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Are European banks informationally weak-form efficient? A dynamic analysis

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Abstract

The efficient market hypothesis (EMH) is a cornerstone of financial theory and is crucial to understanding weak-form efficiency, particularly during extreme events. Detrended fluctuation analysis (DFA) is a robust approach for assessing weak-form efficiency, overcoming some limitations of traditional methods. Given the fundamental role of the banking sector in the economy and its importance during crises, evaluating informational efficiency in this sector becomes even more relevant. In the present study, we applied the DFA with sliding windows to assess the weak-form efficiency in the stock returns of the European banking sector between February 2016 and February 2023 and the efficiency index of Kristoufek and Vosvrda (2013) to rank the weak-form efficiency levels of the analyzed banks. The results indicate that the COVID-19 pandemic increased bank return persistence. In contrast, the Russia–Ukraine war initially led to antipersistent behavior, but banks returned to persistent patterns over time. The efficiency ranking revealed that banks from Belgium, the UK, Spain, and Sweden were less inefficient, whereas those from France and Italy presented higher levels of inefficiency. The findings provide valuable insights for investors and policymakers regarding the development of risk mitigation strategies, risk management, and financial stability efforts.

Keywords: Bank sector, Detrended fluctuation analysis, Extreme events, Efficiency, Sliding windows, Stock returns

Introduction

The price of a financial asset is primarily based on its fair market value. However, extreme and external events such as financial crises, pandemics, and wars can cause deviations (Mensi et al. 2018), highlighting the relevance of analyzing their behavior in these events. The COVID-19 pandemic has triggered unprecedented economic disruptions, impacting financial markets and banking institutions worldwide (Feyen et al. 2021). Although several studies have analyzed the response of financial markets during the COVID-19 pandemic, few studies have examined the effects of COVID-19 on the banking sector [see Shabir et al. (2023) for a literature review]. The recent Russia–Ukraine war added geopolitical risks, affecting investor sentiment and asset prices.

In volatile and uncertain times, understanding weak-form efficiency becomes crucial, as it helps assess how quickly and accurately market prices incorporate new information. Furthermore, understanding how informational efficiency can change in response to extreme events is essential for anticipating market reactions, implementing risk mitigation strategies, and maintaining financial stability amid heightened uncertainty.

The banking sector has played a crucial role during the COVID-19 pandemic by supporting households and businesses (Shabir et al. 2023), making it essential to evaluate the efficiency of bank stocks post-pandemic and war.

Fama's efficient market hypothesis (EMH) theory (1970) is widely used to evaluate financial markets, although it is also controversial. In a weak-form efficient market, current prices fully reflect all the available historical market data. Thus, past price movements and patterns cannot be used to predict future price movements, meaning that the possibility of accurate forecasting is excluded since there are no reliable patterns of asset prices. Additionally, the EMH emphasizes that prices quickly adjust to new public information, ensuring that any news is immediately reflected in asset prices, thus preventing abnormal returns. Consequently, the market cannot be foreseen, and investors cannot obtain abnormal returns systematically.

The EMH proposed by Fama (1970) operates under the assumption that investors act rationally and have no arbitrage opportunities. In contrast, the fractal market hypothesis (FMH) introduced by Peters (1994) considers that markets are driven by long-term memory and irregular patterns, where the markets are not always efficient because of the influence of investors with different time horizons. FMH explains market inefficiencies through fractal structures, where short-term movements do not necessarily reflect long-term stability, diverging from EMH's assumptions of random price movements and market rationality.

The evaluation of EMH has been closely related to time series dependence and predictability. However, several irregularities in the financial time series challenge this theory, leading to the development of alternative approaches such as the rescaled range (R/S) method of Hurst (1951) or the modified R/S method introduced by Lo (1991). However, both approaches are only suitable for measuring long-range dependence in stationary time series, which remains a limitation.

To overcome this limitation, Peng et al. (1994) proposed detrended fluctuation analysis (DFA), a new method that assumes a monofractal time series structure. This approach is robust and can evaluate the presence of long-range dependence in time series even if the data are nonstationary, avoiding spurious detection of long-range dependence due to this type of data. Furthermore, as this approach is less dependent on nonstationary assumptions and noisy data, it is also suitable for quantifying the nonlinear dynamics and complexity in time series (Lahmiri and Bekiros 2019). The exponent of the DFA approach captures the long-term memory of a given time series, and according to theory, financial assets should not show any kind of memory.

In the present study, we applied the DFA approach to evaluate the historical independence of returns and assess the existence of long memory (persistent or antipersistent behavior, i.e., inefficiency as captured by the DFA) using data from the banks that composed the Euro STOXX Banks index in February 2023. Moreover, we performed a sliding window analysis to analyze the continuous existence of efficiency. Although the DFA approach has been applied in several contexts and topics, only Ferreira et al. (2018) used it for this specific topic and world region, highlighting the study's relevance. Additionally, we applied the efficiency index (EI) defined by Kristoufek and Vosvrda (2013) to rank the level of (in)efficiency.

The results demonstrate that the COVID-19 pandemic increased the persistence (inefficiency) of bank returns. In contrast, the Russia–Ukraine war initially led to antipersistent (inefficient) behavior, but banks returned to persistent patterns over time. The efficiency ranking indicated that banks from Belgium, the UK, Spain, and Sweden were less inefficient, whereas those from France and Italy presented higher levels of inefficiency. These findings underscore the dynamic nature of market efficiency and the significant impact of extreme events. Our findings hold particular relevance for investors because understanding the dynamic changes in market efficiency during extreme events provides critical insights into portfolio management and risk mitigation strategies. The results can also be useful for policymakers, allowing for better regulatory responses. Identifying inefficiencies in real time can help implement timely interventions to stabilize financial markets and prevent systemic risk.

The rest of the paper is structured as follows. Section "Literature review" briefly reviews the literature. Section "Data and methods" presents the data and methods. Section "Results and discussion" presents the results and discusses them. Finally, section "Conclusions" summarizes the findings and conclusions.

Literature review

In the financial literature, several studies have focused on the analysis of informational efficiency, in its weak-form, of financial markets [see Shrestha et al. (2023) for a brief literature review]. These studies cover a broad range of markets, sectors, and geographies, with examples such as Baur et al. (2012) and Gebka and Wohar (2013), which analyze stock return autocorrelations across European markets and the U.K., respectively. However, these studies do not focus specifically on the banking sector, particularly in the European context, nor do they directly test the weak-form market efficiency of banks, which leaves a significant gap in the literature regarding how banks, especially during and after financial crises, behave in terms of informational efficiency. Studies that analyze informational efficiency in the banking sector are sparse, especially in the European banking sector. One example includes the study of Ferreira et al. (2018), which dynamically analyzed (applying the DFA approach with sliding windows) the informational efficiency of 63 European banks (both inside and outside the Eurozone) before, during, and after the subprime and Eurozone debt crisis. Although they did not find a definite pattern, after the subprime crisis, most banks changed from antipersistent to persistent behavior.

Additionally, some non-Eurozone banks had effects similar to those of Eurozone banks. After the Eurozone debt crisis (the last considered in the study), most banks were near the efficiency level, with most of the banks that revealed antipersistent behavior being in non-Eurozone countries. After both crises, a smaller number of banks showed antipersistent behavior. The authors also revealed that the most inefficient banks were mostly non-Eurozone banks. It was concluded that the crises impacted the dynamics of bank share efficiency in Europe.

Applying different (but similar in its genesis) approaches, the multifractal detrended fluctuation analysis (MF-DFA) and the multifractal detrended cross-correlation analysis (MF-DCCA), Mensi et al. (2018) analyze the dynamic efficiency and interdependence of Islamic banks and conventional banks in Saudi Arabia. It was found that there was strong multifractality in the daily returns of the analyzed banks, displaying a persistent correlation and demonstrating inefficiency. The rolling window approach also revealed significant changes in the inefficiency levels over time. Using the same approach but focusing on the efficiency of the European sector, Aloui et al. (2018) explored the EMH of 22 European credit market sectors. The authors concluded that all the Eurozone credit market sectors are multifractal, with the credit sectors marked by persistent memory in their short- and long-term components. They also identified not only time-varying levels of market efficiency (for both short- and long-term horizons) but also significant changes under crisis and noncrisis scenarios.

Covering a period from January 2010 until December 2019 and using autocorrelation, run tests, and unit root tests, Vural and Hailu (2020) assessed the weak-form efficiency of Borsa Istanbul banking sector stocks via bank stocks listed in BIST 30. The results of the three types of tests exhibited controversial results, i.e., the autocorrelation tests identified only two banks as efficient, the runs test identified only two inefficient banks, and the unit roots tests identified all the analyzed banks as inefficient. These controversial results highlight the difficulty of reaching a general conclusion regarding the efficiency of the BIST banking sector in a weak-form. Although not covering only the banking sector, Ferreira (2020) analyzed the long-range dependence of 19 of the 20 components of the Swiss Market Index. Some of the 19 components analyzed were from the banking sector (such as Credit Suisse Group and UBS Group), and it was revealed that although some turbulence occurred approximately in 2008, this sector was closely related to efficiency behavior during a considerable part of the sample.

Most recently, Almeida et al. (2023) analyzed the impacts of the fall of Silicon Valley (SVB) and Credit Suisse (CS) banks on five financial indices, including one index of the banking sector. The analyzed index changed its behavior from antipersistent to persistent with the fall of the SVB but did not change its antipersistent pattern with the fall of the CS bank. Both persistent and antipersistent behaviors highlight the inefficiency of this sector. Indeed, the analyzed index composed of banks was one of the least efficient indices. Considering the FinTech market, Shrestha et al. (2023) examined the efficiency of this market considering four S&P Kensho fintech indices and concluded that, with the exception of one of the analyzed indices (Alternative Finance index), the other indices are inefficient. For this index, the authors concluded that the efficiency was violated due to extreme values. Using the event study approach and three of the most commonly used models for estimating theoretical returns (CAPM, Fama–French with three factors, and Fama–French with five factors), Furdui and Șfabu (2023) evaluated the reaction to the shock of the Russian invasion of Ukraine in 2022 for 32 systemically important banks in 12 developed European countries from May 19, 2021, to March 30, 2022. The authors concluded that banks react differently relative to the event date (February 24, 2022) depending on the countries with bank exposure to Russia; the greater the exposure, the more pronounced the reaction. The banks from Sweden, Spain, and the United Kingdom showed statistically significant CAARs only on the event day (in the following days, returns return to normal values on a new level of equilibrium), characteristic of markets with a high level of informational efficiency that developed a high speed in incorporating this new information.

Although some recent studies have analyzed the impact of several extreme events, such as the COVID-19 pandemic or the Russia–Ukraine war, on banking sector efficiency [see Shabir et al. (2023) for a literature review], the analyses have focused primarily on operational or technical efficiency rather than informational efficiency, i.e., they were not performed from the perspective of the EMH. The limited focus on informational efficiency, particularly in the banking sector, motivates this study, given the critical role that market efficiency plays in financial stability. Thus, our contribution is threefold. First, using a robust approach, we extend the test of the weak-form EMH to the European banking sector, covering the world's most recent extreme events via DFA. Second, we provide a dynamic analysis of the persistent and antipersistent behavior of banks' stock returns in response to extreme events, which is underexplored in the current literature. Third, we complement the DFA results with the EI, which allows us to rank banks based on their efficiency levels. This quantitative measure provides an additional layer of analysis by helping to compare the degree of weak-form efficiency across institutions. The sparse literature devoted to the study of the EMH on the banking sector (i.e., informational efficiency), combined with the sector's importance to the broader economy and the fact that extreme events can deviate financial asset prices from their fair market values (Mensi et al. 2018), impacting market efficiency, constitute the main motivations for this study. Our focus on ranking and dynamic analysis offers a clearer understanding of how extreme events shape the efficiency landscape across banks and countries.

Data and methods

Data

This study has three major goals: (i) to evaluate, dynamically, the weak-form efficiency of European banks and identify whether extreme events affect the behavior of that efficiency; (ii) to dynamically evaluate the efficiency, in light of the EMH (i.e., informational efficiency), of the analyzed bank; and (iii) to rank the efficiency level of the analyzed banks, offering a quantitative measure for comparing the degree of weak-form efficiency across institutions. We retrieved data from the Thomson Reuters DataStream for 40 banks from 14 countries that compose the Euro STOXX Banks index (https://stoxx.com/index/sx7e/) on the date of retrieval, i.e., February 22, 2023. However, owing to data limitations (the nonavailability of data), one bank (Komercni Banka, from Czechia) was not included in the analysis, resulting in 39 banks being included in the descriptive statistics and subsequent analyses. The remaining 39 banks represent the major financial institutions in these countries, providing a comprehensive view of the European banking sector.

Table 1 presents the list of banks used in this paper (grouped by country), descriptive statistics (mean, standard deviation, kurtosis, and skewness), the augmented Dickey–Fuller test for stationarity, and the Shapiro–Wilk test for normality. Although the time series retrieved had different start dates, the same start date was considered for all the analyzed banks to ensure better comparability, statistical validity, equity, and generalizability of the results.

Table 1 Description of the data used and descriptive statistics, stationarity (ADF), and normality (S–W) tests

Country	Bank	Mean	Std. Dev	Kurtosis	Skewness	ADF		S–W	
Austria	ERSTE Group Bank AG	0.00018	0.0218	7.607	−0.245	−11.017	***	0.904	***
	Raiffeisen Bank International	0.00017	0.0237	13.587	−1.012	−11.239	***	0.899	***
Belgium	KBC Group	0.00019	0.0212	13.536	−1.120	−12.184	***	0.880	***
Denmark	Danske Bank	−0.00009	0.0183	4.816	−0.370	−11.939	***	0.942	***
	JYSKE Bank	0.00037	0.0186	7.598	0.068	−12.009	***	0.926	***
	Sydbank	0.00033	0.0189	9.683	−0.670	−10.868	***	0.902	***
Finland	Nordea Bank	0.00025	0.0163	8.273	−1.038	−12.129	***	0.909	***
France	BNP Paribas	0.00026	0.0210	10.282	−0.606	−11.559	***	0.909	***
	Credit Agricole	0.00017	0.0207	11.683	−0.733	−11.370	***	0.894	***
	Societe Generale	−0.00009	0.0250	12.212	−1.024	−12.180	***	0.878	***
Germany	Commerzbank	0.00024	0.0269	4.730	−0.220	−12.188	***	0.949	***
	Deutsche Bank AG	−0.00008	0.0261	4.786	−0.075	−12.977	***	0.943	***
Ireland	Bank of Ireland Group	0.00009	0.0298	7.443	−0.684	−11.516	***	0.930	***
Italy	Banco BPM	−0.00022	0.0303	6.099	−0.489	−12.353	***	0.946	***
	BPER Banca	−0.00009	0.0293	9.620	−0.270	−12.916	***	0.912	***
	Intesa Sanpaolo	0.00003	0.0216	18.996	−1.425	−11.838	***	0.872	***
	Mediobanca Group	0.00022	0.0216	17.605	−1.481	−12.226	***	0.868	***
	UniCredit	0.00009	0.0280	9.539	−0.439	−11.892	***	0.914	***
Netherlands	ABN AMRO Bank	−0.00005	0.0229	13.133	−1.008	−11.696	***	0.872	***
	ING Groep	0.00015	0.0223	13.350	−0.552	−11.193	***	0.870	***
Norway	DNB Bank	0.00039	0.0166	6.988	−0.570	−12.118	***	0.919	***
Spain	Banco de Sabadell	−0.00012	0.0285	8.157	−0.273	−13.196	***	0.920	***
	Bankinter	0.00022	0.0201	9.861	−0.153	−11.771	***	0.921	***
	BBV Argentaria (BBVA)	0.00016	0.0224	8.555	−0.422	−11.937	***	0.915	***
	Caixabank	0.00028	0.0225	7.208	−0.417	−12.631	***	0.946	***
	Banco Santander	0.00005	0.0223	11.647	−0.584	−12.598	***	0.918	***
Sweden	Skandinaviska Enskilda Banken A	0.00026	0.0168	10.827	−1.164	−12.236	***	0.888	***
	Svenska Handelsbanken A	0.00006	0.0158	7.676	−0.728	−12.823	***	0.912	***
	Swedbank A	0.00010	0.0170	13.724	−1.742	−12.088	***	0.857	***
Switzerland	Cembra Money Bank AG	0.00014	0.0165	139.897	−6.429	−12.472	***	0.732	***
	Credit Suisse	−0.00092	0.0237	10.048	−1.144	−12.525	***	0.897	***
	Julius Baer Gruppe	0.00024	0.0185	8.252	−0.040	−11.464	***	0.923	***
	UBS Group	0.00014	0.0184	7.048	−0.530	−12.717	***	0.919	***
United Kingdom	Barclays	0.00002	0.0227	12.478	−0.859	−11.421	***	0.883	***
	HSBC	0.00019	0.0160	5.239	−0.027	−12.102	***	0.932	***
	Lloyds Banking Group	−0.00009	0.0208	14.744	−0.810	−12.251	***	0.877	***
	NatWest Group	0.00010	0.0226	8.200	−0.716	−12.660	***	0.916	***
	Standard Chartered	0.00033	0.0219	5.853	0.135	−12.281	***	0.929	***
	Virgin Money UK	−0.00005	0.0319	16.890	−0.688	−11.250	***	0.811	***

(i) The table presents the 39 banks' stock returns analyzed and the country of the bank headquarters; (ii) "Std. Dev." represents the standard deviation; (iii) ADF corresponds to the augmented Dickey–Fuller test; (iv) S–W corresponds to the Shapiro–Wilk normality test; (v) *** indicates that the values are statistically significant at the 1% significance level; (vii) the start date is February 3, 2016, and the end date is February 22, 2023, with a total of 1840 observations

The start date was thus defined considering the bank with the fewest observations, i.e., Virgin Money UK with 1840. This step ensures that all banks are analyzed over the same period, avoiding biases arising from data availability differences. However, future analyses could explore the impact of including banks with varying numbers of observations. The start date is February 3, 2016, and the end date is February 22, 2023. Furthermore, this period allows us to cover extreme events, such as the COVID-19 pandemic (when banks played a fundamental role) and the beginning of the Russia–Ukraine war.

Evaluating individual European banks allows us to capture the heterogeneity in informational efficiency behavior between different institutions. By examining individual banks, we can identify specific inefficiencies and explore how market conditions, rather than operational factors, influence the behavior of returns. This methodology is consistent with previous studies, including those of Ferreira et al. (2018) and Kristoufek and Vosvrda (2013), who also analyzed individual firms and groups of firms to assess market dynamics related to informational efficiency.

Considering that, both statistically and economically, the frequency of data is of utmost importance (Narayan and Sharma 2015), and because we aim to assess the informational efficiency (in its weak-form) of the analyzed European banks, it is essential to have as much information as possible. Since the daily frequency is superior to monthly, quarterly, or weekly data when the objective is to extract maximum information (Bannigidadmath and Narayan 2016; Umar et al. 2020), our data have a daily frequency. The daily return rates of the banks were calculated as the difference in logarithms between consecutive observations, i.e., $r_t = \ln(P_t) - \ln(P_{t-1})$, where P_t and P_{t-1} represent the daily values of a given series on days t and $t-1$, respectively. Table 1 presents the descriptive and preliminary analysis of the return series. The long-range memory is relevant even in daily data when evaluating market efficiency because it reveals the persistence or antipersistence in stock returns, reflecting how past price movements influence future movements. By the DFA, which can handle nonstationary time series, we assess these long-range dependencies, offering insights into the weak-form efficiency of banks in light of extreme events such as the COVID-19 pandemic and the Russia–Ukraine war. This approach ensures that both short-term and long-term dependencies are accounted for, making it suitable for understanding efficiency dynamics in volatile markets.

Approximately one-third of the banks (from eight different countries) suffered losses during the period under analysis, with Credit Suisse registering the highest loss. The kurtosis values are all positive (leptokurtic distribution), meaning that the return distributions exhibit fat tails and a greater likelihood of extreme values than a normal distribution. This nonnormality is a stylized fact in financial markets, as confirmed by the Shapiro–Wilk test results, which reject the null hypothesis of normality for all banks.

With respect to skewness, except for JYSKE and Standard Chartered, all the banks presented negative values, indicating a greater probability of negative returns than positive returns. These findings reflect common patterns in financial return distributions, where nonnormality, including fat tails and skewness, is frequently observed.

To evaluate the stationarity, we perform an ADF test, with the null hypothesis rejected, meaning that the return series are stationary. While the ADF test confirms that the banks' return series are stationary, this does not contradict the application of the DFA approach, as it can be applied to both stationary and nonstationary time series. Its primary strengths are its robust ability to handle nonstationary data and its ability to detect long-range correlations in stationary time series. Thus, although the return series are stationary, DFA remains an appropriate and robust method for evaluating long-term memory and persistence in the data.

Methods

In its weak-form, informational efficiency is based on the independence of returns. While short-range memory in financial series may encourage investors to seek out extra returns (Bariviera 2017), long-range autocorrelations motivate investor decisions because they provide insights into persistent/antipersistent patterns in stock returns, which may allow for more informed decision-making regarding potential future price movements. Furthermore, long-range autocorrelation is an important measure of the inefficiency of a market (Wang and Liu 2020). If a time series has long-range memory (long-range autocorrelation), then the autocorrelation function decays asymptotically and hyperbolically, meaning that the time series behavior is similar to infinite memory. This behavior challenges the random walk hypothesis and may violate the EMH, as the shocks in the distant past may significantly affect the present behavior. Thus, this potentially enables investors to earn abnormal returns, encouraging, as Bariviera (2017) noted that investors seek out inefficiencies in the market in hopes of capitalizing on predictable patterns.

Thus, it is highly important to apply methods that allow the detection of long-range memory rather than simply the presence of short-term memory. A usual measure of long-range dependence is the Hurst exponent (H), which has been widely used to evaluate the EMH (Morales et al. 2012). Several methods (e.g., the R/S method and its modifications) have been applied to estimate H. However, some methods do not address nonstationary data or short-range memory, producing several errors in these cases.

The DFA approach proposed by Peng et al. (1994) is a robust approach that overcomes the identified limitations, allowing the evaluation of long-range dependence in financial time series even when the data are nonstationary. It avoids spurious detection of long-range dependence due to nonstationary data. Owing to its potential, it has been applied in several research areas, including finance [see Anagnostidis et al. (2016); David et al. (2020); Ferreira et al. (2021); Quintino and Ferreira (2021); Sukpitak and Hengpunya (2016); among others]. Considering the referred and the main goal of this research, we applied the DFA of Peng et al. (1994) with sliding windows to the return rate series. As noted by recent research [e.g., Agrrawal et al. (2022)], sliding window estimations, including the choice of window length and frequency, can impact the sensitivity of financial metrics, providing valuable context for our approach. The DFA with sliding windows is a common approach applied in the financial literature [see Ferreira (2020); Santos et al. (2022), among others]. This allows the analysis of the dynamic behavior of the α_{DFA} exponent, i.e., the detection of the dynamic evolution of nonlinear predictability and, thus, the changes in the degree of market efficiency. Although this approach is common in the financial literature, it is not typically applied to bank data.

Considering the return rate time series x_k, with $k = 1, \ldots, t$, the first step of the DFA procedure is to integrate the series to obtain $X_k = \sum_{t=1}^{k} x_i - x$, with x being the average of x. The next step is to divide the integrated time series into nonoverlapping intervals of equal length n (the box size). Then, using ordinary least squares (OLS), the local trend

($\tilde{X}_k$) of each box is calculated. With this step, the profile X_k is detrended, and the fluctuation function $F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(X_k - \tilde{X}_k\right)^2}$ is obtained. The last step is to verify the behavior of the F(n) function. The behavior of this function is verified as a function of n that behaves like a power law, with $F(n) = \propto n^{\alpha}$ in that α is characterized as the long-range autocorrelation exponent of the DFA method. The α exponent corresponds to the slope of the line relating $log(F(n))$ to $log(n)$, which represents the memory effect of the series and allows quantification of the empirical strength of the long-range power–law autocorrelations. Thus, it can be used to identify the level of persistence (Zebende et al. 2017). As the $F(n)$ function behaves as a power of n, α can be interpreted as follows: (i) if $0 < \alpha < 0.5$, the series has long-range antipersistent (negative) autocorrelation; (ii) if $\alpha = 0.5$, there is no long-range autocorrelation in the series (no memory), the series is white noise and can be described as a random walk, which is consistent with the concept of MH, and the market can be considered efficient; (iii) if $0.5 < \alpha < 1$, the series has long-range persistent (positive) autocorrelation. Both (i) and (iii) are related to the market's inefficiency.

As market efficiency changes over time (although not usually constant), it must be evaluated dynamically. Thus, as previously mentioned, we sought to calculate DFA dynamically by sliding windows. This approach can smooth the trend signal and eliminate possible discontinuities in the detrended signal (Almeida et al. 2013). The size of the windows must be defined to apply this approach, which can be understood as a limitation because it covers only a part of the sample. However, this method overcomes the limitation of arbitrarily dividing data into subsamples. The window lengths should not be too large to retain sensitivity to changes in the scaling properties occurring over time, but they must be large enough to provide good statistical significance (Morales et al. 2012). Thus, several window lengths have been applied in the financial literature [see Vogl (2023) for details]. On the basis of the size of our sample and considering Matcharashvili et al. (2016) or Ferreira (2018), we applied windows of 500 observations (nearly two years), which provides enough points to compute the α_{DFA} exponent but is not too large to overshadow the efforts to identify the events that possibly affect the behavior of the banks' stock returns (Hiremath and Narayan 2016). This procedure means that we transform the whole sample into sequential samples of 500 observations, i.e., starting by calculating the DFA for the sample from $t = 1, ..., 500$; then, for $t = 2, ..., 501$; and so on. With this procedure, we have a wide set of exponents, meaning that, in the end, we will have a set of α_{DFA} exponents instead of a single α_{DFA} exponent. As shown in Figs. 1 and 2, we estimated all the α_{DFA} exponents for the 39 banks. As a robustness check, we also applied windows of 750 observations, and in general, the differences are not relevant, as displayed in Appendix A (Figs. 6 and 7). This result was not surprising, considering, for example, the findings of Ferreira (2018), who concluded that the choice of window size in more stable markets does not mean significant differences. The Nordea Bank, the Skandinaviska Enskilda Banken A, and the Julius Baer Gruppe are the only banks whose behavior slightly differs for different window sizes, especially in the final period of the sample: the exponents show some persistence for longer windows, whereas for shorter windows, the results point to some anti-persistence for the first two banks and a behavior close to efficiency for the last. Considering our second and third main goals, i.e., to evaluate over time (in light of the EMH) the efficiency of the analyzed banks and rank their efficiency, we adapted the EI introduced by Kristoufek and Vosvrda (2013). Several studies that have evaluated the efficiency of financial markets have applied this index [see Costa et al. (2019)]. The EI is defined as follows, and its evolution was analyzed considering sliding windows of 500 observations.

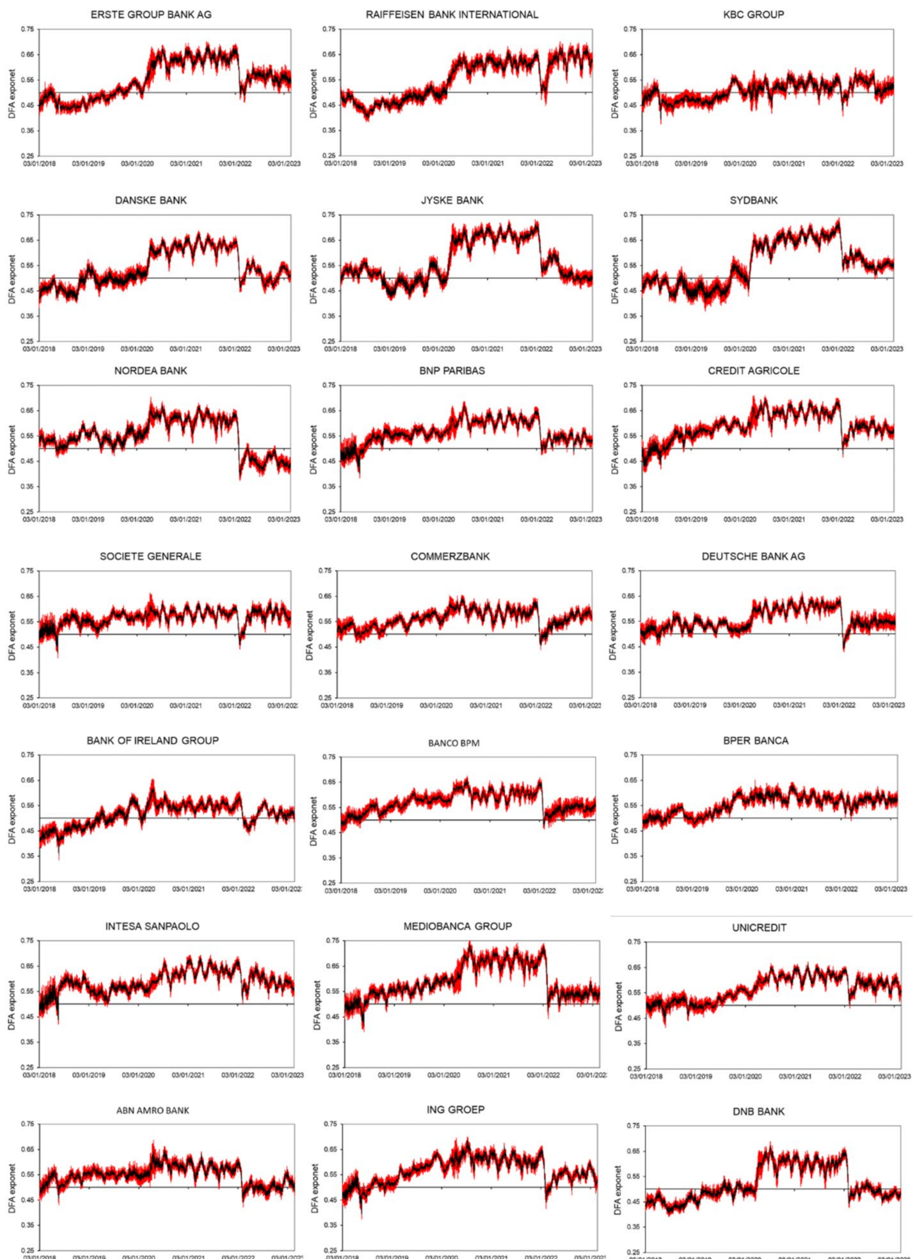

Fig. 1 α_{DFA} exponents for Austrian, Belgian, Danish, Finnish, French, German, Irish, Italian, Dutch, and Norwegian banks. Notes: (i) The time, in days, is represented in the horizontal axis and comprises the period from January 3, 2018, to February 22, 2023; (ii) The data covers the period from February 3, 2016, to February 22, 2023. However, due to applying the sliding window approach with a window size of 500 observations, the figures begin in January 2018; (iii) The α_{DFA} exponent is represented on the vertical axis; (iv) The data is displayed in the format dd/mm/yyyy

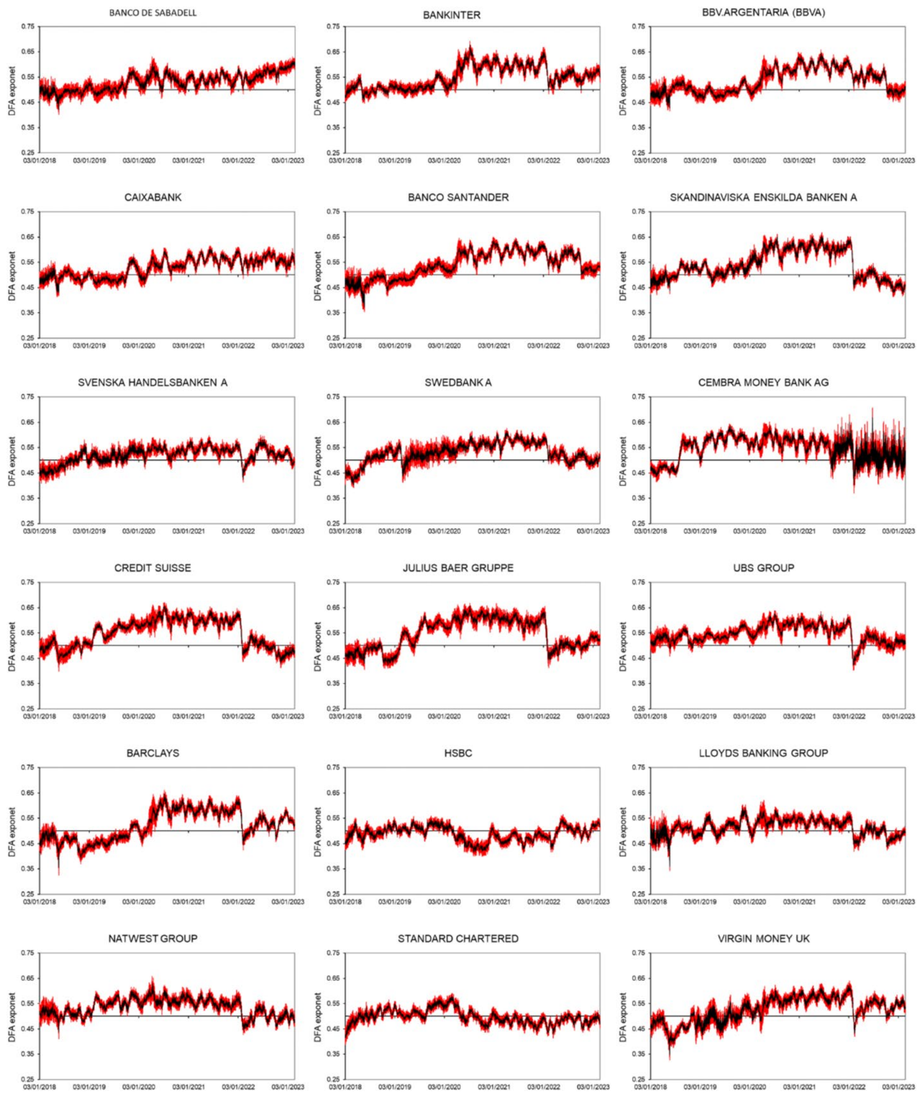

Fig. 2 α_{DFA} exponents for the Spanish, Swedish, Swiss and English bank stock returns. Notes: (i) The time, in days, is represented in the horizontal axis and comprises the period from January 3, 2018, to February 22, 2023; (ii) The data covers the period from February 3, 2016, to February 22, 2023. However, due to applying the sliding window approach with a window size of 500 observations, the figures begin in January 2018; (iii) The $\boldsymbol{\alpha}_{DFA}$ exponent is represented on the vertical axis; (iv) The data is displayed in the format dd/mm/yyyy

$$EI = \sqrt{\sum_{i=1}^{N} \left(\frac{\hat{M}_i - M_i^*}{R_i} \right)^2} \quad (1)$$

where (i) $\hat{M}_i$ is each of the values for the α_{DFA} exponent, (ii) M_i^* is the expected value for market efficiency, which in the case of the DFA is equal to 0.5, and (iii) R_i is the range of the measure, which is equal to one in the case of the DFA. Thus, the distance to the random level (0.5) can be assessed by the difference between $\hat{M}_i$ and M_i^*. The time evolution of the EI is represented in Fig. 3, and the banks were grouped by their headquarters' country. Considering all the sample periods, we estimated the yearly mean of the EI and the mean of the EI to rank the banks in terms of efficiency.

Results and discussion

The analysis of the evolution of the α_{DFA} exponents allows us to dynamically evaluate the behavior of the analyzed bank and identify whether the most recent crises (the COVID-19 pandemic and the invasion of Ukraine from Russia) impacted its behavior (see Figs. 1 and 2).

Before the COVID-19 pandemic, most banks displayed persistent behavior, i.e., the α_{DFA} exponents were higher than 0.5, meaning that upward/downward changes will follow past price changes (up/down) in the future. Exceptions to the referred are the Austrian, Belgian, Danish, Irish, and Norwegian banks and two English banks (Barclays and Virgin Money UK), mostly Northern European banks. Both patterns (persistence and anti-persistence) are associated with non-efficient behavior, meaning the possibility of abnormal gains exists.

Among the banks that display persistent behavior, some display behavior close to the level considered to be efficient, namely, all the Spanish banks, one German bank (the Deutsche Bank), two Italian banks (BPER Banca and UniCredit), and three English banks (HSBC, Lloyds Banking Group, and NatWest Group).

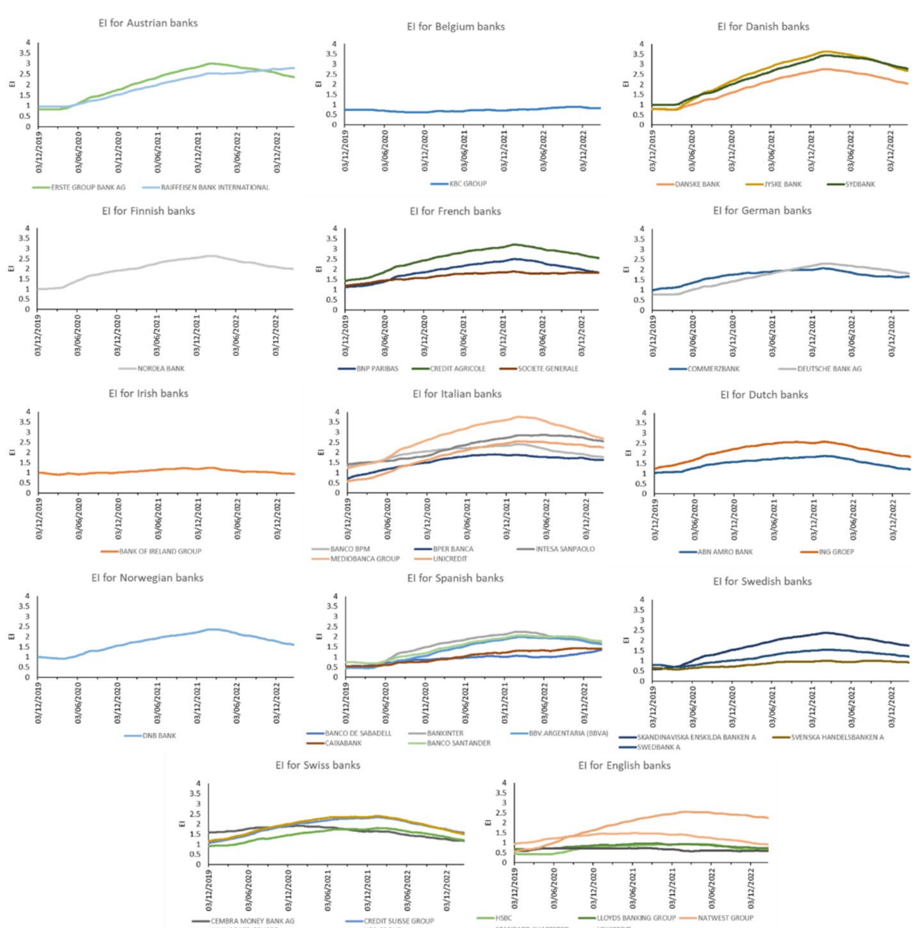

Fig. 3 Time evolution of the EI for all the analyzed banks. Notes: (i) The time, in days, is represented on the horizontal axis and comprises the period from December 3, 2019, to February 22, 2023, due to the application of the sliding window approach with a window size of 500 observations; (ii) the EI is represented on the vertical axis; (iii) the data are displayed in the format dd/mm/yyyy; (iv) the banks are grouped by their headquarters country

The COVID-19 pandemic introduced some instability in the α_{DFA} exponents, impacting the behavior of all banks and increasing their level of persistence (a behavior further away from efficiency). Two English banks, the Standard Chartered Bank and the HSBC, are the exceptions, with the latter also displaying antipersistent behavior.

Considering the period of the beginning of the war between Russia and Ukraine, there were also clear changes in the patterns of the analyzed banks. However, this extreme event impacted behavior differently, reducing the level of persistence, with most of the analyzed banks revealing antipersistent and non-efficient behavior. After the initial shock, the banks increased their levels of persistence, with all the analyzed banks (except the Skandinaviska Enskilda Banken A, Nordea Bank, Credit Suisse, Lloyds Banking Group, and Standard Chartered) again displaying persistent behavior. Some banks, such as the KBC Group, Bank of Ireland, BBVA, and Cembra Money Bank AG, revealed some stability around the value of 0.5 (considered a sign of efficiency) at the end of the sample, a pattern not similar to what happened in a similar period after the beginning of the COVID-19 pandemic. This result could indicate that the COVID-19 pandemic had a greater impact on bank efficiency than did the war between Russia and Ukraine. However, during both crises, the banking sector reacted to information entering the market. The results also reveal the existence of weak-form inefficiency, as long-memory patterns are present for almost all the European banks analyzed, which is in line with the findings of Aloui et al. (2018). Thus, the banking sector's returns do not follow a random walk, possibly making it easier to speculate on asset prices.

Importantly, not all banks reacted homogeneously to the extreme events of the COVID-19 pandemic and the Russia–Ukraine war. For example, while the COVID-19 pandemic has introduced instability in most banks' return patterns, banks such as Standard Chartered banks and HSBC have shown remarkable stability. This result could be attributed to their robust risk management frameworks and diverse exposure across markets, which are less affected by the pandemic or geopolitical tensions. The identified heterogeneity underscores the varying degrees of resilience and adaptability across the European banking sector, as each bank's exposure to market shocks and operational stability play crucial roles in its efficiency patterns. These differences can be explained, for example, by their market position, regulatory environment, and geographic reach.

Another main goal of this study is to examine whether the banking sector's efficiency level (measured by the EI) changes over time and whether extreme events, namely, the COVID-19 pandemic and the war between Russia and Ukraine, affect it. In doing so, we adopted a rolling-window approach where the EI measure is estimated via a fixed window of 500 days. The KBC Group, the Svenska Handelsbanken A, and three English banks (Standard Chartered, Lloyds Banking Group, and HSBC) display a lower level of EI, indicating a lower level of inefficiency. Moreover, these banks display an EI evolution without several fluctuations, which could indicate that extreme events do not impact their efficiency levels. Interestingly, for all the remaining banks, the EI level increased near March 2020, which coincided with the beginning of the COVID-19 pandemic. The level of EI reaches its maximum value (i.e., the higher level of inefficiency) near March 2022, a period near the beginning of the war between Russia and Ukraine. After this date, the level of EI decreased. These data could indicate that these two extreme events impacted informational banking sector efficiency in different ways but similarly for all countries.

Despite the similarities among the countries evaluated, there are some notable particularities. For example, both Austrian banks increased their level of inefficiency at the beginning of 2020 and decreased it in the first quarter of 2022. This decreasing pattern continued until the end of the analyzed period only for the ERSTE Group Bank AG, whereas Raiffeisen Bank International increased their EI. This scenario could be a sign that although the war between Russia and Ukraine impacted the efficiency level of both banks similarly, they revealed different patterns after a short period of shock. This altered pattern could be due to the different exposures of both banks to the Russian and Ukrainian markets.

Additionally, for English banks, the EI level does not reveal several changes during the analyzed period; however, the NatWest Group significantly increased its EI level near the beginning of the COVID-19 pandemic, only stabilizing during the first quarter of 2022 (although at a higher level of EI). Among Danish banks, Danske displayed lower EI levels during all of the analyzed periods, revealing its lower level of inefficiency. As shown by Aloui et al. (2018), market efficiency levels are time-varying and significantly change under crisis scenarios. Thus, any investment or speculative decision requires attention because efficiency levels are dynamic. Furthermore, if investors are interested in exploring some abnormal returns, the banks that display lower values of EI should not be the most appropriate choice.

Since we also sought to rank the efficiency of the analyzed banks, we performed another analysis. We estimated the yearly mean of the EI and ranked the banks in terms of informational efficiency (as displayed in Fig. 4). The greater the number (larger size of the bar) is, the lower the level of EI, i.e., the lower the level of inefficiency. On the other hand, lower numbers (smaller bars) mean higher EI levels, i.e., higher levels of inefficiency. We can read the figure by column, allowing us to rank the analyzed banks in terms of EI for each year. At the same time, we can read the figure by line, allowing us to evaluate how the EI evolved and how each bank's efficiency level changed over the year. As seen, generally, the Belgian, British, Spanish, and Swedish banks have lower levels of inefficiency (higher numbers and sizes of the bars) and are ranked as the least inefficient. In contrast, the French bank Credit Agricole and two Italian banks, Banco BPM and Intesa Sanpolo, display higher levels of inefficiency (i.e., lower levels of efficiency). Especially after 2020, the Swiss and Austrian banks increased their levels of inefficiency. Although the Spanish banks were among the least inefficient, their levels of inefficiency increased over time.

We also estimated the mean of the EI considering all the analyzed periods to rank all the analyzed banks in terms of informational efficiency considering all the sample periods (Fig. 5).

Standard Chartered is the least inefficient bank, whereas the Mediobanca Group is the most inefficient. If we consider the top of the least inefficient banks as the P_{10}, three English banks (Standard Chartered, HSBC, and Lloyds Banking Group) and one Belgian bank (the KBC Group) are the least inefficient. In contrast, we find that one Italian bank (Mediobanca Group), one French bank (Credit Agricole), and two Danish banks (the JYSKE Bank and the Sydbank) are the most inefficient banks. Interestingly, all the Spanish banks are ranked until the P_{50}. As displayed in Fig. 5, 18 banks have an EI below the average of the EI of the European banking sector (represented with a black bar), and 21 banks have an EI above the average of the EI of the European banking sector.

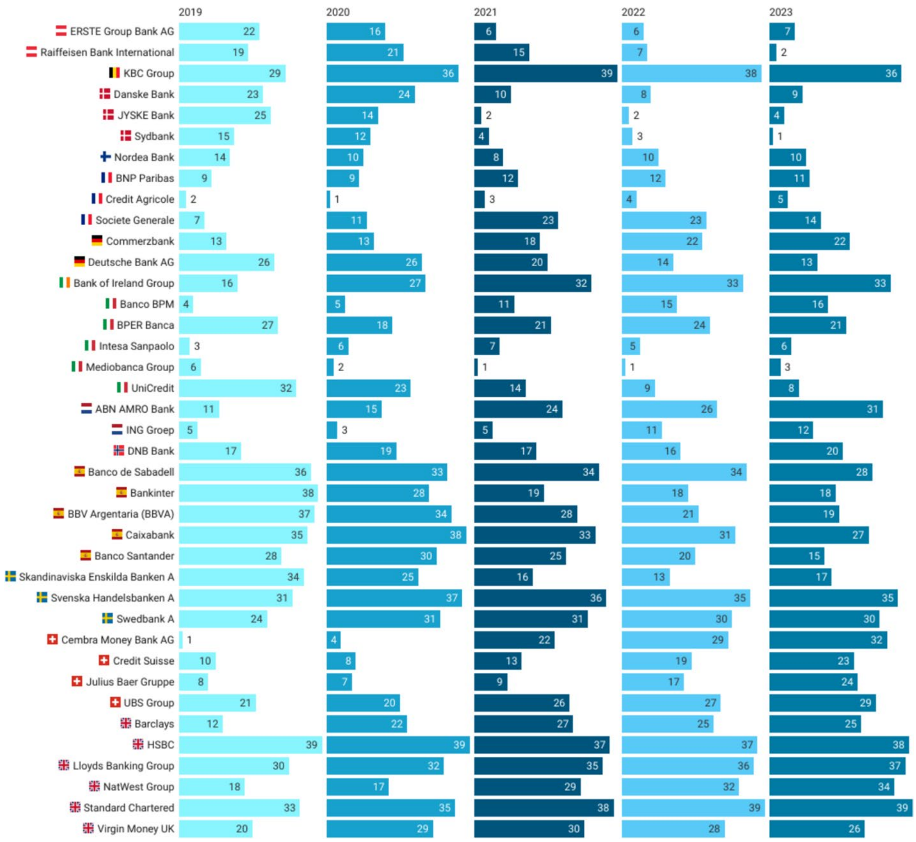

Fig. 4 Annual efficiency rankings of the banks. Notes: (i) The EI for each year was estimated as the mean of the EI for the corresponding year; (ii) a different blue color indicates each year; (iii) the numbers on each bar represent the ranking position of each bank in the year at the top. The greater the number (and size of the bar), the lower the EI level, i.e., the lower the level of inefficiency (higher level of efficiency)

Conclusions

In recent years, the world has experienced two extreme events: the COVID-19 pandemic and the war between Russia and Ukraine. Both are of external origin from financial markets but have impacted financial markets in general and the banking system in particular.

Considering our first main goal, we begin with the analysis of the α_{DFA} exponents, which allow us to dynamically evaluate the behavior of the analyzed banks' stock returns and identify whether the most recent crises impacted their behavior. Without finding a definite pattern, some general results arise. First, before the COVID-19 pandemic, most banks' stock returns displayed persistent behavior, except for Austrian, Belgian, Danish, Irish, and Norwegian banks and two English banks (Barclays and Virgin Money UK). Both situations (persistence and antipersistence) are associated with non-efficient behavior, meaning that the possibility of abnormal gains exists. The spread of the COVID-19 pandemic has introduced some instability in α_{DFA} exponents, impacting the behavior of all banks and increasing their level of persistence (except for Standard Chartered Bank and HSBC, both English banks). This finding could influence the future, as a given pattern of returns is more likely to be repeated, in line with Ferreira et al. (2018). Second, the war between Russia and Ukraine also impacted the behavior of the analyzed banks' returns. In contrast, in this case, the levels of persistence decreased, with most banks revealing antipersistent behavior (but also associated with inefficiency). Third, the

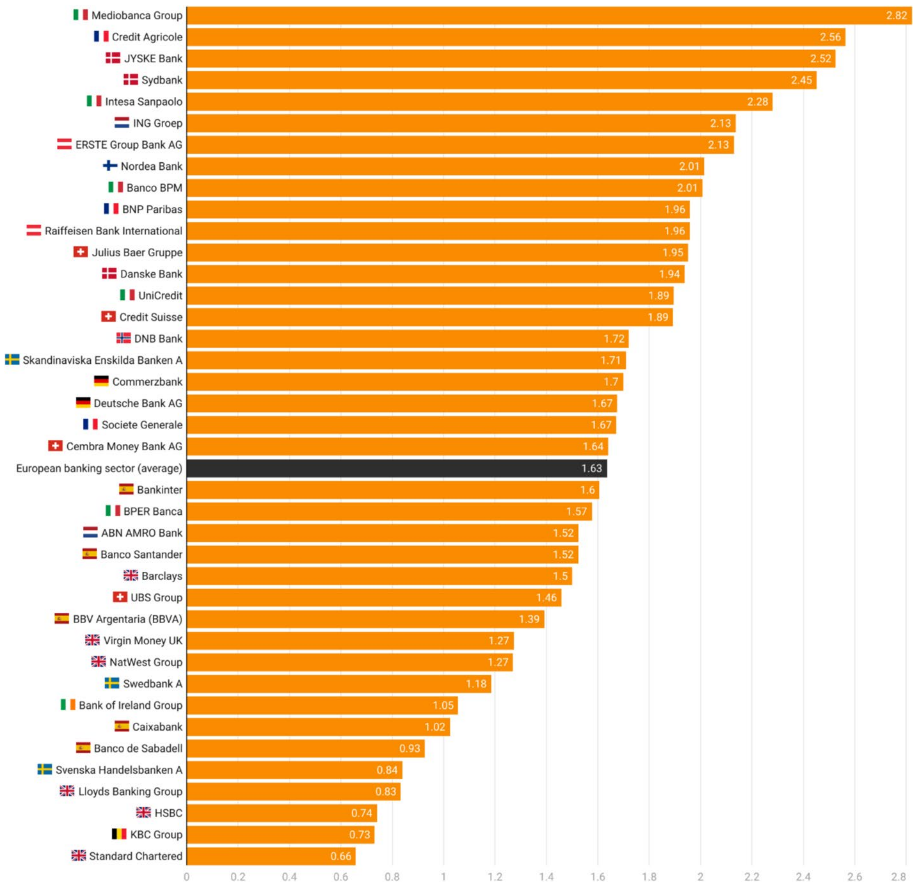

Fig. 5 Ranking of EI for all the analyzed banks. Notes: (i) The EI was estimated as the mean of the EI for all the analyzed periods; (ii) the number on each bar corresponds to the value of the EI. The higher the value of the EI (and the size of the bar), the lower the level of efficiency, i.e., the higher the level of inefficiency

identified trend was not long-lasting. After the initial shock, the banks increased their levels of persistence, with all the analyzed banks returns once again displaying persistent behavior (except the Skandinaviska Enskilda Banken A, Nordea Bank, Credit Suisse, Lloyds Banking Group, and Standard Chartered). Fourth, at the end of the sample period, some banks (such as KBC Group, Bank of Ireland, BBVA, and Cembra Money Bank AG) displayed some stability around the value of 0.5 (considered a sign of efficiency), which could be a good indicator of the stability of these banks. This pattern was not identified after a similar period at the beginning of the COVID-19 pandemic, which could mean that the COVID-19 pandemic had a greater impact on bank efficiency than did the war between Russia and Ukraine. In general, banks in different European countries reacted not homogeneously to both extreme events, with North European banks displaying different efficiency patterns than those in Western Europe. However, for most analyzed banks, the results reveal long-memory patterns (and lack randomness), meaning that the banking sector's returns do not follow a random walk. In this sense, it is possible to speculate more easily on asset prices and obtain abnormal returns.

We also aimed to evaluate whether the efficiency level of the banking sector changes over time and whether the referred extreme events affected it. The results of the EI analysis point in the same direction as the assessment made through the analysis of the α_{DFA}

exponents, thus providing robustness to the performed analyses. Moreover, both analyses also point to time-varying market efficiency levels, with significant changes under extreme event scenarios, in line with Aloui et al. (2018). Thus, any investment or speculative decision requires attention because efficiency levels are dynamic.

Considering our last main goal, i.e., to rank the efficiency of the analyzed banks, we can conclude that banks change their positions in terms of ranking efficiency. Standard Chartered is generally the least inefficient bank, and Mediobanca Groupe is the most inefficient.

This study highlights that extreme events significantly affect the informational efficiency of the European banking sector. The findings suggest that while the COVID-19 pandemic profoundly impacted efficiency levels, geopolitical tensions also introduced notable but different changes. The dynamic nature of market efficiency underscores the importance of investors and policymakers monitoring and adapting to evolving market conditions continuously. The time-varying and not homogeneous efficiency of European banks suggests that these institutions may be under- or overvalued, which is of utmost importance to decisions on whether to buy or sell their shares. Investors and portfolio managers can use the identified differentiated dynamic inefficiency to develop investment strategies that account for the persistent and antipersistent behaviors of bank stocks, particularly during periods of market turbulence.

Additionally, the implications of our findings extend beyond individual investment strategies. Policymakers can use insights into how extreme events affect market efficiency to design regulatory measures to promote financial stability. The dynamic shifts in efficiency during crises highlight the critical need for real-time monitoring tools to detect inefficiencies early, enabling preemptive interventions to mitigate systemic risk. By understanding and considering the identified inefficiencies, different market players can better protect the stability of financial markets, especially in periods of uncertainty.

In future research, other regions could be considered to analyze whether the observed patterns are similar or not, which could provide investors' and other market participants with information about the possibility of certain extreme events, including possible crashes associated with bubbles. In the present study, we calculate the daily stock returns via price returns on the basis of the logarithmic difference between consecutive daily closing prices. Our focus is on price efficiency rather than total shareholder returns, meaning that dividends are not explicitly included. However, we acknowledge that including dividends could provide additional insights, particularly when evaluating the total return performance of these banks, which could be a possible future research direction.

While this study focuses on the European banking sector's dynamic weak-form efficiency within the EMH framework, future research could investigate the influence of variables, such as macroeconomic indicators or bank-specific characteristics, to better explain cross-country differences. Although these variables are typically related to operational or technical efficiency rather than informational efficiency, they could provide complementary insights into the broader context of bank performance.

While our study focuses on weak-form efficiency per the EMH, future research could also explore conditional efficiency, a concept discussed in the related literature. Such studies could examine how efficiency levels change under different economic conditions or market states, adding depth to the efficiency analysis over time.

Appendix A

See (Figs. 6 and 7).

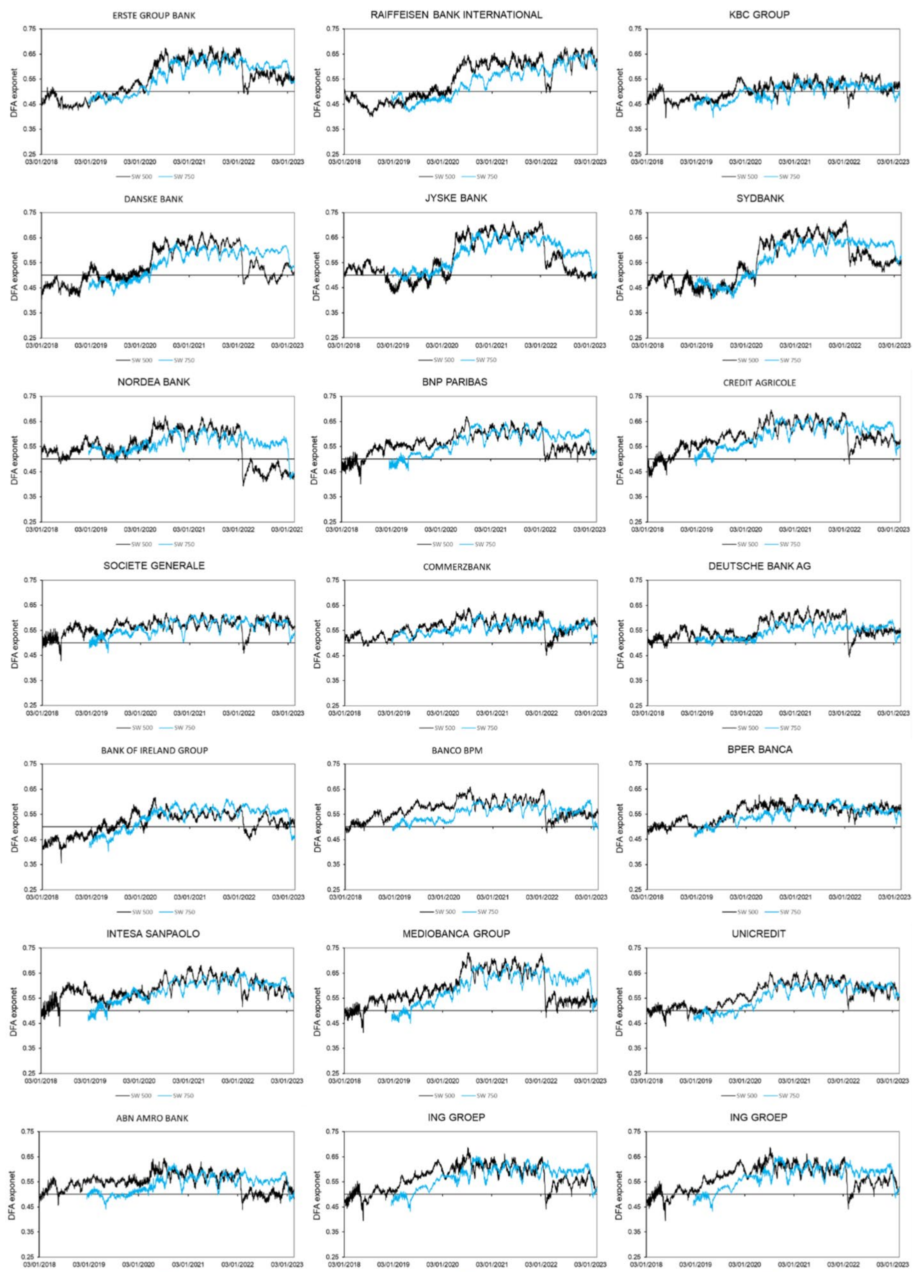

Fig. 6 α_{DFA} exponents of Austrian, Belgian, Danish, Finnish, French, German, Irish, Italian, Dutch, and Norwegian banks, using different window lengths. Notes: (i) The time, in days, is represented on the horizontal axis and comprises the period from January 3, 2018, to February 22, 2023; (ii) the data cover the period from February 3, 2016, to February 22, 2023. By applying the sliding window approach with window sizes of 500 (black line) and 750 (blue line) observations, the figures begin in January 2018. (iii) The α_{DFA} exponent is represented on the vertical axis. (iv) The data are displayed in the format dd/mm/yyyy

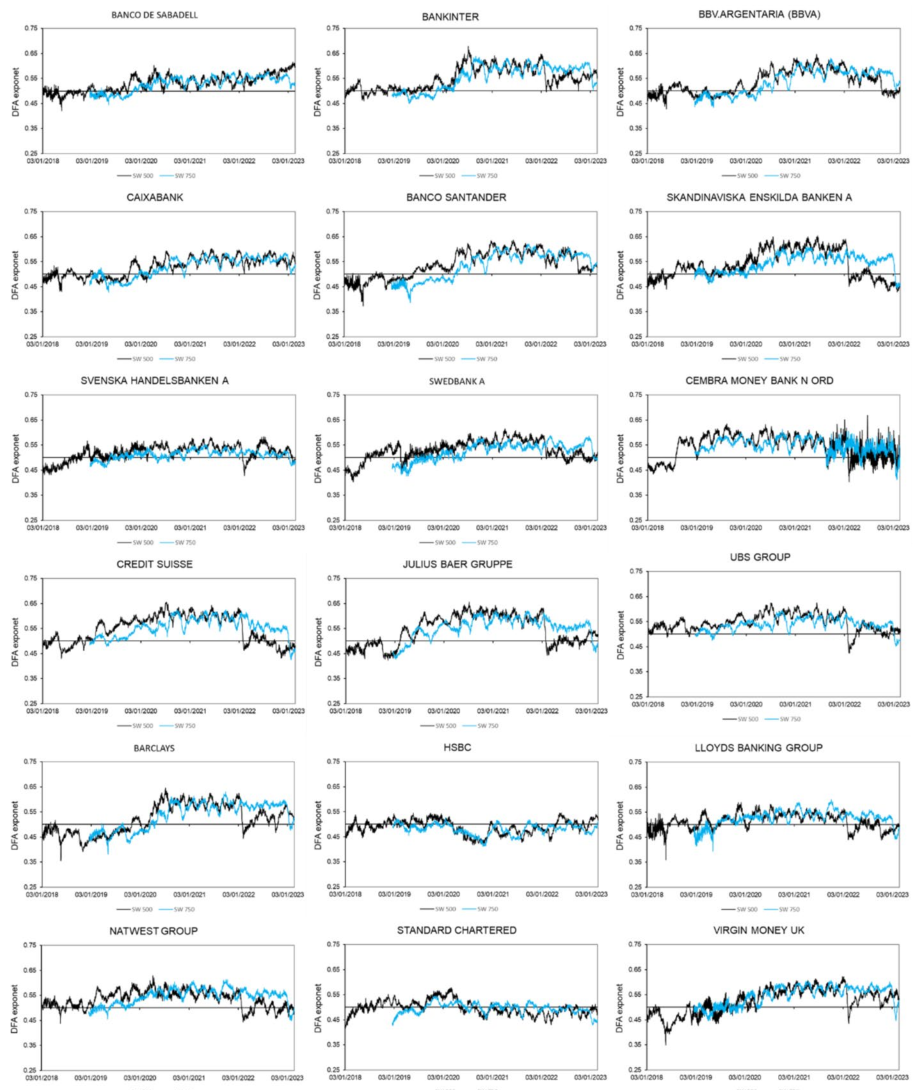

Fig. 7 α_{DFA} exponents of the Spanish, Swedish, Swiss, and English bank stock returns, using different window lengths. Notes: (i) The time, in days, is represented on the horizontal axis and comprises the period from January 3, 2018, to February 22, 2023; (ii) the data cover the period from February 3, 2016, to February 22, 2023. By applying the sliding window approach with window sizes of 500 (black line) and 750 (blue line) observations, the figures begin in January 2018. (iii) The α_{DFA} exponent is represented on the vertical axis. (iv) The data are displayed in the format dd/mm/yyyy

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Author contributions
Conceptualization, D.A., A.D., M.A. and P.F.; data curation, D.A., A.D., M.A. and P.F.; formal analysis, D.A., A.D., M.A. and P.F.; funding acquisition, D.A., A.D., M.A. and P.F.; investigation, D.A., A.D., M.A. and P.F.; methodology, D.A., A.D., M.A. and P.F.; software, D.A., A.D., M.A. and P.F.; validation, D.A., A.D., M.A. and P.F.; visualization, D.A., A.D., M.A. and P.F.; writing—original draft, D.A., A.D., M.A. and P.F; writing—review and editing, D.A., A.D., M.A. and P.F. All authors have read and agreed to the published version of the manuscript.

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Data availability
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Nor applicable.

Competing interests
The authors declare that they have no competing interests.

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