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Impact of early COVID-19 pandemic on the US and European stock markets and volatility forecasting

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ABSTRACT

This study examines the impact of early COVID-19 pandemic on U.S. and European stock indices, implied volatility (IV) indices, and forecasting accuracy of IV indices from daily data of January 2012 to December 2020, using an out-of-sample assessment of COVID-19. Our results show that COVID-19 death and recovery cases have had a significant positive impact on S&P 500, DJIA and NASDAQ 100. On the other hand, VIX, VXD and VXN show a negative association. Again, we also observe the significant impact of COVID-19 on stock trading prices and volatility expectations. Furthermore, the evidence of the point forecasts is more reliable for European IV indices than for U.S. IV indices. Finally, this study validates the informational efficiency of IV indices on the financial markets and has implications for investors regarding portfolio management and investment risk minimisation in similar future pandemic situations.

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1. Introduction

The COVID-19, a new form of coronavirus SARS-CoV-2, caused severe problems worldwide from its first trace out in Wuhan, China, in early 2020. Because of this virus's infectious nature and rapid worldwide spread, the World Health Organization (WHO) announced this disease as a 'global pandemic' in March 2020. The US (United States) reported 1.16 million confirmed cases, 0.11 million death cases and

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0.38 million recovery cases in May 2020. Europe recorded 1.40 million confirmed cases, 0.16 million death cases and 0.13 million recovery cases (Johns Hopkins Coronavirus Resource Center, 2020). This pandemic also affected the stock markets worldwide. Stock trade volume continued to decline initially in the U.S. stock market because of the high daily case reports. Nevertheless, the volatility indices of the Chicago Board Options Exchange (CBOE) global market soared above the previous all-time high in this situation (Wagner, 2020). As a result, investors appeared panicked about overall financial market uncertainty.

Implied volatility (IV), which expresses the market's assessment of the probability of price fluctuations, is considered an important measure in the U.S. and European stock markets and can be used by investors to predict future trends (Zhang et al., 2020a). It is also used to price options contracts. Recently, much debate has been stirred both in academic research and industry regarding whether or not volatility forecasting has helped investors understand the changes in expected returns during the pandemic. Accurate information about stock price fluctuation is essential for better investment decisions, especially during a pandemic. Although a negative stock return increases the leverage that, in turn, increases equity value volatility, investors have become more concerned about the informational efficiency of the stock market's reaction during the pandemic.

A growing body of literature recognises the COVID-19 situation and the stock market volatility. One strand of this literature has shown the impact of the COVID-19 pandemic on the different stock markets (Ashraf, 2020; Liu et al., 2020; Okorie & Lin, 2021; Zaremba et al., 2020; Zhang et al., 2020b). Most of these studies attempt to understand the COVID-19 effects on stock price fluctuations in the stock market globally. Nevertheless, as investors' perceptions have changed regarding the stock trade during the pandemic, more recent studies have investigated the stock market reaction in China (Al-Awadhi et al., 2020; Huo & Qiu, 2020). Furthermore, Aslam et al. (2020) measured the effect of COVID-19 on European stock market indices. On the other hand, the impact of the daily news on -confirmed infection and death cases in the US showed the stock markets' informational efficiency in the COVID-19 situation (Albulescu, 2021; Mazur et al., 2021; Wagner, 2020). Although several studies show evidence of the significant impact of COVID-19 on the stock market, the experimental results are somewhat inconclusive. Furthermore, most studies in the field of stock market reaction during COVID-19 have focussed only on either stock index forecasting or changes in trading volume and investor expectations during this period. To date, however, there is limited empirical evidence showing the impact of COVID-19 on IV indices and the informational efficiency of volatility forecasting.

In addition, a small number of researchers have documented the experimental evidence on the consistency and informational efficiency of IV indices. For instance, Degiannakis et al. (2018), Konstantinidi et al. (2008) and Wang and Wang (2015), have examined the predictability of IV indices before the COVID-19 period. However, most of this research provides mixed findings. Therefore, this study aims to measure the early COVID-19 effects in the U.S. and European stock markets and examine the informational efficiency of IV indices during pandemics. To attain this objective, the following research questions have been investigated: (1) What effect do the daily confirmed, death, and recovery cases have on the U.S. and European IV indices and stock indices? (2) How do the modelling and out-of-sample forecasting of the U.S. and European IV indices help investors understand the changes in expected returns over time in the COVID-19 period? and (3) How do the out-of-sample forecasting of IV indices confirm informational efficiency? As the IV remarks as a re-parameterization of the stock price, these questions fall within a few works of literature on stock price predictability for the COVID-19 period.

Our study makes a novel contribution to the literature on the uncertainty that existed in the U.S. and European stock markets in the early COVID-19 period. First, we employ a comprehensive data set of the U.S. and European IV indices and stock indexes. The design of the data set will show whether or not the findings vary by country and industry segments during the COVID-19 pandemic. Second, we use a sophisticated econometric model, canonical correlation analysis (CCA), to examine the effect of daily confirmed, death and recovery cases on both the stock indices and IV indices of the U.S. and European stock markets. The previously mentioned papers have only considered confirmed and death cases, but we use confirmed, death and recovery cases as group variables in this research. We find that confirmed, death and recovery cases have a positive impact on IV indices on both U.S. and European stock markets but have a negative impact on the stock index. Third, we estimate the out-of-sample point forecasting accuracy using a list of models, including PCA, ARIMA, ARIMA-GARCH, ARIMAX and ARIMAX-GARCH. The results confirmed that modelling and out-of-sample forecasting of IV indices and stock indices ensure informational efficiency for investors regarding their volatility expectations in the pandemic situation. However, the results of out-of-sample forecasting models indicate that the point forecasting predictability of European IV indices is more reliable than the U.S. IV indices in the COVID-19 period. Finally, point forecasts are evaluated by the Diebold–Mariano (DM) and the Harvey, Leybourne, and Newbold (HLN) tests to confirm this study's statistical significance.

This study's findings will help academics, policymakers and investors to evaluate the trends of directional changes of U.S. and European stock returns and IV indices resulting from the COVID-19 crisis. The study also provides interesting insights on the U.S. and European stock markets' informational efficiency, which helps investors make informed decisions on their portfolio risk management during a similar pandemic crisis. The subsequent presentation of the study is as follows: Section 2 addresses the relevant literature; Section 3 depicts the datasets and the methods used; Section 4 describes the empirical findings and analysis and Section 5 concludes the paper. Because of space limitations, incorporating all information in the paper itself is difficult, so an Online Appendix provides more supporting information for the interested reader, structured as follows: Section A1 refers to appendix methodology and Section A2 contains results and robustness analysis.

2. Literature review

We present a review of the literature in two parts. The first covers the contemporary issues addressing the COVID-19 impact on stock markets, and the second describes current research regarding stock market volatility and forecasting.

2.1. COVID-19 impact on stock markets

Literature on the effects of the COVID-19 pandemic on commercial sectors is nascent. Countries across the globe are still grappling with this crisis, and its ultimate effect and continuation are still unknown. The stock market reactions at the early stage of this pandemic indicate that specific measures, including fiscal-policy initiatives, are essential to prevent more negative COVID-19 shock (Wagner, 2020). Zaremba et al. (2020) investigated the influence of national policies to combat the COVID-19 pandemic on the stock market volatility of 67 countries. They suggest that government policy actions significantly increase the volatility in markets. However, the scope of these findings is limited by small sample size.

Additionally, COVID-19 is an alarming crisis that has stirred furious reactions for investors. The exponential spread of the coronavirus has had a significant effect on the world's capital markets. Moreover, the growth of the disease has raised risk to unprecedented levels, leading to substantial losses for investors in a short time (Zhang et al., 2020b). Ashraf (2020) examined the relationship between the COVID-19 pandemic and the stock market response of 64 countries. The results suggest that adverse market reaction was strong in the initial stage of COVID-19 and that the stock market responded sharply to the COVID-19 pandemic. Using the event study method, Liu et al. (2020) evaluated the short-term effect of COVID-19 on the leading stock markets of 21 countries globally. They suggested that Asian countries experienced higher abnormal returns than other countries because of fear of uncertainty and an increasing number of daily confirmed COVID-19 cases. Finally, Ali et al. (2020) investigated the volatility reactions of the global financial market to the COVID-19 pandemic. This study first focuses on the Chinese stock market response and then moves to Europe and finally to the U.S. China, the initial epicentre, has recovered its financial market conditions. However, in a later phase of the pandemic, global markets plunged, especially the U.S. and European markets.

Al-Awadhi et al. (2020) examined COVID-19 effects on Chinese stock markets using panel data analysis. The results indicate that the daily confirmed cases and death cases had a significant negative impact on stock returns. He et al. (2020) investigated the Chinese stock market reaction and response trends in Chinese industries during the COVID-19 pandemic employing the event study method. The results reveal that Chinese industries and stock prices are adversely affected by the pandemic. Finally, Huo and Qiu (2020) examined the stock market performance to the COVID-19 pandemic lockdown in China. The study looked at the industry and firm-level stock performance with the investors' overreactions.

Aslam et al. (2020) assessed the impact of the COVID-19 outbreak on eight European stock markets using five minutes of index data. Among these markets, the Spanish stock market performed efficiently during the pandemic. The result also shows that investors must design a suitable portfolio and risk management strategies to obtain profitable returns. However, this study fails to consider the details of profitable strategies, and guidelines for developing such strategies are not recommended. Albulescu (2021) found that the fertility ratio and infection rate of the coronavirus pandemic is an essential indication of the U.S. stock market's financial volatility, challenging risk management activities. Finally, Mazur et al. (2021) investigated the industry-level data of U.S. stock market on the COVID-19 pandemic. The results indicate that 70% of companies under the S&P 500 have lost their market capitalisation during this pandemic.

2.2. Stock market volatility and forecasting

Another strand of literature focussed on modelling and simulating the volatility of stock returns of various underlying financial capital to IV. Konstantinidi et al. (2008) analysed the out-of-sample forecasting of European and the U.S. IV indices to test the statistical significance of such forecasting. The authors found statistical significance in detecting a predictable pattern using the point and the interval methods. However, this study failed to acknowledge that the result has mixed economic significance. Kanas (2013) suggested 'that a strong and positive risk-return relation for the S&P 500 is uncovered when the IV is allowed in the conditional variance equation' (p. 159). Han and Park (2013) compared in-sample and out-of-sample forecasts of daily S&P 500 index return volatility using the GARCH-X model and HEAVY-r model. The results indicated that realised volatility measure is better fitted in within-sample forecasting (out-of-sample forecasting) than IV because of more information disclosure.

Additionally, Liang et al. (2020) developed two forms of information flow in multiple international markets based on realised volatility (RV) and IV. The DM test has indicated that information run with IV increases the forecasting precision of global RVs across all predictive prospects. Iqbal et al. (2021) measured the volatility of the cryptocurrency market during the COVID-19 pandemic. They found that changing COVID-19 rate intensity levels have had an asymmetric effect on the cryptocurrency market. Albulescu (2021) investigates the impact of COVID-19 daily new cases and fatality ratio on U.S. stock markets volatility. The result shows that the sanitary problem increases the S&P 500 realised volatility.

Previously published studies have been limited to either predicting the stock market or shifts in market volume and investor expectations over the COVID-19 period. As a result, most of these previous studies have provided a mixed and inconclusive opinion about the stock market reaction during the pandemic situation. However, very little is currently known about the impact of COVID-19 on IV indices, and the informational efficiency of volatility forecasting has not yet been appropriately clarified in the existing literature. Hence, this study tries to address this gap by modelling COVID-19 variables with the IV indices and calculating the out-of-sample forecasting of IV indices to measure the informational efficiency of U.S. and European stock market volatility forecasting during the COVID-19 pandemic.

3. Methodology

3.1. Data set

Daily data on six U.S. and European IV indices, stock indexes (closing prices), and economic variables were selected as samples. We considered daily data from 3 January 2012 to 31 December 2020 as a full period. The subset was used for the in-sample evaluation period from 3 January 2012 until 21 January 2020. The subsequent period of the total sample was applied to evaluate out-of-sample data. The out-of-sample evaluation (22 January 2020 to 31 December 2020) addresses the COVID-19 period.

Daily confirmed, death and recovery cases of COVID-19 data were collected from the Johns Hopkins University Coronavirus Resource Centre from 22 January 2020 to 31 December 2020. The dataset was categorised into two sections of daily cases in the US and Europe. The daily cases in Europe consisted of a total of 27 countries. In particular, we opted for three major U.S. (VXN, VIX and VXD) and three European (VSTOXX, VCAC and VDAX-New) indices for modelling and forecasting IV. VXN, VIX and VXD were dependent on the market prices of NASDAQ 100 options index, the S&P 500 and Dow Jones Industrial Average (DJIA), respectively. For the European markets, the VDAX-New was based on the IV of DAX (Germany). On the other hand, VCAC was formed from the IV of CAC 40 (France), and VSTOXX was based on the EURO STOXX 50 index's market prices. Most IV indices and stock price data used in the study were obtained from Investing.com and Google Finance websites (Details of the data sources are available in Online Appendix A1.1, page 01).

In addition, data on the different financial and macroeconomic indicators were used as a predictor to evaluate IV variations. Data on the MSCI EAFE index and U.S./EU exchange rates were derived from Investing.com. WTI (Brent) crude oil price and the LIBOR interest rate (in three-month $U.S.) were retrieved from the Federal Reserve Economic Database (FRED). Finally, the data of EURIBOR were collected from the Euribor Rates website.

3.2. Research method

3.2.1. CCA model

The present study utilises the CCA model to analyse the impact of daily confirmed, death and recovery cases on U.S. and European IV indices and stock indices. CCA

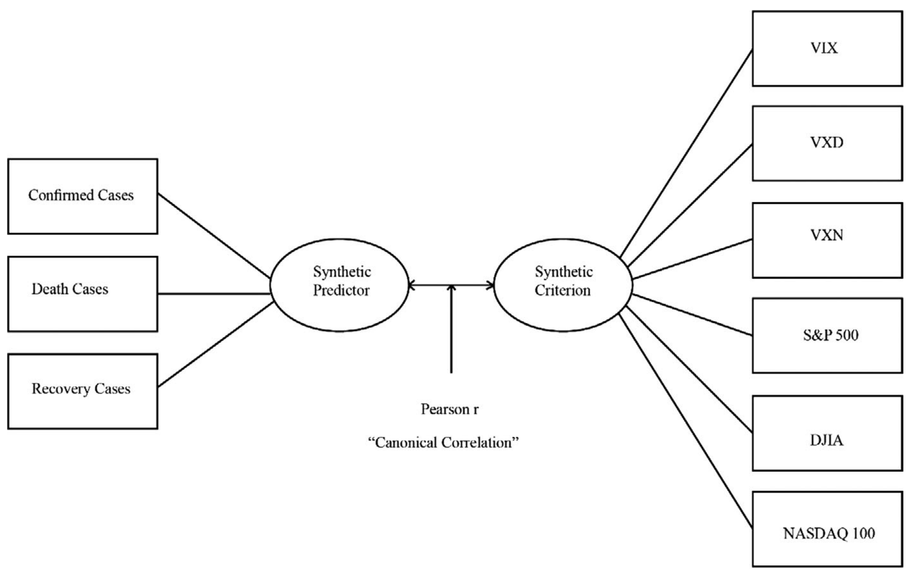

Figure 1. Canonical correlation analysis (CCA) with predictor and criterion variables.

tries to identify the best linear relationship between two multivariate datasets. The researcher might prefer to conduct some factor analysis if only one variable set is available (Sherry & Henson, 2005) (see Figure 1). However, if two sets are present, with multiple variables in both sets, then CCA fits better than factor analysis. (More details of the CCA model are available in Online Appendices A1.3.1 pp. 3–4).

Here, X and Y are adopted for correlation coefficient calculation:

$$X = \begin{pmatrix} x_i \\ x_j \\ \vdots \\ x_n \end{pmatrix}, \quad Y = \begin{pmatrix} y_i \\ y_j \\ \vdots \\ y_n \end{pmatrix}$$

Here, X and Y are used for CCA:

$$X = \begin{pmatrix} x_{ii} & x_{ij} & \cdots & x_{ip} \\ x_{ji} & x_{jj} & \cdots & x_{jp} \\ \vdots & \vdots & \ddots & \vdots \\ x_{ni} & x_{nj} & \cdots & x_{np} \end{pmatrix} = \begin{pmatrix} x_i \\ x_j \\ \vdots \\ x_n \end{pmatrix}$$

$$Y = \begin{pmatrix} y_{ii} & y_{ij} & \cdots & y_{ip} \\ y_{ji} & y_{jj} & \cdots & y_{jp} \\ \vdots & \vdots & \ddots & \vdots \\ y_{ni} & y_{nj} & \cdots & y_{np} \end{pmatrix} = \begin{pmatrix} y_i \\ y_j \\ \vdots \\ y_n \end{pmatrix}$$

Mathematically, we consider the following two equations:

$$T_m = a_{m1}X_1 + a_{m2}X_2 + \cdots + a_{mp}X_p \tag{1}$$

$$S_m = b_{m1}Y_1 + b_{m2}Y_2 + \cdots + b_{mq}Y_q \tag{2}$$

where T_m and S_m denote linear equations of the X and Y variable, respectively.

3.2.2. The principal components analysis (PCA) model

Numerous techniques have been applied in the literature to establish the evolution of out-of-sample forecasting of IV indices. The current study adopts the PCA approach. PCA is a commonly used exploratory multivariate statistical model for defining latent structures (Jackson, 2005). To begin this process, we use PCA to adjust the first four IV indices, and the first PC shifts of all the IV in a similar direction are explained as a global factor. Therefore, we measure the principal components' forecasting power using the last-day values of the first four PCs IV indices:

$$\Delta IV_t = \omega + r_{1i}PC1_{t-1} + r_{2i}PC2_{t-1} + r_{3i}PC3_{t-1} + r_{4i}PC4_{t-1} + \varepsilon_t \tag{3}$$

where ΔIV_t is IV indices and *PC1* to *PC4* are principal components lagged 1 to lagged 4. ϵ_t is the error term.

3.2.3. ARIMA, ARIMAX, ARIMA-GARCH and ARIMAX-GARCH models

To avoid the limitations of the single forecasting methods and improve reliability, this study includes another four different integrated approaches: for example, ARIMA (1,1,1), ARIMA (1,1,1)-GARCH (1,1), ARIMAX (1,1,1) and ARIMAX (1,1,1)-GARCH (1,1). Following Ahoniemi (2006), this study uses these models to understand the potential existence of short-term and long-term memory characteristics and the informational efficiency of the IV indices. According to Simon (2003) and Ahoniemi (2006), using log value is reliable with the positive skewness for IV data. Thus, the models are constructed by log IV first differences I(1) rather than daily levels I(0). In addition, logarithms draw from the IV indices observations to prevent negative volatility forecasts. All IV indices demonstrate a clear weekly paradigm, with Monday's index level averaging the maximum and Friday's minimum. Therefore, we assume that the day-of-the-week dummy for Mondays and Fridays would most likely be significant. (More details of these models are shown in Online Appendix A1.3.2, p. 03). The estimated linear equation of the ARIMA model is defined as

$$\Delta IV_t = \omega + \emptyset_1 \Delta IV_{t-1} + \theta_1 \epsilon_{t-1} + \sum_{i=1}^{r} \emptyset_i X_{i,\ t-1} + \sum_{k=1}^{5} \gamma_k D_{k,t} + \epsilon_t \tag{4}$$

where ΔIV_t is the log-returns of the IV indices and the weekly dummy variable $D_{k,t}$ obtains the value of 1 on day k and zero for other days. The θ_1 is the parameters of the moving average part, and the ϵ_t is the error terms. Vector X presents the group of all other explanatory variables except for AR and MA components.

The ARIMA model represents a first-order model, given that no second lags prove statistically significant. Therefore, when extending the equation model with a conditional variance model, a GARCH (1,1) prerequisite is considered appropriate, with the parameters as follows:

$$\epsilon_t = N(0,\ h_t^2)$$

$$h_t^2 = \kappa + \alpha_1 \in_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{5}$$

where κ is the constant in the conditional variance, and α_1 is the coefficient value.

4. Results and analysis

4.1. Descriptive statistics

The IV indices have been relatively stable between 2012 and 2019 in the U.S. and European stock markets but more volatile from the first quarter of 2020 because of the COVID-19 crisis. (Detailed results of descriptive statistics are available in Online Appendix A2.1, p. 04).

Table 1. Canonical solution for effect of COVID-19 on the U.S. stock market for Functions 1 and 2.

	Function 1			Function 2			
Variable	Coef.	r_s	r_s^2 (%)	Coef.	r_s	r_s^2 (%)	h^2 (%)
Panel A – CCA model of the U.S. stock market							
VIX	0.466	−0.426	18.14	−2.92	−0.070	0.49	18.63
VXD	−0.023	−0.465	21.62	0.948	0.072	0.52	22.14
VXN	−0.367	−0.287	8.24	0.521	−0.076	0.58	8.82
S&P 500	0.027	0.775	60.06	−2.954	−0.296	8.76	68.82
DJIA	−0.507	0.621	38.56	−0.331	−0.376	14.13	52.69
NASDAQ 100	1.446	0.951	90.44	1.935	−0.121	1.46	91.90
R_c^2			95.60			59.10	
Confirmed	0.058	0.897	80.46	6.673	−0.396	15.68	96.14
Death	1.291	0.992	98.40	1.434	−0.115	1.32	99.72
Recovery	−0.380	0.878	77.08	−8.443	−0.451	20.34	97.42

Panel B – Multivariate tests of significance for CCA model

Root no.	Test name	Value	Approx. *F*	Hypoth. DF	Error DF	Canon cor.	Sq. cor.	Sig. of *F*
1	Pillais	1.862	63.54	18.00	699	0.978	0.956	0.000
2	Hotellings	24.102	307.53	18.00	689	0.768	0.591	0.000
3	Wilks	0.012	136.72	18.00	653	0.560	0.314	0.000

Note: coef. = standardised coefficient; R_c^2 = squared canonical coefficient; r_s^2 = squared structure coefficient; r_s = structure coefficient; h^2 = communality coefficient.

4.2. CCA model analysis for COVID-19 effects on the U.S. stock market

Table 1, Panel B, summarises the results of three continuous functions having a square of canonical (SC) correlations (R_c^2) of 0.96, 0.59 and 0.32, respectively. As shown in Table 1, Panel B, we observe that the statistical significance of the aggregated model derives from all functions by applying the Wilks's $\lambda = 0.012$ criterion, $F(18, 136.72)$, $p < .001$. Although Wilks's λ demonstrates the variance unexplored by the model, $1 - \lambda$ (estimated from Table 1(Panel B)) produces the complete model's effect size in an r^2 metric. In addition, the effect size of the r^2 type is calculated as $1 - 0.012 = 0.988$, which shows that the complete model represents a significant portion, approximately 98%, of the variance shared between the variable sets. Therefore, the first two functions are most appropriate for this analysis (95.60% and 59.10% of the shared variance, respectively).

Table 1, Panel A, lists the standardised canonical functions and the structure coefficients (r_s) result for Functions 1 and 2. The total value of two functions' squared structure coefficients (r_s^2) over each variable is represented by the communalities (h^2). The squared structure coefficients (r_s^2) of Function 1 suggest that related criterion variables are mainly NASDAQ 100 and S&P 500, with VXD building secondary contributions to the synthetic criterion variable, which have higher canonical function coefficients. The only notable exception concerns VIX and VXN, which have moderate function coefficients with the lowest structure coefficients. Furthermore, except for NASDAQ 100, DJIA and S&P 500, all of the structure coefficients (r_s) of criterion variables have an equal sign, representing that all are negatively correlated.

As shown in Function 1, confirmed and death cases are the principal contributors to the predictor variable concerning the synthetic predictor variable. Nevertheless, the recovery variable makes a secondary contribution. As the structure coefficient (r_s) functions for confirmed, death and recovery cases are positive, these variables show a

Table 2. Canonical solution for the effect of COVID-19 on the European stock market for Functions 1 and 2.

	Function 1			Function 2			
Variable	Coef.	r_s	r_s^2 (%)	Coef.	r_s	r_s^2 (%)	h^2 (%)
Panel A – CCA model of the European stock market							
VDAX-New	1.570	−0.056	0.31	−1.397	0.308	9.48	9.79
VCAC	0.582	−0.035	0.12	−0.399	0.318	10.11	10.23
VSTOXX	−2.853	−0.110	1.21	1.599	0.333	11.08	12.29
DAX	−0.044	−0.024	0.05	−4.292	−0.416	17.31	17.36
CAC 40	−2.997	−0.491	24.11	−6.557	−0.261	6.81	30.92
STOXX 50	2.092	−0.326	10.63	9.936	−0.248	6.15	16.75
R_c^2			85.80			73.10	
Confirmed	−1.047	−0.162	2.63	−2.084	−0.942	88.73	91.36
Death	2.161	0.322	10.37	−0.428	−0.868	75.34	85.71
Recovery	−1.033	−0.128	1.64	1.554	−0.859	73.78	75.42

Panel B – Multivariate tests of significance for the CCA model

Root no.	Test name	Value	Approx. *F*	Hypoth. DF	Error DF	Canon cor.	Sq. cor.	Sig. of *F*
1	Pillais	1.767	55.69	18.00	699.00	0.926	0.858	0.000
2	Hotellings	8.989	179.42	18.00	689.00	0.855	0.731	0.000
3	Wilks	0.031	114.70	18.00	653.70	0.421	0.177	0.000

Note: coef. = standardised coefficient; R_c^2 = squared canonical coefficient; r_s^2 = squared structure coefficient; r_s = structure coefficient; h^2 = communality coefficient.

positive correlation between all stock market indices except for NASDAQ 100, DJIA and S&P 500.

Looking at Function 2 in Table 1, Panel A, the coefficient's value indicates that all criterion variables are statistically significant. Concerning Function 2, recovery is now the dominant predictor. However, this variable is also negatively related. Considering all structure coefficient (r_s) functions, we get that the recovery case is negatively related to VXD but positively related to the VIX, VXN, S&P 500, DJIA and NASDAQ 100. As the daily recovery cases increase, the trends of VIX and VXN indices also change in similar directions, which means that the high stock market returns are associated with a low volatility rate. Therefore, more daily recovery cases may increase the stock prices that help recover the stock market fluctuations.

4.3. CCA Model analysis for COVID-19 effects on the European stock market

Table 2, Panel B, indicates the three functions with squared canonical (SC) correlations (R_c^2) of 0.86, 0.73 and 0.18, respectively, for each continuous function. The first two functions only seem appropriate for this analysis (85.80% and 73.10% of the shared variance, respectively). However, only 17.70% of the variable lists' existing variance is justified by the last functions after removing the previous functions. In Table 2, Panel B, the complete model across all functions is statistically significant, applying Wilks's $\lambda = 0.031$ criterion, $F(18, 114.7)$, $p < .001$.

An overall summary of the standardised canonical function and the structure coefficients (r_s) for Functions 1 and 2 is shown in Table 2, Panel A. The squared structure coefficients (r_s^2) of Function 1 suggest that primary criterion variables are mainly CAC 40, STOXX 50 and VSTOXX. VCAC and DAX constitute secondary contributions to the synthetic criterion variable. These stock market indices also tend to have higher canonical function coefficients. DAX, CAC 40 and STOXX 50 are positively related to all other criterion variables. Concerning the synthetic predictor variable defined in Function 1, confirmed and death cases are the principal contributors to the predictor variable, with a secondary contribution by recovery cases. As the structure coefficient functions (r_s) for death cases, this variable is negatively correlated with all IV indices (VDAX-New, VCAC and VSTOXX), and stock returns the index (DAX, CAC 40 and STOXX 50). Function 1 indicates that the trends of IV indices (VDAX-New, VCAC and VSTOXX) increase in a similar direction when daily confirmed cases have increased. Therefore, this function shows theoretically consistent relationships that help investors diversify their portfolios by including a mix of investments.

According to Function 2 in Table 2, Panel A, the coefficients' value proposes that all criterion variables are relevant. Concerning attachment, the only confirmed case is now the dominant predictor. Considering all of the structure coefficient functions, we get that confirm, death and recovery are negatively related to VDAX-New, VCAC and VSTOXX but positively related to the DAX, CAC 40 and STOXX 50. The result indicates that a daily increase in the recovery rate may increase stock return trends, which is a positive sign for European stock markets.

4.4. In-sample evidence

Tables 3–5 summarise the performance of the PCA, ARIMA, ARIMA-GARCH models, respectively. In-sample evidence shows IV indices performance of the pre-COVID-19 period.

The results of the PCA model [Equation (3)] are shown in Table 3. We observe that the model best fits to all IV indices, where R^2 = 0.84, 0.83, 0.81, 0.89, 0.99 and 0.89, respectively. All the lagged first four principal components are statistically significant. However, the only exception occurs for VXN where $PC3_{t-1} = -0.892$, $p = .064$ and VCAC where $PC4_{t-1} = -0.007$, $p = .466$.

A summary of the ARIMA (1,1,1) model is given in Table 4, representing that the value of AR and MA parameters are statistically significant in all six IV indices. The dummy variables for positive Monday (γ_1) are also statistically significant for all six

Table 3. Estimation results of principal components analysis (PCA) model.

	ΔVIX_t	ΔVXD_t	ΔVXN_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
ω_t	0.001	0.001	0.001	0.002	0.001	0.002
	(.066)	(.084)	(.006)	(.049)	(.465)	(.533)
$PC1_{t-1}$	1.407	−0.662	0.660	−1.102	1.373	0.464
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
$PC2_{t-1}$	−4.773	−0.463	−4.159	4.219	−3.550	−3.820
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
$PC3_{t-1}$	−3.953	1.393	−0.892	2.350	−1.591	1.239
	(.000)	(.000)	(.064)	(.000)	(.005)	(.000)
$PC4_{t-1}$	−0.065	0.514	−0.057	0.126	0.087	0.039
	(.000)	(.000)	(.000)	(.012)	(.567)	(.000)
R^2	0.84	0.83	0.81	0.89	0.99	0.89

Note: ω_t = coefficient value; $PC1_{t-1}$ = principal components lagged 1; $PC2_{t-1}$ = principal components lagged 2; $PC3_{t-1}$ = principal components lagged 3; $PC4_{t-1}$ = principal components lagged 4. *p* Values are given in parentheses.

Table 4. Estimation results of ARIMA (1,1,1) model.

	ΔVIX_t	ΔVXD_t	ΔVXN_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
ω	−0.002	−0.001	−0.002	−0.002	−0.005	−0.003
	(.302)	(.578)	(.069)	(.122)	(.125)	(.005)
ϕ	0.915	0.908	0.924	0.904	0.577	0.906
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Θ	−0.984	−0.979	−0.985	−0.973	−0.831	−0.981
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
γ_1	0.021	0.014	0.021	0.013	0.023	0.016
	(.000)	(.000)	(.000)	(.000)	(.023)	(.000)
γ_5	−0.013	−0.011	−0.009	−0.004	0.003	0.002
	(.006)	(.006)	(.015)	(.234)	(.776)	(.649)
BIC	−2.311	−2.550	−2.628	−2.760	−1.522	−2.516
R^2	0.047	0.041	0.046	0.033	0.093	0.038

Note: ω = coefficient; ϕ = AR term; Θ = MA term; γ_1 = Monday dummy variable; γ_5 = Friday dummy variable; BIC = Bayesian information criteria. p Values are given in parentheses.

Table 5. Estimation result of ARIMA (1,1,1)-GARCH (1,1) model.

	ΔVIX_t	ΔVXD_t	ΔVXN_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
ω	−0.001	−0.001	−0.001	−0.003	−0.003	−0.004
	(.725)	(.524)	(.136)	(.317)	(.205)	(.178)
ϕ	0.914	0.924	0.943	0.901	0.901	0.902
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Θ	−0.987	−0.987	−0.997	−0.972	−0.989	−0.979
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
γ_1	0.019	0.016	0.019	0.014	0.019	0.015
	(.027)	(.000)	(.000)	(.034)	(.009)	(.064)
γ_5	−0.015	−0.012	−0.012	−0.005	−0.003	0.001
	(.074)	(.001)	(.001)	(.443)	(.712)	(.976)
K	0.003	0.002	0.001	0.002	0.003	0.003
	(.001)	(.000)	(.000)	(.013)	(.000)	(.017)
α_1	0.599	0.598	0.598	0.599	0.593	0.600
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
BIC	−2.168	−2.622	−2.687	−2.643	−1.503	−2.341
R^2	0.046	0.039	0.044	0.033	0.063	0.037

Note: ω = coefficient; ϕ = AR term; Θ = MA term; γ_1 = Monday dummy variable; γ_5 = Friday dummy variable; K= constant in the conditional variance; α_1 = GARCH coefficient; BIC = Bayesian information criteria. p Values are given in parentheses.

IV indices. However, Friday (γ_5) is not statistically significant for all European indices such as VDAX-New, VCAC and VSTOXX, where $p > .05$. It shows a negative correlation for VIX, VXD, VXN and VDAX-New indices. The result also suggests that the positive Monday dummy is reliable. All six IV indices tend to increase on Mondays. The negative Friday dummy experiences an average drop of all IV indices on Fridays. The finding is consistent with earlier evidence of the effect of IV in stock markets on weekly seasonality (Ahoniemi, 2006).

Table 5 shows that the ARIMA-GARCH model appears as a preferred specification when applying the entire in-sample timeframe for evaluating and contrasting goodness-of-fit with the Schwarz Information Criterion (BIC). For all six IV indices, the value of AR and MA parameters are very close; however, the estimated value of the uncertainty of volatility is not very consistent. In all cases, the GARCH parameters are estimated to be close to 0.598, which means data stationarity is achieved. The coefficients result is statistically significant for both the GARCH and ARCH terms. For the weekday dummy variable's expected signs, the positive Monday dummy (γ_1)

Table 6. Out-of-sample forecasting performance for each IV index.

	ΔVIX_t	ΔVXD_t	ΔVXN_t	$\Delta VDAX\_New_t$	$\Delta VCAC_t$	$\Delta VSTOXX_t$
Panel A – Principal components analysis (PCA) forecasting						
RMSE	0.033	0.037	0.034	0.039	0.022	0.050
MAE	0.025	0.026	0.025	0.030	0.016	0.034
CP	0.976	0.985	0.952	0.998	0.988	0.959
SMAPE	73.706	81.301	86.503	77.042	50.705	73.922
Panel B – ARIMA (1,1,1) forecasting						
RMSE	0.088	0.073	0.077	0.080	0.092	0.088
MAE	0.060	0.052	0.052	0.058	0.068	0.065
CP	0.203	0.190	0.227	0.149	0.197	0.145
SMAPE	171.68	176.104	166.604	175.021	172.08	179.231
Panel C – ARIMA (1,1,1)-GARCH (1,1) forecasting						
RMSE	0.088	0.073	0.077	0.081	0.092	0.089
MAE	0.060	0.052	0.052	0.058	0.068	0.066
CP	0.211	0.219	0.228	0.166	0.183	0.143
SMAPE	172.545	173.933	169.794	172.953	176.585	178.298
Panel D – ARIMAX (1,1,1) forecasting						
RMSE	0.120	0.119	0.081	0.065	0.085	0.066
MAE	0.069	0.066	0.052	0.046	0.061	0.046
CP	0.550	0.628	0.663	0.980	0.999	0.998
SMAPE	95.060	107.963	100.573	102.345	112.447	92.095
Panel E – ARIMAX (1,1,1)-GARCH (1,1) forecasting						
RMSE	0.214	0.216	0.130	0.083	0.090	0.067
MAE	0.140	0.133	0.088	0.062	0.062	0.046
CP	0.439	0.554	0.566	0.998	0.990	0.993
SMAPE	93.896	99.051	89.050	135.309	112.184	92.664

Note: The root mean squared prediction error (RMSE), the bias proportion (BP), mean absolute prediction error (MAE), covariance proportion (CP) and symmetric mean abs. percent error (SMAPE) of the degree of change in the implied volatility index value is provided.

is statistically significant for all IV indices except $VSTOXX_t$. It continues to increase on Mondays. On the other hand, the negative Friday dummy (γ_5) is constant with the IV indices that experience the average decrease on Fridays.

The results of the ARIMAX and ARIMAX-GARCH models are summarised in the online Appendix. There is no evidence that macroeconomic variables are statistically significant except for the lagged log return of the all-stock parameter (□ 1) indices (such as S&P 500, NASDAQ 100, DJIA, DAX, STOXX 50, CAC 40). (Interested readers can find more detailed information about ARIMAX and ARIMAX-GARCH models in Online Appendix A2.2, pp. 6–9).

Overall, the PCA, ARIMA and ARIMA-GARCH models perform suitably, among other models considered. U.S. indices generally fit better than European indices. Therefore, this comparison suggests that each U.S. index has a particular, predictable dynamic pattern that could be employed by information derived from other IV indices. The ARIMAX and ARIMAX-GARCH methods are not involved in the changes of IV decision purpose. Therefore, these two models have mixed evidence regarding macroeconomics variables in the U.S. and European stock markets.

4.5. Out-of-sample forecasting

We evaluate the out-of-sample performance for each model's specification. From 22 January 2020 to 31 December 2020, the out-of-sample performance is achieved by one observation through increasing sample size and re-evaluating each model. Point forecasts are developed for each of the six IV indices, and the forecasts are measured with the RMSE, MAE, CP and SMAPE metrics. Table 6 shows the forecast results of the various models.

The IV's adjustment from day $t-1$ to day t is decreased with the time related to and counting day $t-1$ on all specified variables. We use the calculated parameter values to forecast the IV transition from day t to day $t+1$ and the day t values. Even the dummy variables are handled individually (i.e., the day $t+1$ dummy variable is employed when predicting day t to day $t+1$ shift in IV). In Table 6, Panel A, VCAC has the lowest and VSTOXX has the highest RMSE and MAE PCA forecasting results. For ARIMA forecasting in Panel B, VXD has the lowest and VCAC has the highest RMSE and MAE value. Using a more extended in-sample period for model estimation seems useful when evaluating point forecasts with RMSEs. The PCA and ARIMA models are currently performing better than the ARIMA-GARCH, ARIMAX and ARIMAX-GARCH models.

In addition, for the ARCH test, the null hypothesis is not rejected for GARCH errors when conditional heteroscedasticity is exhibited. The DM test and the HLN test are employed to check whether any model outperforms is statistically significant in the RMSE, MAE, CP and SMAPE metrics. The result shows that the DM test and the HLN test do not deny the null hypothesis of similarly predictive accuracy. (Detailed information about the heteroscedasticity test and the DM and HLN tests is available in Online Appendix Tables A5 and A6, p. 09).

4.6. Robustness analysis

In this section, we choose another period of a dataset to ensure the robustness of the results. The selected in-sample period is 1 January 2016 to 21 January 2020. Financial market conditions can change quickly, and only the most recent information may be helpful for forecasting. The second sample period was chosen to determine if forecast performance might be improved with only a short observation period. We also try to investigate whether the nature of the IV indices is sensitive to the effects of stock price changes. (Robustness analyses are presented in Online Appendix A2.3, p. 10).

5. Discussion

We discuss the findings of the COVID-19 impact on the U.S. and European stock indices and IV indices in the existing literature. This topic reveals a new insight about the changes in stock market volatility in the COVID-19 period. Considering the structural coefficients (r_s) of the CCA model for Function 1 of the U.S. stock market in Table 1, Panel A, we observe that daily confirmed and death cases negatively affect VIX, VXD and VXN indices. However, these cases positively affect stock indices S&P 500 and DJIA, but not NASDAQ 100. The result suggests that the trends of COVID-19 and IV indices are similar. However, the daily confirmed and death cases and stock indices have opposite trends, which indicates that the increase of confirmed and death cases seem to cause the stock prices to fall. Therefore, this function helps investors diversify their portfolios by including a mix of investments that correlate negatively to the stock market.

On the other hand, Function 1 for the European stock markets in Table 2, Panel A, shows that death cases are negatively correlated with all IV indices (VDAX-New, VCAC and VSTOXX) and stock indexes (DAX, CAC 40 and STOXX 50). The result of Function 2 suggests that stock indices always show the opposite relation with IV indices. Function 2 for both the U.S. and European stock market recovery cases indicates a positive sign for stock indices. This result suggests that as more COVID-19 patients recover, current stock market conditions may improve. These results are in line with those of previous researchers (Albulescu, 2021; Al-Awadhi et al., 2020; Mazur et al., 2021; Wagner, 2020) and support our research question 1. Tables 1 and 2 report our results, which indicate that U.S. stock markets have the best-fit model, rather than European stock markets.

The evidence of the point forecasts predictability is more reliable for U.S. IV indices than for European indices. The PCA and ARIMA models perform better among all of the competing models. As suggested in the earlier research, some predictability tends to shift in the IV indices' direction. Degiannakis et al. (2018) use parametric and non-parametric forecasting techniques for ten trading days of ahead forecasting. Degiannakis et al. (2018) suggest that IV has no additional evidence related to volatility forecasting. The predictable patterns in Table 6 are consistent with Konstantinidi et al. (2008), but these are not economically significant. However, the result is significant when market risk needs to be quantified, as per Fernandes et al. (2014). The DM model confidence test shows that the best predictive capacity exhibits the market's IV (Liang et al., 2020). Hence, the modelling and out-of-sample forecasting of the IV indices in Table 6 helps investors understand the changes in expected returns over time in the COVID-19 situation, which supports our research question 2. Additionally, we apply the HLN test to check whether any outperforming model is statistically significant.

Past studies of low-frequency stock indices (daily or weekly) and IV have provided contradictory conclusions regarding IV modelling and informational efficiency. Our DM test and the HLN test of time series data (Details are shown in Online Appendix Table A6, p.10) using PCA, ARIMA, ARIMA-GARCH, ARIMAX and ARIMAX-GARCH techniques confirmed that IV might be more informative in daily indices that support our research question 3. This finding is in agreement with the recent evidence of Han and Park (2013) and Fernandes et al. (2014) but is inconsistent with that of Wang and Wang (2015), who provided a mixed opinion. The ARCH effects and the heteroskedasticity test were applied for all of the model stipulations. They help identify the non-constant volatility of conditional heteroskedasticity when future high and low volatility intervals are not identifiable.

6. Conclusion

The present study is designed to measure the impact of COVID-19 on the U.S. and European stock indices, IV indices and to determine the forecasting precision for understanding IVs informational efficiency during the early COVID-19 period. We used the CCA model to identify the impact of the COVID-19 crisis on the U.S. and European stock market indices. Five alternative model specifications such as PCA, ARIMA, ARIMA-GARCH, ARIMAX and ARIMAX-GARCH generate point forecasts. The out-of-sample forecast accuracy has been assessed both in a statistical and economic context. This study adds new insights into the literature about the COVID-19 pandemic effects on the IV indices and informational efficiency in the stock market returns during the early COVID-19 period. The stock returns for all six IV indices are statistically significant for the first differences of IV estimation. The PCA and ARIMA models are the best fit for the datasets. However, ARIMAX and ARIMAX-GARCH modelling proved unsuccessful regardless of the high constancy in time series and the IV indices' explanatory variables except for stock indices.

Our study has implications for academics, policymakers and investors. As the COVID-19 pandemic is now becoming an alarming health epidemic worldwide, we need to worry not only about the solutions to potential public health challenges but also about financial matters. Controlling the COVID-19 situation involves a logical approach, meaning that policymakers can advise people promptly about what they and the healthcare system can do without creating confusion. This analysis indicates that owing to the COVID-19 crisis, investors should determine the patterns of directional changes in U.S. and European stock indices and IV indices. Therefore, investors need careful attention to diversifying their investment portfolio to reduce the increased risk of abnormal fluctuations during the COVID-19 outbreak.

This study has some limitations. First, it covers only the early stage of the COVID-19 outbreak. Second, we do not consider options trading measurement, which is also an essential factor for better understanding the IV directional changes. Another limitation is that we do not consider demographic variables such as age, education and investors' experience in stock business because of data unavailability in the U.S. and European stock markets. This study provides the following directions for future research. First, the post-COVID-19 is an essential consideration for future study because the stock markets try to recover from the pandemic after implementing stimulus packages and administering vaccines. Second, the more extended horizons can be considered to understand the more significant informational efficiency estimation of stock market volatility.

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Data availability statement

The current paper applies a publicly available dataset. Therefore, data sources are cited in the text.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Ahoniemi, K. (2006). Modelling and forecasting implied volatility-an econometric analysis of the VIX index. *Helsinki School of Economics Archives*. https://core.ac.uk/download/pdf/14912922.pdf

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, *27*, 100326. https://doi.org/10.1016/j.jbef.2020.100326

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, *38*, 101699. https://doi.org/10.1016/j.frl.2020.101699

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19) – An epidemic or pandemic for financial markets . *Journal of Behavioural and Experimental Finance*, *27*, 100341. https://doi.org/10.1016/j.jbef.2020.100341

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, *54*, 101249. https://doi.org/10.1016/j.ribaf.2020.101249

Aslam, F., Mohti, W., & Ferreira, P. (2020). Evidence of intraday multifractality in European stock markets during the recent coronavirus (COVID-19) outbreak. *International Journal of Financial Studies*, *8*(2), 31. https://doi.org/10.3390/ijfs8020031

Degiannakis, S., Filis, G., & Hassani, H. (2018). Forecasting global stock market implied volatility indices. *Journal of Empirical Finance*, *46*, 111–129. https://doi.org/10.1016/j.jempfin.2017.12.008

Fernandes, M., Medeiros, M. C., & Scharth, M. (2014). Modelling and predicting the CBOE market volatility index. *Journal of Banking & Finance*, *40*, 1–10. https://doi.org/10.1016/j.jbankfin.2013.11.004

Han, H., & Park, M. D. (2013). Comparison of realised measure and implied volatility in forecasting volatility. *Journal of Forecasting*, *32*(6), 522–533. https://doi.org/10.1002/for.2253

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID -19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, *56*(10), 2198–2212. https://doi.org/10.1080/1540496X.2020.1785865

Huo, X., & Qiu, Z. (2020). How does China's stock market react to the announcement of the COVID-19 pandemic lockdown? *Economic and Political Studies*, *8*(4), 436–461. https://doi.org/10.1080/20954816.2020.1780695

Iqbal, N., Fareed, Z., Wan, G., & Shahzad, F. (2021). Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. *International Review of Financial Analysis*, *73*, 101613. https://doi.org/10.1016/j.irfa.2020.101613

Jackson, J. E. (2005). *A user's guide to principal components*. John Wiley & Sons.

Johns Hopkins University Coronavirus Resource Center . (2020). *Covid-19 dashboard [Online]*. Date: 22/01/2020 to 31/12/2020. Retrieved January 2, 2021, from https://coronavirus.jhu.edu/map.html

Kanas, A. (2013). Implied volatility and the risk-return relation: A note. *International Journal of Finance & Economics*, *18*(2), 159–164. https://doi.org/10.1002/ijfe.449

Konstantinidi, E., Skiadopoulos, G., & Tzagkaraki, E. (2008). Can the evolution of implied volatility be forecasted? Evidence from European and U.S. implied volatility indices. *Journal of Banking & Finance*, *32*(11), 2401–2411. https://doi.org/10.1016/j.jbankfin.2008.02.003

Liang, C., Wei, Y., & Zhang, Y. (2020). Is implied volatility more informative for forecasting realised volatility: An international perspective. *Journal of Forecasting*, *39*(8), 1253–1276. https://doi.org/10.1002/for.2686

Liu, H., Wang, Y., He, D., & Wang, C. (2020). Short term response of Chinese stock markets to the outbreak of COVID-19. *Applied Economics*, *52*(53), 5859–5872. https://doi.org/10.1080/00036846.2020.1776837

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, *38*, 101690. https://doi.org/10.1016/j.frl.2020.101690

Okorie, D. I., & Lin, B. (2021). Stock markets and the COVID-19 fractal contagion effects. *Finance Research Letters*, *38*, 101640. https://doi.org/10.1016/j.frl.2020.101640

Sherry, A., & Henson, R. K. (2005). Conducting and interpreting canonical correlation analysis in personality research: A user-friendly primer. *Journal of Personality Assessment*, *84*, 37–48. https://doi.org/10.1207/s15327752jpa8401_09

Simon, D. P. (2003). The Nasdaq volatility index during and after the bubble. *The Journal of Derivatives*, *11*(2), 9–24. https://doi.org/10.3905/jod.2003.319213

Wagner, A. F. (2020). What the stock market tells us about the post-COVID-19 world. *Nature Human Behaviour*, *4*(5), 440–440. https://doi.org/10.1038/s41562-020-0869-y

Wang, J., & Wang, J. (2015). Forecasting stock market indexes using principal component analysis and stochastic time effective neural networks. *Neurocomputing*, *156*, 68–78. https://doi.org/10.1016/j.neucom.2014.12.084

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected markets: Novel coronavirus, government Interventions, and stock return volatility around the globe. *Finance Research Letters*, *35*, 101597. https://doi.org/10.1016/j.frl.2020.101597

Zhang, D., Hu, M., & Ji, Q. (2020a). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

Zhang, S., Liu, Y., Chen, H., Zhu, C., Chen, C., Hu, C., Xu, L., & Yang, Y. (2021b). The level effect and volatility effect of uncertainty shocks in China. *Economic Research-Ekonomska Istraživanja*, *34*(1), 172–193. https://doi.org/10.1080/1331677X.2020.1780145