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A crisis like no other? Financial market analogies of the COVID-19-cum-Ukraine war crisis

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ABSTRACT

In this paper, we examine the dynamic behaviour of the US stock market due to the subsequent impact of the COVID-19 outbreak and the war in Ukraine. To that end, we analyse daily data of Dow Jones Industrial Average returns from 2 January 1900 to 31 October 2022. Firstly, we identify past crisis episodes similar to the current situation. Then, we compare the volatility dynamics, variation-fluctuation correlation functions, and correlation with uncertainty indicators with those induced by the COVID-19 epidemic and the subsequent Russo-Ukrainian conflict. Our findings suggest that the consecutive occurrence of these unexpected events has had more severe adverse effects on the US stock market than those recorded in similar past episodes. Additionally, we found that the events are highly correlated with indicators of economic policy uncertainty and financial market fear.

> *"Todo temporal nos regala una enseñanza"*
> *Ismael Serrano*

1. Introduction

The COVID-19 pandemic significantly impacted stock market returns and volatility worldwide (see, e.g., Baker et al., 2020; and Zhang et al., 2020), and the war in Ukraine further exacerbated tensions in international financial markets (see, e. g., Singh et al., 2022; Yousaf et al., 2022; Izzeldin et al., 2023; Kumar et al., 2023; and Patel et al., 2023).

Previous research has examined the impact of infectious disease outbreaks on financial market performance and the effect of war and geopolitical risks. Several studies have been conducted on these topics, such as Ichev and Marinč (2018), Olds (2020), Mei and Guo (2004), Rigobon and Sack (2005), and Salisu et al. (2022). However, the combination of these two 'black swan' events in the early 2020s has resulted in unprecedented reactions in the stock market, according to the International Monetary Fund (2022).

The financial markets in the 2020s have been characterised by strong fluctuations, which are more intense than those experienced during the 2008 global financial crisis, according to a study by Shehzad et al. (2020). This behaviour is largely due to the increased level of uncertainty, which has led to greater fear among stock investors, as documented by López et al. (2023). Recent research has

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emphasised the crucial role of unexpected variations or uncertainties in the evolution of the stock market (see, e.g., Chuliá et al., 2017).

Based on the given background, the purpose of this paper is to explore the financial patterns of unexpected events by examining past occurrences where the returns of the Dow Jones Industrial Average (DJIA) index were similar to the recent sub-sample during the COVID-19 outbreak and the Russian invasion of Ukraine. The aim is to provide valuable insight into the financial patterns of such a combination of events by examining historical analogies.

A historical analogy is an inference based on the idea that if two or more events at different times are in one respect, they may also be similar in another. The fundamental idea is to select past episodes of the time series related to the one we want to analyse. The capacity of the method used to determine the analogies and the number and diversity of the episodes from which to establish the analogies impact how strong historical analogies are. Therefore, we rely on a powerful, non-parametric, distribution-free test for comparing distributions and identifying appropriate analogies and apply it to a sample covering an extended period that encompasses a large number and variety of past episodes of market turmoil to look for analogies relevant to the most recent sub-sample covering the COVID-19 outbreak and the Russian invasion of Ukraine, helping us illuminate what happened during this last episode.

Our research makes significant contributions to the existing literature in a number of ways. Firstly, an improved statistical test is applied to establish historical analogies by detecting past sub-periods in the sample resembling the episode under study. Secondly, we analyse significant volatility dynamics and variation-fluctuation correlation functions in the detected episodes and compare them with the ongoing COVID-19-cum-Ukraine war crisis. Finally, we examine the impact of several uncertainty indicators on the stock market dynamics during these episodes.

The remainder of this paper is as follows. Section 2 describes the data and methodology. Section 3 reports the results of our analysis, and Section 4 concludes.

2. Data and methodology

2.1. Data

We have collected the daily data of DJIA returns covering January 2, 1900, to October 31, 2022. After eliminating weekends and holidays, we obtained 32,123 data points (see Fig. 1, left side). Given that January 2, 2020, was the first market day after the WHO's first COVID-19 Disease Outbreak News Report (WHO, 2020), we take this date as the beginning of the pandemic on the stock market and consider the period January 2, 2020-October 31, 2022 as representative of the COVID-19-cum-Ukraine war crisis.

2.2. Anderson Darling test

The two-sample Anderson-Darling test (hereafter, *TSAD*) was introduced by Darling (1957) and studied in detail by Pettitt (1976). The *TSAD* test based on the empirical distribution function (EDF) avoids the arbitrary binning of histograms and the small number of entries per bin in the χ^2 test (Bohm and Zech, 2017). The *TSAD* test is a refinement of the Kolmorogov-Smirnov test (Massey, 1951), and it is especially sensitive at the tails of the distribution than near the centre or the median, and there is evidence that is better capable of detecting very small differences, even between large sample sizes (Engmann and Cousineau, 2011).

Let $X_1, X_2, \ldots, X_n$ and $Y_1, Y_2, \ldots, Y_n$ be independent random samples of returns having unknown continuous distribution functions $F(x)$ and $G(x)$, respectively. We consider the sample distribution functions defined as $F_n(x)$ of the X-sample, $G_n(x)$ of the Y-sample and the $H_n(x) = \frac{nF_n(x)+mG_n(x)}{N}$ with $N = m + n$, the sample distribution function of the pooled sample. So, $nF_n(x)$ $(mG_n(x))$ is defined as the number of the random sample $X_1, X_2, \ldots, X_n(Y_1, Y_2, \ldots, Y_n)$ which is not greater than x. Let us consider the statistic

$$A^2_{n,m} = \frac{nm}{N}\int_{-\infty}^{\infty} \frac{\{F_n(x) - G_m(x)\}^2}{H_n(x)\{1 - H_n(x)\}} dH_n(x) \tag{1}$$

The null hypothesis that X and Y come from the same continuous distribution is rejected if $A^2_{n,m}$ is larger than the correspondent critical value.[1]

2.3. Remnant volatility

Let $P(t')$ be the daily closing price of a stock market index at time t', we then define the logarithmic price return over a time interval Δt as

$$R(t', \Delta t) = \ln P(t' + \Delta t) - \ln(t') \tag{2}$$

where we set $\Delta t = 1$ day. For simplicity, the volatility is then defined as the absolute value of returns, $|R(t', \Delta t)|$, which measures the magnitude of the price fluctuation. For comparison of different financial episodes, we introduce the normalised return

$$r(t') = [R(t', \Delta t) - \langle R(t', \Delta t)\rangle]/\sigma \tag{3}$$

[1] Under the null hypothesis $H_o, A^2_{n,m}$ converges to the same limiting distribution as the *AD* test statistic for one sample A^2_n (Pettitt, 1976).

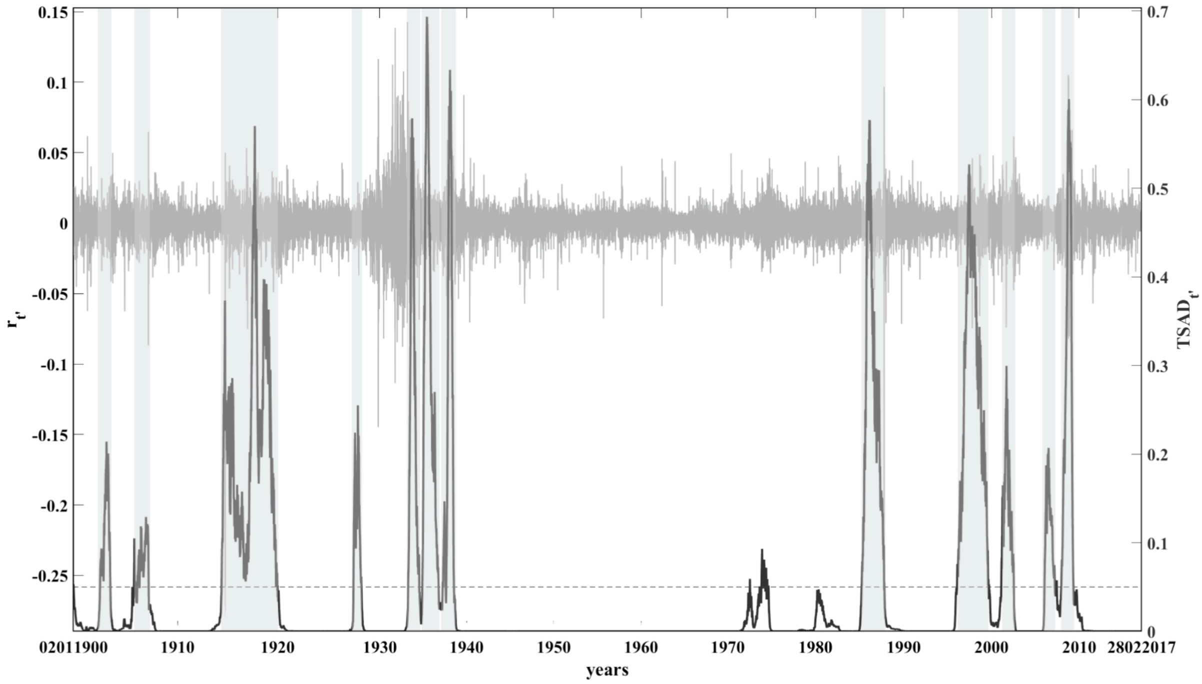

Fig. 1. Historical evolution of p −values of the *TSAD* test comparing the DJIA returns in the current crisis with past episodes. The dashed line red corresponds to the significance level of 5%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where $\sigma = \sqrt{\langle R^2 \rangle - R^2}$ is the standard deviation of $R(t', \Delta t)$, and $\langle ... \rangle$ represents the average over time t'. To explore the dynamic relaxation after large volatilities, we introduce the remnant volatility,

$$v_{+}(t') = \left[\langle |r(t' + t)| \rangle_c - \overline{v} \right] / Z \tag{4}$$

where $Z = \langle |r(t')| \rangle_c - \overline{v}$, $\overline{v}$ is the average volatility, and $\langle ... \rangle_c$ represents the average over those times t' which fulfill the large volatilities condition. The remnant volatility $v_{+}(t')$ describes how the dynamic system relaxes from extreme volatility to the stationary state. In our analysis, we determine the large volatilities with the condition $|r(t')| > \xi$, where the given threshold ξ is well larger than $\overline{v}$, e.g., $\xi = 4\overline{v}$. For reducing the fluctuations, we consider the cumulative function:

$$V_{+}(t') = \sum_{t'=0}^{t} v_{+}(t') \tag{5}$$

$V_{+}(t')$ may approximately exhibit a power-law-like behaviour up to a given time period, since extreme shocks in volatilities are typically followed by a succession of aftershocks (see, e.g., Lillo and Mantegna, 2003; Jiang et al., 2013). Thus, the cumulative function $V_{+}(t')$ could be written as $V_{+}(t') \sim t^p$, with p being the exponent, and this is one of the defining features of stock market dynamics.

2.4. Variation-fluctuation correlation function

The return-volatility correlation function is defined by

$$L(t) = \left[\left\langle r(t') |r(t' + t)|^2 \right\rangle - \left\langle |r(t')|^2 \right\rangle \right] / L_0 \tag{6}$$

where $\langle ... \rangle$ represents once again the average over time t' and $L_0 = \left\langle |r(t')|^2 \right\rangle^2$. For $t > 0$,$L(t)$ describes the correlation between the past variation $r(t')$ and the future fluctuation $|r(t' + t)|$. The phenomenon of a negative $L(t)$ is called the leverage effect (Black, 1976), when past negative returns increase future volatility (see, e.g., Bouchaud et al., 2001; or Qiu et al., 2007, for evidence in recent times). Since large volatilities dominate the variance-fluctuation correlation in stock market dynamics, as demonstrated by Shen and Zheng (2009), this would suggest that the leverage effect would be stronger when there are significant market fluctuations.

2.5. Correlation between uncertainty indicators and stock market dynamics

To empirically investigate the relationship between stock market dynamics and uncertainty, we define the uncertainty-fluctuation correlation function as follows:

$$C(t) = \langle \Delta u(t') \cdot |r(t'+t)| \rangle - \langle \Delta u(t') \rangle \cdot \langle |r(t'+t)| \rangle \tag{7}$$

where if the daily uncertainty index at time t' is denoted with as $U(t')$, then its difference over a time interval Δt is given by:

$$\Delta u(t', \Delta t) = U(t' + \Delta t) - U(t')$$

For the comparison of different financial episodes, we introduce the normalised difference:

$$\Delta u(t') = [\Delta u(t', \Delta t) - \langle \Delta u(t', \Delta t) \rangle]/\sigma \tag{8}$$

where $\langle \ldots \rangle$ represents the average over time t', and $\sigma = \sqrt{\langle \Delta u^2 \rangle - \langle \Delta u \rangle^2}$ is the standard deviation of $\Delta u(t', \Delta t)$.

3. Empirical results

3.1. Anderson Darling test

Fig. 1 (right side) shows the past episodes longer than approximately 200 days where the TSAD test does not reject the null hypothesis (at a 95 % confidence level) of equal distribution of stock returns to the last 714 days (from January 2, 2020, to October 31, 2022) crisis compared with all historical sample distributions of returns computed using a moving window of 714-days on January 2, 1900 to February 28, 2017 period. Therefore, we consider these episodes as analogous to the COVID-19-cum-Ukraine war crisis.

Table 1 reports the identifying analogous episodes. The final dates of these episodes are also indicated, including the 714 days in the window. As can be observed, we find parallels to significant financial crises, some of which had severe repercussions on the real economy, such as the Panics of 1901 and 1907, the World War I Recession and the 1918 Flu Pandemic, the Wall Street Crash of 1929, the Great Depression, the Black Monday, the Dotcom Bubble Collapse, the Asian Financial Crisis, the Global Financial Crisis and the Great Recession. As can be seen, the episode with the highest number of analogous periods of 714 days corresponds to the World War I Recession and the 1918 Flu Pandemic (1598 successive days).

It should be noted that the method used to establish the analogies does not aim to characterise all the different historical crises, only to detect the most similar ones to the COVID-19 outbreak and the Russian invasion of Ukraine. An in-depth investigation of the characteristics and origins of the different crises identified as analogous is beyond the scope of this article. We leave this line of research for future studies.

Once similar past crisis episodes are identified, we compare their volatility dynamics, variation-fluctuation correlation functions and correlation with uncertainty indicators with those induced by the COVID-19 epidemic and the later overlap of the Russo-Ukrainian conflict. For each of the days in these episodes, we have calculated those measures for a window of 714 days, considering the average values in Figs. 2–6.

3.2. Remnant volatility

The cumulative function $V_+(t)$ of the remnant volatility describes the time correlation of the large fluctuations, and we computed it as a function of lag t for the COVID-19-cum-Ukraine war and past crisis episodes. We choose the highest threshold to reduce fluctuations $\xi = 4\overline{v}$ and to $t = 1,2,\ldots 20$ to gain some samples for average. Fig. 2 reveals that the cumulative function $V_+(t)$ of the remnant volatility in the current COVID-19-cum-Ukraine war episode increases much more drastically than that from the detected past analogous episodes, and the exponent p is much larger. It is interesting to note that Fig. 2 indicates that only during the episode corresponding to the Global Financial Crisis of 2007–2008, $V_+(t)$ registers a similar behaviour (although less intense) (being in line with the findings in Shehzad and Kazouz, 2020; and Choi, 2021), followed at some distance by the episodes covering the Wall Street Crash of 1929 and the Great Recession. Therefore, our results indicate that the aftershocks of the large fluctuations caused by COVID-19-cum-Ukraine war crisis are far more severe than those registered in previous analogous episodes of financial turmoil, including some of the world's most severe financial crises. By recognising the gravity of the situation, the economic authorities had the opportunity to take proactive measures to mitigate its impact and pave the way for a stronger and more resilient future.

3.3. Variation-fluctuation correlation function

In Fig. 3, the return-volatility correlation function $L(t)$ is displayed for the daily Dow Jones Industrial Average Index. $L(t)$ describes the correlation between the past variation $r(t')$ and the future fluctuation $|r(t'+t)|$. We computed $L(t)$ as a function of lag t for COVID-19-cum-Ukraine war crisis and past analogous episodes of financial turbulence. In negative time direction, $L(t)$ fluctuates around zero for all episodes analysed and we find some significant positive correlations up $t =$ -4 days in episode 3 (the World War I Recession and the 1918 Flu Pandemic), which might reflect the fact that large daily drops are often followed by positive "rebound" days as investors grow more sensitive to good news. In general, it implies $r(t')$ is weakly correlated to volatilities in the past times. Regarding positive

Table 1
Episodes where the *TSAD* test cannot reject the null hypothesis.

Episode	Start date of the episode	End date of the episode	End date of the total episode including the 714-day window
1.	29 July 1902	23 July 1903 (294)	6 December 1905 (1008)
2.	12 May 1906	23 March 1907 (261)	7 August 1909 (975)
3.	31 March 1914	17 December 1919 (1598)	8 May 1922 (2312)
4.	9 April 1927	10 January 1928 (227)	29 September 1930 (941)
5.	18 April 1933	25 July 1934 (319)	1 January 1937 (1033)
6.	5 December 1934	7 October 1936 (465)	16 August 1939 (1179)
7.	27 August 1937	15 July 1938 (222)	22 May 1941 (936)
8.	29 March 1985	21 October 1987 (648)	16 August 1990 (1362)
9.	1 February 1996	24 August 1999 (899)	27 June 2002 (1613)
10.	14 February 2001	26 July 2002 (361)	25 May 2005 (1075)
11.	30 January 2006	4 April 2007 (297)	2 February 2010 (1011)
12.	2 January 2008	14 May 2009 (345)	13 March 2012 (1059)

Note: In parenthesis, we show the number of days.

time direction in Fig. 3, $L(t)$ shows negative values, substantially different from zero, up to at least 15 days for COVID-19-cum-Ukraine war crisis and 11 days for the analogous episode 4 (the financial crisis of 1929), reflecting the well-known leverage effect. This phenomenon is less important in other past episodes. Recall that the leverage effect indicates that a negative $r(t')$ induces higher volatility, while a positive $r(t')$ may lead to stable stock prices, as investors become receptive to bad and good news, respectively (Segal et al., 2015). Therefore, our results suggest that large volatilities dominated the variation-fluctuation correlation in the stock market dynamics during the COVID-19-cum-Ukraine war crisis. These large volatility fluctuations were more pronounced than those experienced during the episode covering the Wall Street Crash of 1929. This finding aligns with the results of Bekaert and Wu (2000) and Wu (2001), who conclude that asymmetric volatility is most noticeable during stock market crashes.

3.4. *Correlation between uncertainty indicators and stock market dynamics*

To gain further insights, we empirically investigate the relationship between stock market dynamics and uncertainty indices from January 3, 1900, to October 31, 2022. To that end, we use three main daily uncertainty indicators: the Economic Policy Uncertainty Index for the United States (EPU),[2] the Equity Market-related Economic Uncertainty Index (EMU),[3] and a “fear gauge” of financial market sentiment (FEAR).[4] As can be seen in Figs. 4–6,[5] for $t < 0$, $C(t)$ fluctuates around zero for all episodes analysed, including the COVID-19-cum-Ukraine war crisis and for for $t > 0$, $C(t)$ presents higher positive values with EPU and FEAR and a lower correlation with EMU. The former finding suggests that EPU and FEAR have some valuable information content up to seven and fifteen days after the shock, respectively, while the latter is in line with Aven (2013) and Orlik and Veldkamp (2014), who document that surprising extreme event cannot be captured with present knowledge about the market dynamics.

4. Concluding remarks

This paper adds to the existing body of research on the adverse financial consequences of rare and unpredictable events, known as black swan events. It achieves this by identifying similar events in the historical performance of the Dow Jones Industrial Average (DJIA) index to the current impact of the COVID-19 pandemic and the Russian invasion of Ukraine and by comparing their large-volatility dynamics to put into perspective the severity of the current situation.

According to our findings, in a world that is more prone to shocks, the consecutive occurrence of unexpected and unknowable events has had negative effects on the dynamics of the US stock market. These effects have been found to be more severe than those recorded in similar past episodes and are highly correlated with indicators of economic policy uncertainty and fear in the financial market.

[2] EPU is based on daily news from newspapers in the United States. We have completed the original index backwards using the same methodology as Baker et al. (2015) with partial information obtained from Wikipedia and Google Search.

[3] EMU is constructed by analysing newspaper articles containing terms related to equity market uncertainty. We have completed the original index backwards using the same methodology as Baker et al. (2015) with partial information obtained from Wikipedia and Google Search.

[4] FEAR is based on VIX, the Chicago Board Options Exchange volatility index measuring market expectation of near-term volatility conveyed by stock index option prices. Market participants and media consider it the “fear gauge” of financial market (Whaley, 2000). We have completed the original index backwards using Parkinson’s (1980) estimation of the daily variance. Therefore, on day t, we have for $t<0$, $\widetilde{\sigma}_t^2 = 0.36\left[\ln(P_t^{MAX}) - \ln(P_t^{MIN})\right]^2$, where P_t^{MAX} is the maximum (high) price in the market on day t, and P_t^{MIN} is the daily minimum (low) price. Given that $\widetilde{\sigma}_t^2$ is an estimator of the daily variance, the corresponding estimate of the annualised daily per cent standard deviation (volatility) is $\widehat{\sigma}_t^2 = 100\sqrt{365\widetilde{\sigma}^2}$..

[5] To save space, Figs. 4 to 6 show the results for the COVID-19-cum-Ukraine war crisis and the average of the 12 detected past analogous episodes in Table 1. Detailed figures displaying $C(t)$ for each uncertainty indicator during each of those 12 episodes are available from the authors upon request.

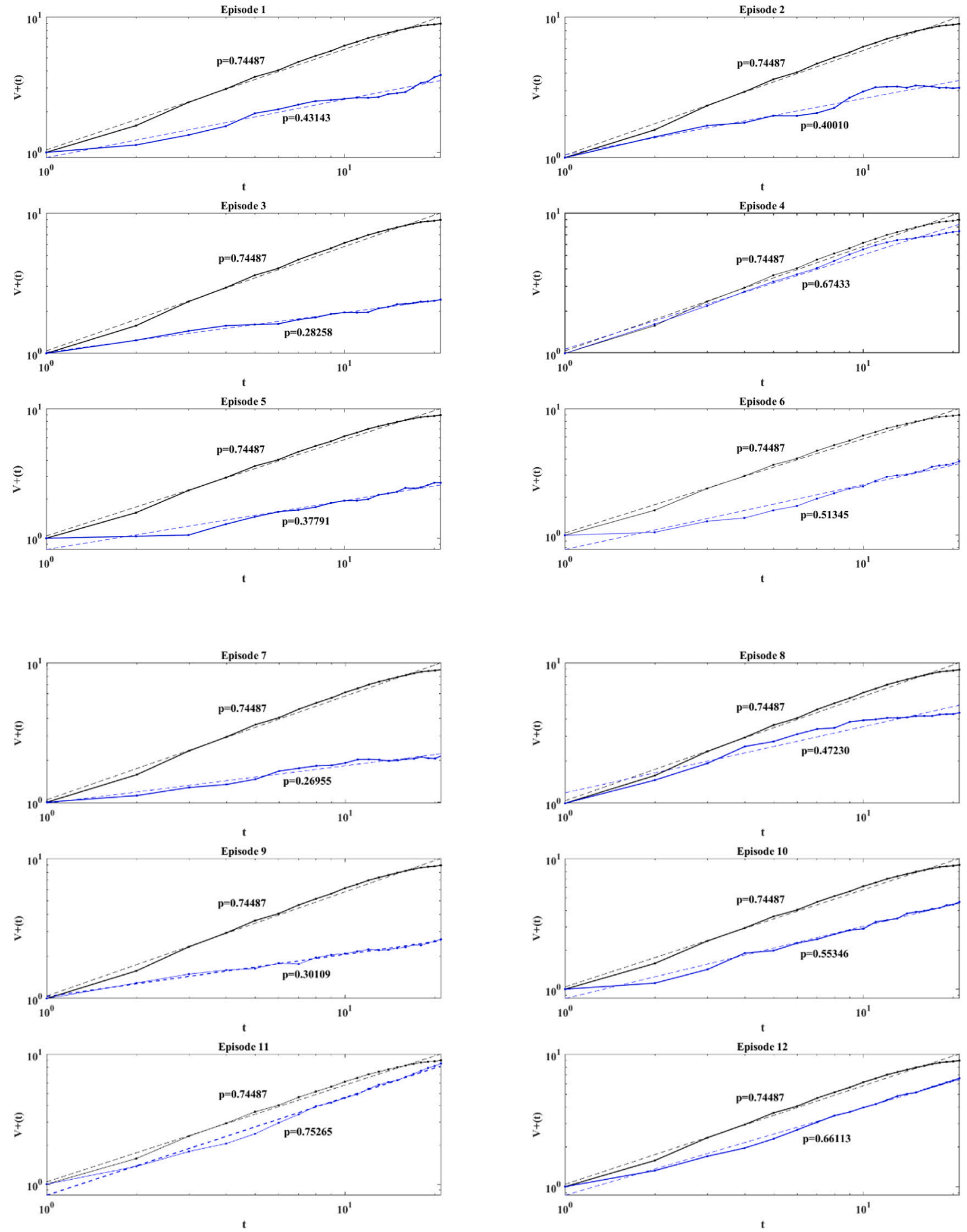

Fig. 2. The cumulative function $V_+(t)$ of the remnant volatility. The black dots represent the COVID-19-cum-Ukraine war crisis and in blue dots correspond to the detected past analogous episodes in Table 1. The exponent p is the slope of the cumulative function $V_+(t)$ in double-log coordinates. The extreme volatilities are selected by the condition $|R(t')| > \xi$ with $\xi = 4\bar{v}$ and $\bar{v}$ is the average volatility. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Since the primary basis of our research is US market data, it would be interesting for future studies to examine this unique succession of unforeseen shocks in other stock markets so that we can have a deep understanding of how they have impacted stock markets globally. Another natural extension of the analysis presented in this article would be using an event study to examine abnormalities

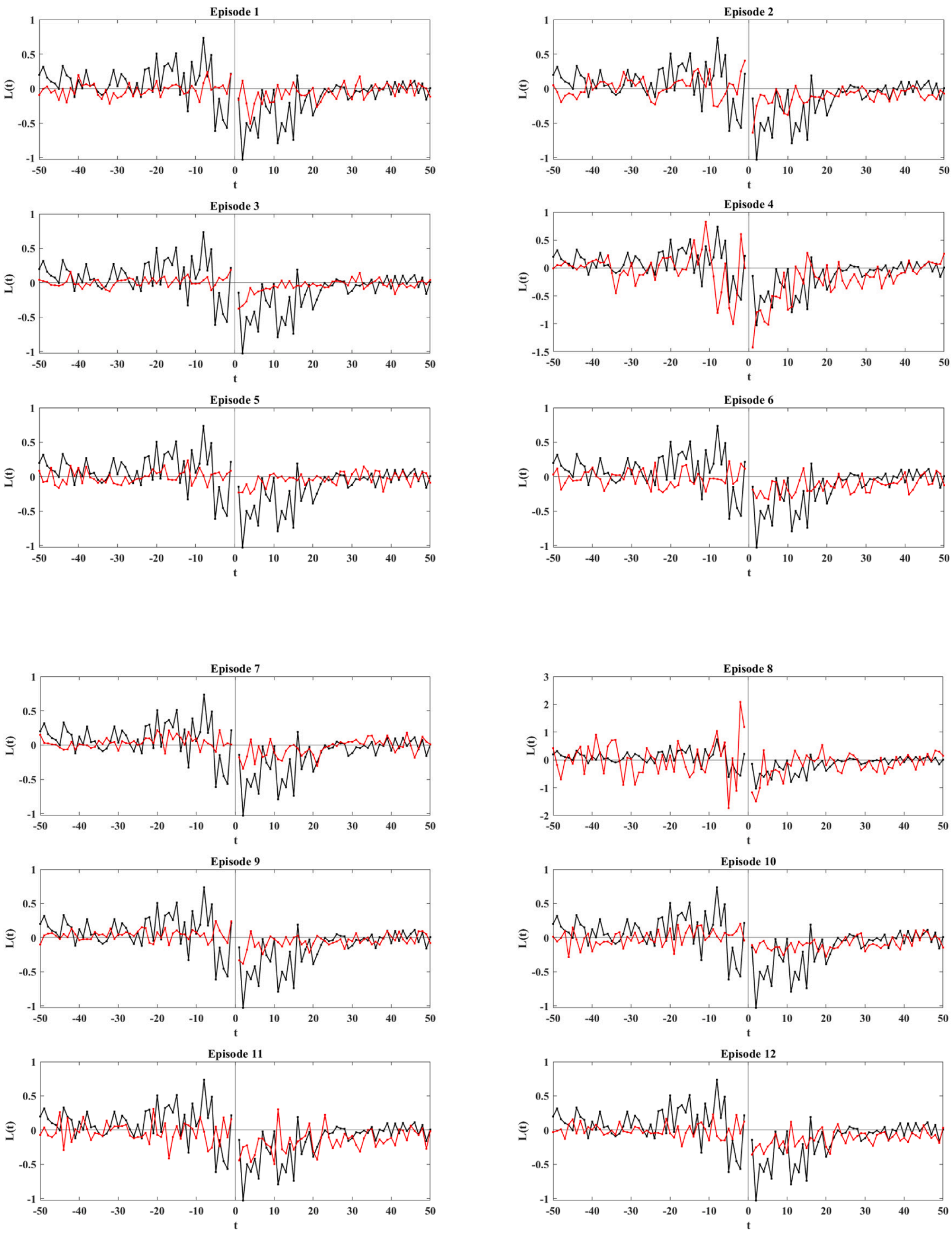

Fig. 3. The variation-fluctuation correlation function *L(t)* as a function of lag *t* for DJIA during different episodes. The black line represents the COVID-19-cum-Ukraine war crisis and in red line corresponds to the detected past analogous episodes in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

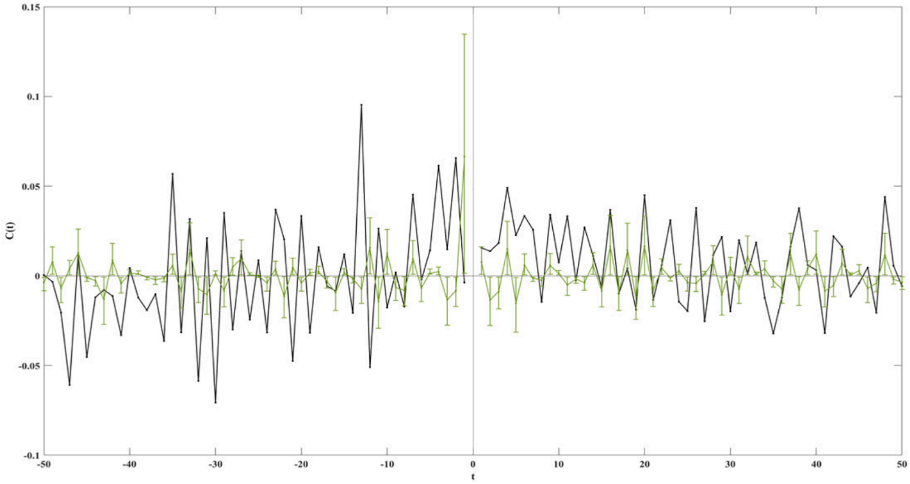

Fig. 4. The EPU-fluctuation correlation function *C(t)* as a function of lag *t* for DJIA during different episodes. The black line represents the COVID-19-cum-Ukraine war crisis and in green line corresponds to the average (95% bootstrap confidence interval(Given that our data are non-normally distributed, we make us of bootstrap methods for producing good approximate 95% confidence intervals (see, e g., Bradley and Tibshirani, 1993; or DiCiccio and Efron, 1996).)) of the 12 detected past analogous episodes in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

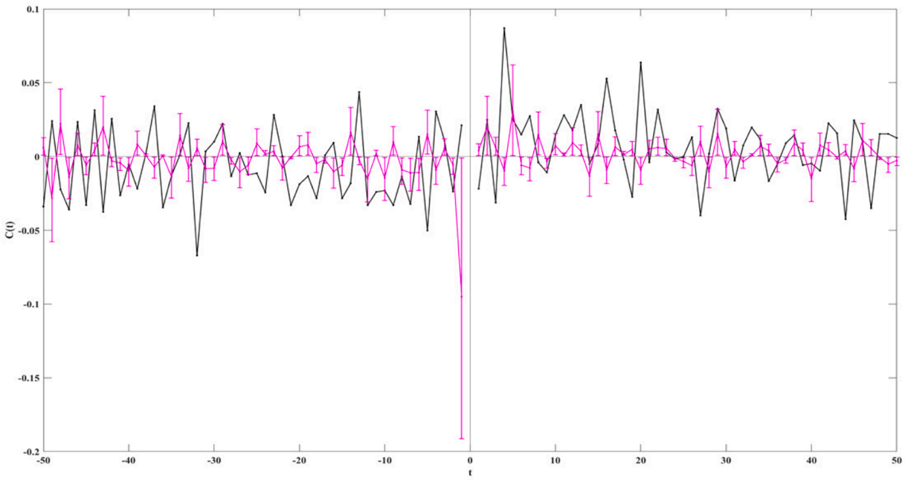

Fig. 5. The EMU-fluctuation correlation function *C(t)* as a function of lag *t* for DJIA during different episodes. The black line represents the COVID-19-cum-Ukraine war crisis and in pink line corresponds to the average (95% bootstrap confidence interval) of the 12 detected past analogous episodes in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(volume, prices, and volatility) to explore further the nature of the detected analogies.[6] These extensions are items in our future research agenda.

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CRediT authorship contribution statement

Julián Andrada-Félix: Data curation, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review

[6] We are grateful to an anonymous referee for suggesting this extension.

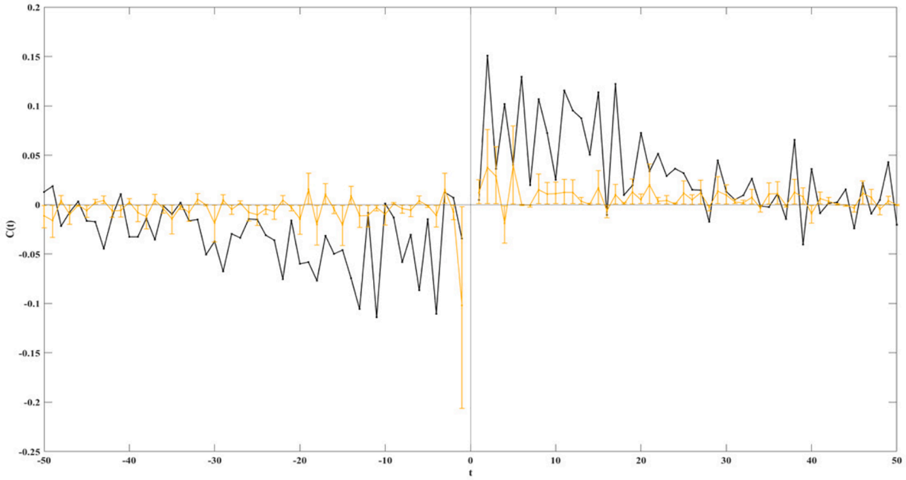

Fig. 6. The FEAR-fluctuation correlation function *C(t)* as a function of lag *t* for DJIA during different episodes. The black line represents the COVID-19-cum-Ukraine war crisis and in orange line corresponds to the average (95% bootstrap confidence interval) of the 12 detected past analogous episodes in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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