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When two banks fall, how do markets react?

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Abstract

The most recent fall of the Silicon Valley (SVB) and Credit Suisse (CS) banks increased the fear of a worldwide banking crisis. We analyse the impacts of their fall on five financial indices. We apply detrended fluctuation analysis, static and with sliding windows. We find a higher impact of the SVB fall on the efficiency dynamic of the studied indices, which revealed fluctuating efficiency and a loss of efficiency during the period of the falls. The fall of both banks contributed to some persistence in stock indices returns. The Nasdaq and STOXX Europe 600 Banks are the most and the least efficient indices, respectively. Despite the apparent evidence of inefficiency, it might not necessarily mean a capacity for abnormal profits.

Keywords: Bank fall, Credit Suisse Bank; Detrended fluctuation analysis; Silicon Valley Bank; Sliding windows.
JEL Classification Codes: C19, C58, G01, G14, G15.

1. Introduction

Silicon Valley Bank (SVB) was one of the top 20 banks in the US and one of the major banks for venture-backed companies. This bank had not only a UK arm but also a Chinese joint venture (The SPD Silicon Valley Bank), which was set up in 2012 and targeted the country’s tech elite. On 10 March 2023, the SVB was closed. Since the closure of Washington Mutual in 2008, it was the largest bank to have closed, dragging the banking sector down and shaking investor confidence worldwide. One week later, Credit Suisse (CS) and the Union Bank of Switzerland (UBS) entered into a merger agreement, with UBS being the surviving entity. The CS was one of the largest lenders in Europe, and the Financial Stability Board categorised it as one of the 30 “global systemically important” banks. Global stock markets sank on 20 March 2023, with fear of a worldwide banking crisis. For different reasons, these two banks have worldwide relationships. Thus, the referred events allied to financial markets integration can impact the financial system's stability and resilience and spread contagion effects worldwide.

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Furthermore, in these cases, some agents try to seize the opportunity to earn extraordinary profits in their investment strategies. Regarding this, it is important to analyse how financial markets behave and look for differences in patterns before and after the crashes of those banks. This, allied with the importance of the stability of the banking system and financial markets, are our main motivation to evaluate the impact of the fall of SVB and CS on the efficiency of different world financial markets.

In the financial literature, several studies evaluate the serial dependence of financial markets and, consequently, respective efficiency. The work of Fama (1970), formalizing the efficiency market hypothesis (EMH), became a cornerstone of empirical and theoretical finance. Although EMH is a fundamental benchmark of modern finance, efficiency drifts have been observed in several markets.

The weak form of efficiency states that all future prices cannot be predicted using the information on their past behaviour, meaning that their series has no memory. If memory exists, it could be linked to some market imperfections, such as illiquidity, risk, speculation, non-linearities, and time dependence. Several approaches, from linear to non-linear, have been used to analyse financial markets. Although the linear approaches (e.g., Granger and Morgenstern, 1963; Ferreira and Dionísio, 2014) confirmed the random behaviour of financial markets (the basis of EMH) and the non-dependence of financial data, particular features of financial markets, known as stylized facts (e.g., fat-tailed returns, volatility clusters, autocorrelation in variance, etc.), have been found. However, even if linear autocorrelation does not exist, non-linear dependencies could make markets inefficient (Darbellay, 1998; Granger et al., 2004; Mohti et al., 2019). As non-linear approaches allow a more thorough analysis of financial markets, with several studies revealing evidence of long-range dependence in them (e.g., Sadique and Silvapulle, 2001; Ferreira, 2020; Murialdo et al., 2020), they have become more common.

Aiming to analyse the dynamics and historical independence of five world financial indices and evaluate their efficiency in the context of the most recent fall of two important financial institutions (SVB and CS), we adopt detrended fluctuation analysis (DFA), static and with sliding windows. This study aims to answer two main research questions: (i.) was the efficiency of world financial indices affected by the SVB and CS bank fall? (ii.) the efficiency of world financial indices was similarly affected by these two banks' falls? As far as we know, no studies are dedicated to the analysis of these two banks' fall (Yadav et al. (2023), Yousaf et al. (2023) and Yousaf and Goodell (2023) analysed the impact of only SVB's fall on several financial markets but using a different approach - the event study), which is the main contribution of this study. Furthermore, this study is not only focused on the impact of these two banks' fall on the efficiency of individual stocks or industries, but it also evaluates the impact of these two banks' fall on the efficiency of global financial indices.

The remainder of the article is organized as follows: Section 2 presents the methods applied; Section 3 explains the data used; Section 4 presents the results; and Section 5 provides conclusions.

2. Methods

Long-range dependence is a feature of time series autocorrelations. If the series has long-range dependence, the autocorrelation function decays asymptotically and hyperbolically. Thus, the series behaves as if it has infinite memory, i.e., the shocks in a distant past may significantly affect present behaviour. Such behaviour may constitute a violation of the efficient market hypothesis. The Hurst exponent (H) is a characteristic measure of long-range dependence, and it has been used several times to describe various phases of the financial markets and their connection to the efficient markets (Morales et al., 2012). Among the various methods to estimate

H, the DFA approach allows the evaluation of the presence of long-range dependence in financial time series even when dealing with nonstationary data, avoiding spurious detection of long-range dependence due to nonstationary data. As it is less dependent on non-stationarity assumptions and noisy data, it is also suitable for quantifying nonlinear dynamics and complexity in time series (Lahmiri & Bekiros, 2019). Due to these reasons, and in order to evaluate the historical independence of returns and assess the existence of long memory, we use DFA (Peng et al., 1994), a method that has been widely used in other research areas, including finance (Cao and Zhang, 2015; Anagnostidis et al., 2016; López and Contreras, 2013; Ferreira et al., 2017; Ferreira, 2016; Quintino and Ferreira, 2021; among others). Given the huge number of studies that use this method, it would be extremely difficult to give an entire notion about the state of the art. A thorough review of the literature in this field can be found, for example, in Gallegati (2016), Jovanovik and Schinckus (2016), Schinckus (2017), or Pereira et al. (2017). DFA starts with the integration of return, i.e., $x(k) = \sum_{t=1}^{k} r(t) - \langle r \rangle$, where $\langle r \rangle$ is the average value of returns r. This new series is divided in *N/s* mutual exclusive boxes of equal dimension s and, for each segment i, the trend $z_i(t)$ is obtained with an ordinary least squares estimation, used to detrend the previous series. This procedure allows the calculation of the DFA function, given by Eq. 1.

$$F(s) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left[x_s\ (\mathrm{t})\right]^2} \qquad (1)$$

We repeat the procedure for all different values of s (box), and the results constitute the power-law behaviour $F(s) \propto s^{\alpha}$. The long-range power-law exponent α gives information about the historical independence of the time series. If $\alpha = 0.5$, the time series is represented by a random walk (no long memory); if $0.5 < \alpha < 1$, the time series is persistent, and if $\alpha < 0.5$, the time series is anti-persistent, it being expected that under the EMH, time series should behave like a random walk.

In addition to static analysis, a dynamic one is also needed as the market efficiency is typically not constant but changes over time. Furthermore, analysing the time-dependent Hurst exponent, based on DFA, can predict crashes in the stable market with well-defined and long-lasting trends (Kristoufek, 2010a). Thus, we aim to perform our analysis both statically and dynamically. Considering this, we also estimate the DFA with a sliding windows approach, a relatively common approach in financial literature (see, for example, Cajueiro and Tabak 2004a, 2004b, 2006, 2008), which can smooth the trend signal and eliminate the possible discontinuities in the detrended signal (see, for example, Almeida et al., 2013). It also allows the detection of the evolving nature of non-linear predictability and hence the changing degree of market efficiency as well as the analysis of the dynamic behaviour of the DFA exponent.

Several window lengths have been used in financial literature (for a detailed overview, see for example, Vogl, 2023). According to Morales et al. (2012) they should not be too large to retain sensitivity to changes in the scaling properties occurring over time. Still, they must be large enough to provide good statistical significance. Thus, given the dimension of our samples for the five-minute series, the calculations were based on a window of 500 observations (about eight hours), as Hiremath and Narayan (2016) applied, for example. This means that we transform our whole sample in 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. Thus, in the end, we will have a set of DFA exponents instead of a single DFA exponent.

With the base to evaluate historical independence, we may also analyse the efficiency of the time series under analysis. For this purpose, we apply the efficiency index (EI) defined by Kristoufek and Vosvrda, (2013), given by Eq. 2.

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

where $\widehat{M}_i$ is each of the values for the DFA exponent, M_i^* is the expected value for market efficiency (0.5 in the case of DFA), and R_i the range of the measure (in the case of DFA, equal to 1). This measure was already applied in several studies to infer about the efficiency of financial markets (see, for example, Costa et al., 2019).

Standardizing the EI values, we obtain the limits for the measures that lie between zero and one. For the efficient market, we have $EI = 0$, and for the least efficient market, we have $EI = \frac{\sqrt{N}}{2}$, where N is the number of measures considered (in our case, $N = 1$).

3. Data

The aim of this paper is to analyse the dynamics of five financial indices from different world markets, in the context of the fall of SVB and CS. The main issue is the evaluation of the efficiency of those indices and analysis of respective behaviour within the period under study. We obtained intraday data (one minute, five minutes, and 30 minutes) for the STOXX Europe 600 Banks EUR Price Index (Banks), EURO STOXX Index, Hang Seng Index, Nasdaq Composite Index, and NYSE Composite Index for the period between 22 January and 22 March, 2023. In this paper, we show the results for the five-minute periodicity, although we use all the periodicities to evaluate the robustness of our conclusions.

Table 1 presents the list of indices used in this paper, with the second column representing the code applied for each one. There are slight differences in the number of observations (n). However, as the methodology focuses on the analysis of the time series independently, the use of different samples does not constitute a problem.

Table 1. Description of sample

Index	Code	n
STOXX Europe 600 Banks	Banks	4453
EURO STOXX Index	Eurostoxx	4449
Hang Seng Index	HangSeng	2760
Nasdaq Composite Index	Nasdaq	3215
NYSE Composite Index	NYSE	3293

Return rates were calculated as usual, considering the logarithm difference of series, i.e., $r_t = ln(p_t) - ln(p_{t-1})$, where r_t is the return rate at moment t and p_t the index value at the same moment. Tables 2, 3, and 4 present the descriptive statistics for all the indices for the entire period, and for subperiods before and after the fall of SVB and CS. The cut-off date for the SVB fall was 13 March, 2023. For the CS fall, the date used was 17 March 2023. Both cut-off dates are represented in Figure 1 by the orange-shaded area.

The analysis of the descriptive statistics presented in Tables 2, 3, and 4 does not allow us to draw any conclusions about significant differences in the mean returns of the several subperiods under study. Indeed, we can see a slight increase in average returns in the subperiods after the fall of both banks, which could indicate the possibility of markets anticipating these events. All the indices show very high kurtosis values, i.e., leptokurtic distributions, which is a common stylized fact in financial markets. Furthermore, after the fall of each bank, almost all the indices revealed positive skewness, meaning that positive returns are more frequent than negative ones.

Table 2. Descriptive statistics for the whole period

	Banks	Eurostoxx	HangSeng	Nasdaq	NYSE
Mean	-1.10E-05	0.00E+00	-4.90E-05	1.90E-05	-1.50E-05
Median	0.00E+00	2.20E-05	-8.00E-06	2.50E-05	4.00E-06
Std. Dev.	0.002	0.001	0.002	0.002	0.001
Kurtosis	102.95	75.75	32.17	33.05	72.06
Skewness	-1.416	0.0047	-1.096	-0.025	-2.719
N	4452	4448	2759	3214	3292

Table 3. Descriptive statistics before and after the fall of SVB

	Before					After				
	Banks	Eurostoxx	HangSeng	Nasdaq	NYSE	Banks	Eurostoxx	HangSeng	Nasdaq	NYSE
Mean	2.00E-06	-1.00E-06	-6.80E-05	-1.00E-06	-2.10E-05	-7.00E-05	1.00E-06	2.50E-05	1.14E-04	1.30E-05
Median	0.00E+00	2.20E-05	-2.80E-05	1.70E-05	1.00E-06	-6.50E-05	0.00E+00	5.50E-05	8.70E-05	4.40E-05
Std. Dev.	0,001	0,0013	0,001	0,002	0,001	0,003	0,002	0,002	0,002	0,0022
Kurtosis	249,30	92,04	31,38	38,55	21,30	25,38	38,29	29,84	15,36	52,94
Skewness	-8,613	-1,863	-2,163	-0,492	-1,431	1,147	1,463	1,095	1,502	-2,862
N	3639	3639	2207	2651	2716	813	809	552	563	576

Table 4. Descriptive statistics before and after the fall of CS

	Before					After				
	Banks	Eurostoxx	HangSeng	Nasdaq	NYSE	Banks	Eurostoxx	HangSeng	Nasdaq	NYSE
Mean	-2.30E-05	-9.00E-06	-6.30E-05	1.60E-05	-2.00E-05	1.08E-04	8.50E-05	7.40E-05	5.50E-05	4.60E-05
Median	0.00E+00	2.20E-05	-2.40E-05	2.30E-05	4.00E-06	6.60E-05	4.60E-05	1.26E-04	6.00E-05	0.00E+00
Std. Dev.	0,002	0,001	0,002	0,002	0,001	0,003	0,002	0,002	0,001	0,001
Kurtosis	146,25	82,01	33,19	33,33	75,68	19,56	40,54	24,21	16,22	44,36
Skewness	-1,984	-0,812	-1,594	-0,110	-3,613	-0,322	4,024	2,664	1,921	3,846
N	4055	4055	2483	2963	3035	397	393	276	251	257

Notes: Std. Dev. represents the standard deviation.

4. Results

Firstly, we evaluate the presence of historical independence of the financial series statically, using DFA for the entire period and for the subperiods before and after the fall of the two banks. Tables 5, 6, and 7 present the results for this measure.

Table 5. DFA exponent for the entire period

Index	DFA Exponent	Behaviour
Banks	0.495 ± 0.0007	Anti-persistent
Eurostoxx	0.483 ± 0.0004	Anti-persistent
HangSeng	0.483 ± 0.0005	Anti-persistent
Nasdaq	0.509 ± 0.0006	Persistent
NYSE	0.441 ± 0.0003	Anti-persistent

The series under analysis exhibits a non-random behaviour (which may be a sign of non-efficient behavior) for the entire period, with Nasdaq presenting persistent behaviour (positive long-range dependence) and all the other indices being anti-persistent (negative long-range dependence). For Nasdaq, this could mean that a change in price (up/down) in the last period will be followed in the next one by upward/downward change in the following period. Thus, this index has long periods of stability interrupted by sudden, sharp discontinuities (Los & Yu, 2008). Thus, investing in that persistence could promote opportunities for abnormal gains by arbitrage. The remaining indices have a fast reversion to the mean.

Table 6. DFA exponent for the subperiods before and after the fall of the SVB

	Before				After			
Index	**DFA Exponent**			**Behaviour**	**DFA Exponent**			**Behaviour**
Banks	0.485	±	0.000463	Anti-persistent	0.518	±	0.000828	Persistent
Eurostoxx	0.485	±	0.000355	Anti-persistent	0.507	±	0.000456	Persistent
HangSeng	0.486	±	0.000458	Anti-persistent	0.529	±	0.000411	Persistent
Nasdaq	0.511	±	0.000558	Persistent	0.413	±	0.000221	Anti-persistent
NYSE	0.449	±	0.000261	Anti-persistent	0.445	±	0.000279	Anti-persistent

Table 7. DFA exponent for the subperiods before and after the fall of CS

	Before				After			
Index	**DFA Exponent**			**Behaviour**	**DFA Exponent**			**Behaviour**
Banks	0.483	±	0.000571	Anti-persistent	0.462	±	0.000426	Anti-persistent
Eurostoxx	0.463	±	0.000374	Anti-persistent	0.449	±	0.000186	Anti-persistent
HangSeng	0.482	±	0.000489	Anti-persistent	0.551	±	0.000294	Persistent
Nasdaq	0.506	±	0.000583	Persistent	0.439	±	0.000139	Anti-persistent
NYSE	0.426	±	0.000292	Anti-persistent	0.496	±	0.000175	Anti-persistent

When we split the period into two subperiods, with point the fall of the SVB as a reference, we can see that NYSE was the only index that maintained its behaviour regarding historical dependence, being anti-persistent in both subperiods, meaning that this series is more frequently mean-reverting than a random one (Kristoufek, 2010b). The remaining indices changed their behaviour, which could mean that some instability could be caused by the SVB fall. For the Banks, Eurostoxx, and HangSeng indices, the shocks seem to have a persistent impact on returns (changing the behaviour from anti-persistent to persistent). This means that a given result has a greater likelihood of being repeated, which could have an influence in the future, because a given pattern of returns is more likely to be repeated. The results not only provide evidence against the EMH (since they imply non-linear dependence at the moments of distribution and consequently a potentially predictable component), but also trends that may be unexpectedly disrupted by discontinuities. Thus, it could mean the SVB fall could have increased the risk level of these indices. As the analysed indices are global financial indices, this could also mean that the SVB fall could have increased the systemic risk.

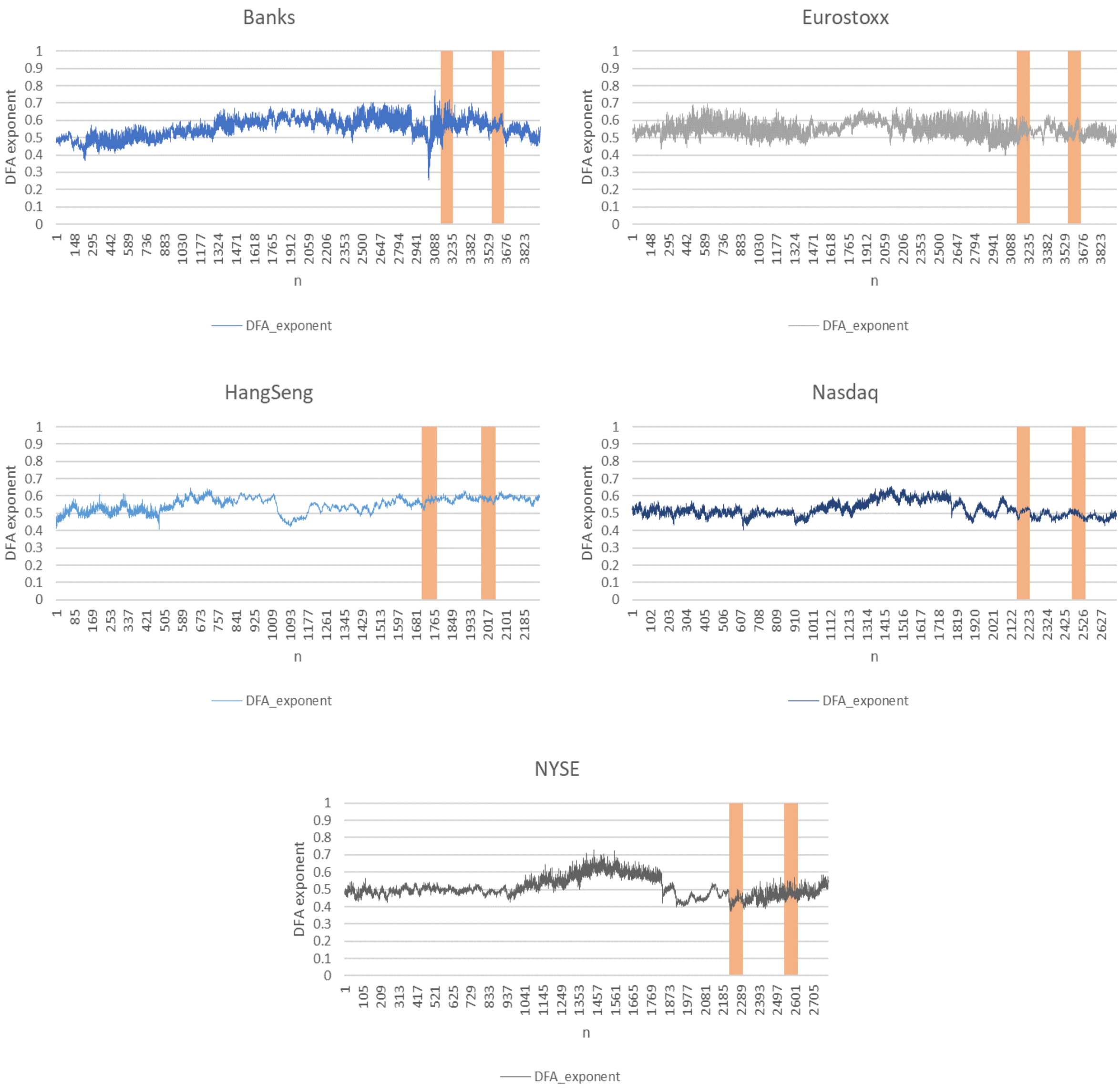
When the cut-off point is the fall of CS, the HangSeng and Nasdaq indices changed their behaviour, but with different changes. The former changed from an anti-persistent behaviour to a persistent one, while the second changed from a persistent behaviour to an anti-persistent one.

Four world financial indices changed their behaviour after the SVB fall, while only two financial indices changed their behaviour after the CS fall. Thus, the results seem to indicate that the fall of SVB had a greater impact on markets behaviour. However, the non-efficient behaviour of the evaluated financial indices does not seem to change due to both banks' fall.

In order to evaluate the dynamic behaviour of the historical independence measure by DFA, we performed a sliding windows analysis using a 500-observation window. Figure 1 presents the results for the five indices under study.

According to Figure 1, some indices show abnormal behaviour (i.e., no-efficient behaviour) at the reference moments of the banks' fall, especially the Banks and the Eurostoxx indices, which may be justified by the composition of each of these indices (the former composed only by banks and the second with the banking sector and technology one with a weight of about 25%). However, at the end of the sample, the Banks, Eurostoxx, and Nasdaq DFA exponents become more centred around 0.5, which could mean they tend to be efficient, in alignment with the prior results of Lim et al. (2008) and Anagnostidis et al. (2016), for whom major stock indices have fluctuating efficiency and may encounter a loss of efficiency during financial crisis. These findings reveal that although the efficiency of world financial indices was affected by both banks' fall, it was not similarly affected by these falls.

Figure 1. Dynamic DFA estimated with a 500-observation window.



Note: *n* represents the number of DFA exponents

Finally, to evaluate the efficiency level for the financial series, we calculate the efficiency index using the estimated values of the dynamic DFA as a reference (Table 8). The results of Table 8 allow us to conclude that the American financial indices were the least inefficient (with the lowest EI levels), while Banks, HangSeng, and Eurostoxx indices are the least efficient indices, as they have the highest EI levels. However, the differences between the EI for the financial indices are quite small, considering the upper limit for this measure in our study, 0.5.

Table 8. Efficiency index (EI)

Index	EI
Nasdaq	0.0484
NYSE	0.0582
Eurostoxx	0.0607
HangSeng	0.0655
Banks	0.0759

5. Concluding remarks

The memory of the bankruptcy of Lehman Brothers on September 15, 2008, still haunts many investors and the idea of the fall of a bank can make many financial markets tremble. In this study we intend to assess the possible change in behaviour in financial indices caused by the fall of the SV and CS banks. For this purpose, intraday data of five stock market indices were analysed.

Before each of those two banks' fall, all the financial indices (except Nasdaq) displayed anti-persistent behaviour, i.e., negative long-range dependence. However, the behaviour of the Nasdaq index was similarly affected by both banks' falls, changing from anti-persistent behaviour (before) to persistent behaviour (after). Reversly, the HangSeng index was the only one which changed its behaviour from anti-persistent (before) to persistent behaviour (after) in both banks' fall. Generally, it is possible to conclude that the fall of CS had a minor impact on the dynamic of the efficiency of the indices studied than SVB, maybe due to the quick intervention of the Swiss central bank (a credit loan of 51 billion euros) and the merger agreement with UBS, which can have contributed to mitigating the increase of the systemic risk. The HangSeng and Nasdaq indices were the only ones whose behaviour changed due to both banks' falls, while NYSE was the only one that do not have changed its behaviour due to both banks' falls. These findings allow us to conclude that the contagion effects from major banks' fall can spread worldwide, impacting global markets.

Considering the dynamic analysis, the fall of both banks contributed to some persistence in the returns of the stock indices analysed, which shows that it could have increased the risk levels in the financial system. However, the last coefficients show some stability around 0.5, except for HangSeng and NYSE, which could mean that the worst for financial markets due to both banks' falls has passed, i.e., the effect of both banks' fall was not sustained (in line with Yousaf et al. (2023)). Thus, investors should hold their stocks rather than sell due to such type of collapse temporarily.

Nasdaq and Banks are the most and the least efficient indices, respectively. The sector of activity on that occurred the falls was the banking sector, which may justify the evidence for the least efficient index. As dependencies could raise the possibility of some predictability, the evidence of dependence for the different indices could have practical implications for how markets work. The higher signal of the inefficiency of the Banks index (aligned with the finding of Yousaf et al. (2023) and Yousaf and Goodell (2023), which found that the banking industry was more seriously impacted by the bank run than other markets) could give information about where to make investments in the context of a bank falling. Despite the apparent evidence of inefficiency, some caution is needed, as this might not necessarily mean a capacity for abnormal profits because this depends on several issues (e.g., liquidity, transaction costs, etc.).

Our findings provide important implications for policymakers and investors. As external shocks have a different impact on financial markets, which may be related, among others, to differences in markets' characteristics and economic fundamentals, policymakers and investors should account for these differences by analysing the effects of this kind of global events on financial markets. On the other hand, a clear understanding of efficiency ranking could be useful for authorities and policymakers to apply adequate regulation on financial markets. The heterogeneous impact of these two banks' fall highlights the importance of diversifying investment portfolios among different sectors and world regions in order to minimise exposure to idiosyncratic risks. Potential systemic risks should also be mitigated through effective risk management, regulatory frameworks, and prudent investment strategies.

Although we performed our analysis for different periodicities of intraday data (one minute, five minutes, and 30 minutes) in order to evaluate the robustness of our conclusions, and although the DFA is able to detect long-range correlations, it does not allow us to understand the underlying mechanisms or causality behind these correlations. This may be a possible limitation of our study. Being conscious of this possible limitation, future research could also be performed using robust approaches to complex systems, nonlinear data and that do not require rigid assumptions about the underlying model (conversely to the event studies approach), but able to allow us to overcome the identified limitation. This analysis could be performed, for example, using some information-theory-based measures, for example, mutual information and transfer entropy.

Despite the changes identified in the time series regimes may also be due to other different factors than these both banks' fall (and we identify this as a possible limitation of our study), our study may be useful for investors, assisting them in making informed investment decisions and providing new insights into risk management in the financial sector.

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