geopolitical tensions, and financial crises.

An important issue for understanding the long-run behavior of both returns and their volatility is whether they exhibit long memory, which is a property of time series that decays slowly over time, or mean reversion, which is the tendency to return to a long-run average over time. According to the efficient market hypothesis (EMH - Fama, 1970), stock prices should reflect all available information and follow a random walk. However, numerous empirical studies have found evidence of persistence in both returns and their volatility, which implies that markets might not be efficient. Various volatility measures have been used in the literature, including estimates based on the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982) and on the generalized autoregressive conditional heteroskedasticity (GARCH) model of Bollerslev (1986), as well as on realized volatility and simple proxies such as absolute and squared returns.

Ding et al. (1993) proposed the autoregressive fractionally integrated moving average (ARFIMA) model to analyze long memory in stock market returns. This is a generalized version of the autoregressive integrated moving average (ARIMA) model, which allows for fractional integration. They found evidence that past returns have persistent effects on future returns, even after accounting for short-term dependencies. This suggests that stock prices exhibit a degree of predictability, which can be exploited by investors. Granger and Hyung (2013) showed that when a time series contains occasional breaks, the long-memory property may be distorted or even disappear. To address this issue, they proposed a new model called the Occasional Long Memory (OLM) model, which allows for occasional breaks in the data while still capturing the long-memory property; this model is a combination of the Fractional Integrated GARCH (FIGARCH) and the Autoregressive Conditional Heteroscedasticity (ARCH) models, and it has been shown to outperform other models that do not account for occasional breaks. Marra et al. (2021) analyzed the persistence and predictability of stock return volatility (using both ARCH and GARCH estimates) in G7 countries (Canada, France, Germany, Italy, Japan, the UK, and the US) from 2000 to 2018 and found that stock return volatility was persistent and predictable in all cases and that there was evidence of volatility clustering.

The present study examines the long-memory properties of both returns and their volatility (proxied by absolute and squared returns) in the case of the five main European stock indices—the IBEX 35, the DAX, the CAC, the EuroStoxx 50, and the FTSE 100—at daily, weekly, and monthly frequencies over the period from January 2018 to January 2023. For this purpose, it applies very general fractional integration techniques to estimate the differencing parameter d, which is allowed to take any real value, including fractional ones, and represents a measure of persistence. This parameter provides information about whether the series of interest exhibit either long memory or mean reversion. Specifically, a value of d greater than 0 indicates the presence of long memory in the series, while a value less than 1 implies mean reversion, with the effects of shocks being transitory.

The remainder of the paper is organized as follows: Section 2 describes the data, Section 3 outlines the econometric methodology, and Section 4 presents the empirical results. Section 5 offers some concluding remarks.

2. Data Description

The series analyzed are the French CAC, the Spanish IBEX 35, the German DAX, the British FTSE 100, and the Euro Stoxx 50 stock market indices at daily, weekly, and monthly frequencies over the period from January 2018 to January 2023. The data sources are Investing.com and Yahoo Finance. The five indices are constructed as follows:

IBEX 35

The IBEX 35 is the Spanish benchmark stock market index and measures the combined performance of the 35 most traded companies among those listed on the Electronic Stock Exchange Interconnection System (SIBE) on the four Spanish stock exchanges (Madrid, Barcelona, Bilbao and Valencia). It comprises stocks of companies from different sectors, including banking, energy, telecommunications, insurance, and construction, among others, which best meet the parameters of capitalization, liquidity, and traded volume required by the technical advisory committee. The weighting of each company in the index is based on its market capitalization and liquidity.

Euro Stoxx 50

The Euro Stoxx 50 is a market capitalization-weighted stock index of 50 large, blue-chip European companies operating within 12 Eurozone countries, and its composition is reviewed quarterly or semiannually. These companies belong to 19 different sectors, including banking, oil and gas, mining and technology, with the financial institutions having the greatest weight. Some of the companies included in this index are the AXA Group, SAP, Unilever, Banco de Santander and Daimler. This index captures approximately 60% of the free-float market cap of the EURO STOXX total market index (TMI).

DAX 30

The DeutscherAktienindex (DAX 30) is the German stock index for the Frankfurt Stock Exchange. It includes the 30 most influential German companies (such as BMW, Adidas, Bayer, and Allianz), again from various sectors, but it is especially well-known for those in the automotive, textile, and chemical sectors. It is weighted by market capitalization, and the list of stocks included is subject to a quarterly review.To qualify for index membership, a company must be included in the German Prime Standard market, and none can have a weight greater than 20%. The composition of the index is reviewed annually in September.

CAC 40

CAC stands for continuous assisted quotation - its value varies continuously every working day every 15 seconds, and it is made up of 40 stocks of companies belonging to the top 100 in terms of capitalization. Many of those included are multinational; thus, 45% of the index is represented by companies whose headquarters are in other countries, with German companies accounting for 21% of the index, followed by British, Japanese, and American companies. The top 10 companies included in this index are LVMH, Total Energies, Sanofi, L'Oréal, Schneider Electric, Air Liquide, Airbus, BNP Paribas Act, Essilor Luxottica, and Vinci.

FTSE 100

FTSE 100 is an acronym for Financial Times Stock Exchange 100. It is colloquially known as the Footsie 100 and is the benchmark index of the London Stock Exchange and one of the top 5 European stock indices. It began operating in 1984, including a total of 1,000 UK companies, but now only comprises the top 100 in terms of market capitalization (representing 70% of the total value of the London stock market), on which weights are based. It is reviewed on a quarterly basis

Tables 1, 2 and 3 report descriptive statistics for these five indices at monthly, weekly and daily frequencies, respectively. At the monthly frequency (Table 1), there are sizeable differences between the maximum and minimum values (especially in the case of the DAX), which suggests the presence of significant fluctuations in stock prices. The IBEX 35 and FTSE 100 are the most and least volatile indices, respectively, on the basis of their standard deviations.

However, at both weekly (Table 2) and daily (Table 3) frequencies, high and low values do not vary significantly across markets, and all stock indices have similar standard deviations. Again, the IBEX 35 and FTSE100 indices have the highest and lowest standard deviations, respectively.

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Table 1

Descriptive statistics for the European stock indices at a monthly frequency

Index	Maximum	Minimum	Std. Deviation	Mean
CAC	0.08202	-0.07961	0.02444	-0.00232
DAX	0.077990	-0.06074	0.02476	-0.00168
IBEX 35	0.109100	-0.09754	0.02583	0.00059
FTSE 100	0.064533	-0.05058	0.017984	-0.00079
Eurostoxx 50	0.077256	-0.07211	0.024436	-0.00159

Table 2

Descriptive statistics for the European stock indices at the weekly frequency

Index	Maximum	Minimum	Std. Deviation	Mean
CAC	0.0961636	-0.0441424	0.013199	-0.0004011
DAX	0.0969766	-0.0449588	0.013539	-0.0002063
IBEX 35	0.1015286	-0.0542041	0.013436	0.0002958
FTSE 100	0.0807443	-0.0329721	0.010642	-0.0000882
Eurostoxx 50	0.0968489	-0.0451393	0.013279	-0.0002168

Table 3

Descriptive statistics for the daily European stock indices

Index	Maximum	Minimum	Std. Deviation	Mean
CAC	0.0568854	-0.03499	0.005656	-0.00008
DAX	0.0566965	-0.04523	0.005869	-0.00004
IBEX 35	0.0658007	-0.0357219	0.005683	0.000061
FTSE 100	0.0499978	-0.0376395	0.004909	-0.0000039
Eurostoxx 50	0.0575028	-0.0383667	0.005764	-0.0000451

3. Econometric Methodology

The empirical analysis in this study uses fractional integration methods, which are more general than the standard methods based on the dichotomy between stationarity and nonstationarity. Note that a series is said to be integrated of order 0, or I(0), if it is covariance stationary and the infinite sum of its autocovariances is finite. That is, given a covariance stationary process, x_t, t = 0, ±1, ±2, …,, with an autocovariance function $\gamma_u = E[x_t - \mu)(x_{t+u} - \mu)]$, where μ is the mean of the process, x_t is said to exhibit short memory or be I(0) if:

$$\sum_{u=-\infty}^{\infty} \gamma_u < \infty. \tag{1}$$

This definition includes a wide range of processes, such as white noise processes, as well as those characterized by weak time dependence, such as the stationary and invertible autoregressive moving average (ARMA) class of models.

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In the standard approach, if a series is nonstationary, first differences are taken, i.e., (1 – L)xt is modeled, where L is the lagoperator defined as Lxt $=x_{t-1}$. In such a case, the original series is said to be integrated of order 1. However, in the 1980s, authors such as Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981) noticed that many aggregated series that were apparently nonstationary I(1) once they were differenced became over differenced, which suggested that the appropriate degree of differentiation might be fractional.

A series is said to be integrated of order d and is denoted as I(d) if it can be represented as:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \dots, \tag{2}$$

where u_t is a short-memory or I(0) process and d is a fractional number, which is a measure of persistence. If d is positive, x_t exhibits the long-memory property because the infinite sum of its autocovariances is infinite, i.e.,

$$\sum_{u=-\infty}^{\infty} \gamma_u = \infty. \tag{3}$$

Specifically, the fractional integration model we estimate is the following:

$$x_t = \alpha + \beta t + z_t, \quad (1 - L)^d z_t = u_t, \qquad t = 1, 2, \dots, \tag{4}$$

where x_t is the observed time series (in logs), α and β are unknown coefficients, *t* is a linear time trend, and the regression errors, z_t, are I(d), such that u_t is an I(0) process that is assumed to be weakly autocorrelated and for which the exponential spectral model of Bloomfield(1973) is applied. This is a nonparametric method to approximate ARMA models by using a log-spectral density that is similar to that of AR structures. The parameters are estimated using the Whittle function in the frequency domain (Dahlhaus, 1989), as in the testing approach developed in Robinson (1994), which is widely used in empirical applications (see, e.g., Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2007; Abbritti et al., 2016, 2023; etc.).

4. Empirical Results

Tables 4, 5 and 6 report the results for returns and the two volatility proxies (absolute and squared returns)at the monthly, weekly and daily frequencies, respectively. Each table displays the estimates of d (and the corresponding 95% confidence intervals) for three different model specifications:

1) without deterministic terms (i.e., setting α = β = 0 in Equation (4)),
2) with an intercept only (i.e., setting β = 0)
3) with both an intercept and a linear time trend

The values in bold in the tables are those for the specifications selected on the basis of the statistical significance of the regressors.

Concerning the monthly results (Table 4), the selected model for returns includes both deterministic terms in the case of the CAC, FTSE 100, and IBEX 35 indices and an intercept only in the case of the DAX and EuroStokk50 indices. Furthermore, the estimated coefficients for the differencing parameter d are in all cases in the I(0) interval, i.e., their confidence intervals include the value 0, which supports the null hypothesis of short-memory or I(0) returns. This implies that stock prices are I(1) and thus follow a random walk, which is consistent with the efficiency markets hypothesis (EMH). For volatility persistence, for both absolute and squared returns, the estimates of d are all negative, and once more, all of them are within the I(0) interval; thus, there is no evidence of long-memory behavior in the volatility series.

Table 4

Estimates of d. Monthly data

Series	No terms	An intercept	An intercept and a linear time trend
		i) Stock market returns	
CAC	-0.28 (-0.59, 0.16)	-0.28 (-0.59, 0.17)	**-0.43 (-0.78, 0.10)**
DAX	-0.39 (-0.64, 0.13)	**-0.42 (-0.78, 0.13)**	-0.41 (-0.79, 0.16)
EURO STOKK50	-0.38 (-0.69, 0.24)	**-0.42 (-0.83, 0.24)**	-0.42 (-0.94, 0.25)
FTSE 100	-0.28 (-0.55, 0.16)	-0.28 (-0.56, 0.17)	**-0.42 (-0.76, 0.12)**
IBEX 35	-0.39 (-0.81, 0.17)	-0.39 (-0.76, 0.17)	**-0.49 (-1.91, 0.14)**
		ii) Absolute returns	
CAC	-0.17 (-0.31, 0.29)	**-0.17 (-0.42, 0.20)**	-0.23 (-0.54, 0.16)
DAX	-0.16 (-0.30, 0.18)	**-0.32 (-0.65, 0.15)**	-0.27 (-0.64, 0.20)
EUROSTOKK50	-0.16 (-0.29, 0.11)	**-0.41 (-0.79, 0.12)**	-0.41 (-0.79, 0.12)
FTSE 100	-0.15 (-0.31, 0.28)	**-0.18 (-0.42, 0.20)**	-0.23 (-0.54, 0.17)
IBEX 35	-0.18 (-0.29, 0.00)	**-0.40 (-0.67, 0.01)**	-0.40 (-0.69, 0.01)
		iii) Squared returns	
CAC	-0.22 (-0.37, 0.11)	**-0.26 (-0.53, 0.12)**	-0.28 (-0.54, 0.11)
DAX	-0.19 (-0.36, 0.09)	**-0.28 (-0.57, 0.12)**	-0.27 (-0.56, 0.13)
EUROSTOKK50	-0.22 (-0.38, 0.03)	**-0.36 (-0.63, 0.04)**	-0.35 (-0.65, 0.05)
FTSE 100	-0.22 (-0.39, 0.11)	**-0.26 (-0.53, 0.11)**	-0.29 (-0.56, 0.10)
IBEX 35	-0.17 (-0.34, 0.13)	**-0.22 (-0.48, 0.14)**	-0.22 (-0.48, 0.14)

The estimates and confidence intervals for the selected model for each series are shown in bold.

Regarding the weekly data (Table 5), the selected model for returns is the one without regressors, and the estimates of d are all in the I(0) interval. In contrast, the preferred specification for absolute returns includes an intercept only, and the values of d are now all positive, ranging from 0.35 (IBEX 35) to 0.43 (DAX), which implies the

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presence of long memory in these series. The same conclusion is reached in the case of the squared returns, although the selected model now does not include any regressors, and the estimates of d range between 0.26 (IBEX 35) and 0.42 (FTSE 100).

Table 5
Estimates of d. Weekly data

	i) Stock market returns		
Series	No terms	An intercept	An intercept and a linear time trend
CAC	**-0.12 (-0.27, 0.07)**	-0.13 (-0.28, 0.06)	-0.12 (-0.27, 0.06)
DAX	**-0.15 (-0.28, 0.04)**	-0.15 (-0.29, 0.04)	-0.15 (-0.29, 0.06)
EURO STOKK50	**-0.14 (-0.30, 0.06)**	-0.14 (-0.30, 0.06)	-0.14 (-0.28, 0.08)
FTSE 100	**-0.06 (-0.22, 0.17)**	-0.06 (-0.22, 0.17)	-0.06 (-0.25, 0.18)
IBEX 35	**-0.15 (-0.30, 0.05)**	-0.15 (-0.31, 0.05)	-0.15 (-0.31, 0.05)
	ii) Absolute returns		
CAC	0.39 (0.23, 0.63)	**0.37 (0.22, 0.61)**	0.37 (0.22, 0.61)
DAX	0.45 (0.29, 0.69)	**0.43 (0.28, 0.66)**	0.43 (0.28, 0.67)
EURO STOKK50	0.42 (0.26, 0.66)	**0.42 (0.25, 0.63)**	0.42 (0.25, 0.63)
FTSE 100	0.39 (0.22, 0.62)	**0.37 (0.23, 0.62)**	0.39 (0.22, 0.62)
IBEX 35	0.37 (0.22, 0.58)	**0.35 (0.22, 0.56)**	0.35 (0.22, 0.57)
	iii) Squared returns		
CAC	**0.35 (0.19, 0.60)**	0.35 (0.20, 0.60)	0.35 (0.20, 0.60)
DAX	**0.36 (0.19, 0.62)**	0.36 (0.20, 0.60)	0.36 (0.20, 0.60)
EURO STOKK50	**0.34 (0.20, 0.59)**	0.35 (0.20, 0.59)	0.35 (0.20, 0.59)
FTSE 100	**0.42 (0.23, 0.67)**	0.42 (0.23, 0.70)	0.42 (0.23, 0.70)
IBEX 35	**0.26 (0.11, 0.47)**	0.26 (0.12, 0.47)	0.26 (0.12, 0.47)

The estimates and confidence intervals for the selected model for each series are shown in bold.

Finally, at the daily frequency (Table 6), the selected model without regressors provides evidence of long memory in the returns themselves in the case of the CAC and IBEX 35 indices, while for the DAX, EuroStokk50 and FTSE100 indices, the I(0) hypothesis of short-memory behavior cannot be rejected. Similar to the weekly case, long memory is found instead in both volatility proxies, the preferred specification including a constant in the case of absolute returns and no regressors in the case of square returns.

Table 6
Estimates of d. Daily data

	i) Stock market returns		
Series	No terms	An intercept	An intercept and a linear time trend
CAC	**0.07 (0.00, 0.14)**	0.07 (0.00, 0.14)	0.07 (0.00, 0.14)
DAX	**0.06 (-0.01, 0.15)**	0.06 (-0.01, 0.15)	0.06 (-0.01, 0.15)
EURO STOKK50	**0.06 (-0.01, 0.16)**	0.06 (-0.01, 0.16)	0.06 (-0.01, 0.16)
FTSE 100	**0.00 (-0.06, 0.07)**	0.00 (-0.06, 0.07)	0.00 (-0.07, 0.08)
IBEX	**0.11 (0.04, 0.21)**	0.11 (0.04, 0.21)	0.12 (0.04, 0.21)
		ii) Absolute returns	
CAC	0.41 (0.36, 0.47)	**0.41 (0.36, 0.48)**	0.41 (0.36, 0.48)
DAX	0.38 (0.32, 0.44)	**0.38 (0.32, 0.42)**	0.36 (0.32, 0.42)
EURO STOKK50	0.39 (0.33, 0.45)	**0.39 (0.33, 0.44)**	0.39 (0.33, 0.44)
FTSE 100	0.34 (0.28, 0.39)	**0.33 (0.29, 0.39)**	0.33 (0.29, 0.39)
IBEX	0.39 (0.33, 0.45)	**0.38 (0.33, 0.45)**	0.38 (0.33, 0.45)
		iii) Squared returns	
CAC	**0.45 (0.38, 0.51)**	0.43 (0.38, 0.51)	0.43 (0.38, 0.51)
DAX	**0.36 (0.30, 0.42)**	0.36 (0.30, 0.42)	0.36 (0.30, 0.42)
EURO STOKK50	**0.41 (0.34, 0.47)**	0.41 (0.35, 0.47)	0.41 (0.35, 0.47)
FTSE 100	**0.33 (0.28, 0.40)**	0.33 (0.28, 0.40)	0.33 (0.28, 0.40)
IBEX	**0.44 (0.35, 0.53)**	0.44 (0.35, 0.54)	0.44 (0.35, 0.54)

The estimates and confidence intervals for the selected model for each series are shown in bold.

5. Conclusions

This paper applies fractional integration methods to analyze persistence in stock market returns and volatility at different frequencies in the case of various European indices, specifically the French CAC, the Spanish IBEX 35, the German DAX, the British FTSE 100, and the Euro Stoxx 50, over the period from January 2018 to January 2023. Returns are calculated as the first differences of the logged prices, while absolute and squared returns are used as volatility proxies. The results vary depending on the data frequency. More precisely, evidence of long memory is found for returns at the daily frequency only and for volatility proxies at both the weekly and daily frequencies but not at the monthly frequency.

The analysis can be extended in several ways. For instance, the stochastic behavior of alternative measures of volatility such as realized volatility can be used. Two other important issues that can be analyzed are the possible presence of nonlinearities and/or breaks in the series. The former can be modeled using orthogonal polynomials in the time of Hamming (1973) and Bierens (1997) in the context of fractional integration, as in Cuestas and Gil-Alana (2016); Fourier functions in time, as in Gil-Alana and Yaya (2021); or neural networks, as in Yaya et al. (2021). To test for the latter, both the Bai and Perron (2003) approach and the methods proposed by Gil-Alana (2008) and Hassler and Meller (2014) can be used, the latter being specifically designed for the case of fractional integration. Future work will address these issues.

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