JEL Classifications: C22, F36, I15, I18

Keywords: COVID-19, stock market indices, time-varying cointegration test, wild bootstrap likelihood ratio test, abnormal returns

Stock Markets Reaction to COVID-19: Evidence from Time-Varying Cointegration, Leveraged Bootstrap Causality and Event Analysis

Chien-Chiang LEE - Research Center of the Central China for Economic and Social Development & School of Economics and Management, Nanchang University, China

Godwin OLASEHINDE-WILLIAMS – Department of Economics, Faculty of Business, Istanbul Ticaret University, Istanbul, Turkey (goowilliams@ticaret.edu.tr) corresponding author

Ifedola OLANIPEKUN - Adeyemi College of Education, Ondo, Nigeria

Abstract

This paper examined the interconnectedness of COVID-19 and stock markets in some of the most affected countries—USA, Italy, Spain and Germany. To this end, a time-varying cointegration technique was first employed to examine for the presence of comovements between daily infections and stock market changes. A time-varying wild bootstrap likelihood ratio test was then employed to determine whether COVID-19 is a significant predictor of stock market performance. Lastly, an event study analysis was conducted to investigate the short-term effect of the outbreak on stock market returns. Findings revealed the existence of comovements between COVID-19 infections and stock price indices in all the selected countries. The rejection of the null hypothesis of no predictability was also recorded in all of the countries sampled. The event study analysis revealed that significant negative cumulative abnormal returns were predominant in all the countries. The reactions of the stock markets of the three European Union member countries included in the study to the pandemic are quite similar, suggesting that countries that are regionally and economically integrated are likely to experience relatively similar effects. The USA stock market was the most resilient to the impact of the outbreak.

1. Introduction

The Coronavirus disease (COVID-19) is a pandemic that has claimed thousands of lives across the world within a very short period since its outbreak in December 2019. This has brought an increased level of uncertainty and risk as both people and governments of affected countries take notable measures to contain the spread of the novel disease. The measures involve sudden alterations in economic

https://doi.org/10.32065/CJEF.2022.04.02

We would like to thank the editor and the anonymous referees for their highly constructive suggestions. Chien-Chiang Lee is grateful to the National Social Science Foundation Key Project of China for financial support through Grant No: 22AJL004.

activities with consequential notable economic damages across the world (Barro *et al.,* 2020; Fernandes, 2020; Nicola *et al.,* 2020; Ramelli & Wagner, 2020; Wang et al., 2022). Among the numerous significant economic impacts was the reaction of stock markets to the situation. As an important indicator of movements and stability in the financial markets, the performance of stock market indices in this period has drawn obvious attention. This increased interest is due to the difference a global pandemic might make between market expectations and the actual payoff values. A clear understanding of how a global pandemic impacts stock markets offers effective risk management directions to investors now and ahead of when stock market anomalies are triggered during similar unexpected occurrences. Furthermore, the accompanying mixed effects of COVID-19 on other domestic and international factors which have been ascertained to have effects on stock market activities in the past may linger. As these factors—such as government spending, consumption, supply, global and domestic economic policy uncertainty, oil prices, international trade, tourism and foreign direct investment—are being affected by the pandemic, they simultaneously affect stock returns (see Ashraf 2020; Mazur, 2020; Zhang et al., 2022). This knowledge is important for the response of both investors and policymakers as they may have to find a balance between their choice strategies of minimizing investment risks and minimizing the health consequences of global health-related crises.

Infectious disease outbreaks in the past have shown a connection between the general economy and the human health. The experience from the outbreak of the influenza pandemic which plagued the world about a century ago (1918-19) created global fears and responsive cautions to the outbreak of subsequent deadly diseases that threaten mankind without vaccine (Barry, 2004; Barro *et al.,* 2020). Although there were direct and indirect, quantifiable and unquantifiable economic losses (McKibbin & Sidorenko, 2006; Guimbeau *et al.,* 2020), the stock market did not respond to the pandemic a century ago (Baker *et al.,* 2020c). The stock markets effects of disease outbreak were however noticeable during the outbreak of Severe Acute Respiratory Syndrome (SARS) in 2003 (Lee & McKibbin, 2004; Chen *et al.,* 2018a) and Ebola in 2014-2016 (Ichev & Marinč, 2018). This recent pattern can be attributed to the amplification of market anxiety as a result of a more integrated world in which information travels faster and market signals are received within seconds. According to the United Nations Economic Commission for Africa (UNECA, 2015), pandemic-induced anxiety can be as disruptive as the disease itself, especially when there is no cure. This is because it creates overreactions in the economy. This is even more so with COVID-19, as it is more infectious than previous similar viruses (Salisu & Akanni, 2020). For instance, Haroon and Rizvi (2020), Salisu and Vo (2020), Olasehinde-Williams, et al (2021) and Özkan, et al (2022) report that news related to COVID-19 heighten sentiment, uncertainty and volatility in financial markets. Also, the potential for a greater global effect of the pandemic has been driven up by the increased size and complexity of global supply chains characterized by strong interdependencies between firms located across several countries. These factors are even more at play today than they were years back when the SARS and Ebola outbreaks occurred. The outbreak of COVID-19 pandemic is therefore likely to have a greater effect on stock markets across the world when compared with previous outbreaks of infectious diseases.

COVID-19 was declared a public health emergency on January 30, 2020[1] by the World Health Organization (WHO, 2020). The policy response of governments to contain the spread of this disease triggered a global uncertainty. The increase in stock market volatility during this period can be attributed to the outbreak because of the rise in risk aversion caused by the high level of uncertainty experienced across the world. As explained by Pástor and Veronesi (2006), the level and volatility of stock prices are positively related through uncertainty about future profitability. Theoretically, following the conventional rule which states that observations with absolute median deviations larger than three times the interquartile range are extreme events, the COVID-19 pandemic qualifies to be classified as an extreme event (Stock & Watson, 2005). Iglesias (2022) shows that the COVID-19 pandemic is one of only two extreme events (the other being the Brexit referendum) to have created a decline of over 5% in global equity markets over the past decade. The pandemic therefore brings to the fore the kind of enormous impact that health-related news can have on stock markets.

Border closures and lockdown of affected cities—urgent measures taken to contain the situation—have mostly affected normal business lives, generated gradual economic depression, and an eventual financial crisis is being predicted (Lee *et al.,* 2019; Barro *et al.,* 2020; Lee & Chen, 2020a; Ramelli & Wagner, 2020a; Zhang *et al.,* 2020). Currently, firms producing non-essentials have suspended operations, while oil price has tumbled sharply (by over 30%) to the lowest figures in recent decades. These are apart from the expected long-run effects of business collapse, unemployment rise and structural change in production, especially from labour-intensive to technology-intensive. Since asset prices are determined by investors' future expectations (Shiller, 1981; Campbell & Shiller, 1988), anxiety over how anti-pandemic policies imposed in different countries will affect economic conditions, both in the short and long run, has altered the future expectations of investors. The consequent changes in the risk-return expectations of investors has caused widespread reallocation of portfolios, leading to severe market fragility, especially in epicentres (Baker *et al.*, 2020c; Mushir & Suryavanshi, 2021).

As business and production activities are being disrupted, investors are now anxious about the prediction that this pandemic will cause another economic recession (Atkeson, 2020b; Guerrieri *et al.,* 2020; Nicola *et al.,* 2020; Ozili & Arun, 2020). Companies which halted operations have had their shares drop significantly. For example, the shares of major airline companies have dropped by over 15%[2], while prices of investments in Asia (Hong Kong, Japan, the Philippines, Singapore and Indonesia) have nosedived into bear markets[3]. There was over 10% drop in global stock markets, recounting global losses of over 6 trillion dollars since January

[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen

[2] https://www.bbc.com/news/business-51829852

[3] https://www.bloomberg.com/news/articles/2020-03-09/perfect-storm-is-plunging-asia-stocks-to-bear-markets-one-by-one

2020,[4,5] while market indices had fallen by about 20% as at March 12, 2020[6]. During this period, the mostly affected countries have had the highest market volatility and standard deviation (Zhang *et al.,* 2020; Wang and Lee, 2022).

To this end, we intend to empirically assess the connection between the COVID-19 pandemic and the stock markets of the most affected countries. This will add to the growing body of literature investigating whether comovements exist between COVID-19 infections and stock markets, whether the situation in stock markets can be predicted by the outbreak of this disease, and how precisely the stock market returns have reacted to the announcement of the outbreak of COVID-19. This study contributes significantly to extant literature in three ways. First, it empirically investigates the nexus between COVID-19 and stock markets using a time-varying cointegration analysis that is robust to parameter instabilities, nonlinearities, regime shifts and time variations. This approach is especially useful in modelling the relationship because outbreaks of diseases generally display patterns that vary with time (Ho, Lubik & Matthes, 2020). Second, it examines the ability of COVID-19 to predict stock market performance by employing the wild bootstrap likelihood ratio test that is capable of generating time-varying results that are robust to non-normality, small sample bias, endogeneity and conditional heteroscedasticity, all common features of the financial time series. Third, it examines the sensitivity of the selected stock markets to the unanticipated outbreak of COVID-19 within an event study set-up.

The findings from this study will be useful to business and financial studies in determining the potential impact of global pandemics that may surface in the future. The insights gleaned from investors' sentiments toward uncertainty associated with disease outbreaks and the degree of sensitivity of stock markets to pandemics might be helpful for preparing and managing investments under similar situations, and also provide policymakers with insights on better precautionary and management options to prevent weakening of markets, volatility of markets and the reallocation of assets that could occur due to market disintegration.

The rest of the paper is organized in the following form; a review of literature is presented in Section 2, the methodology employed is detailed in Section 3, the data and empirical results are discussed in Section 4, and the conclusion and recommendation are presented in Section 5.

2. Literature Review

Following the observed trend of COVID-19 outbreak and its spread across different countries, it became expedient to evaluate the global impact of the rising pandemic as it has become a major challenge to the world. While some assessed the global economic impact of COVID-19 (Maital & Barzani, 2020; McKibbin &

---

[4] https://www.bloomberg.com/news/articles/2020-02-28/global-stock-losses-hit-6-trillion-as-virus-fear-spreads-chart

[5] https://www.reuters.com/article/us-china-health-markets-global/going-viral-six-charts-and-the-6-trillion-loss-idUSKCN20M2F6

[6] https://www.bbc.com/news/business-51829852

Fernando, 2020; Ozili & Arun, 2020; Lee *et al.,* 2021; Shen et al., 2022), some established appropriate models for the assessment of the impact of the pandemic which could assist in drawing inferences for better policies (Atkeson, 2020a; Harris, 2020; Stock, 2020). Most of these studies generally confirmed that it has detrimental effects on the economy (Atkeson, 2020b; Barro *et al.,* 2020; Guerrieri *et al.,* 2020; Jordà *et al.,* 2020; Lee & Chen, 2020b; Lewis *et al.,* 2020; Ludvigson *et al.,* 2020; Maital & Barzani, 2020; McKibbin & Fernando, 2020; Ozili & Arun, 2020). Others have also shown the diverse impact of COVID-19 on firms (Bartik *et al.,* 2020; Fu & Shen, 2020; Hassan *et al.,* 2020), labour markets (Coibion *et al.,* 2020; Dingel & Neiman, 2020), income inequality (Schmitt-Grohé *et al.,* 2020), households (Baker *et al.,* 2020b), economic uncertainty (Baker *et al.,* 2020a), commodity markets (Gil-Alana & Monge, 2020; Liu *et al.*, 2020b) and asset markets (Alfaro *et al.,* 2020; Baker *et al.,* 2020c; Liu *et al.,* 2020c). Stock markets responded swiftly to the potential economic consequences of the disease in the early days of the outbreak, and these eventually graduated into large market movements within two weeks (Ramelli & Wagner, 2020b).

Goodell (2020) highlighted the economic costs of previous events which had similar characteristics to COVID-19. Drawing from the past therefore leads us to visualizing the potential financial costs of such significant events. On the impact of SARS outbreaks on stock markets, Nippani and Washer (2004) compared the performance of stock markets between the affected period and the period without SARS. Stock indices of stock markets in two out of eight countries were negatively affected. Using an event-study methodology (ESM), Chen *et al.* (2007) showed how the SARS outbreak caused a sharp decline and negative cumulative mean in the Taiwanese hotel stocks. Chen *et al.* (2018a) provided evidence that the integration in Asian stock markets between 1998 and 2008 must have been weakened by the SARS pandemic. During the outbreak of Ebola, stock prices of US companies that were connected with West African countries were predominantly affected (Ichev & Marinč, 2018). This shows that stock markets in disease epicenters are highly vulnerable to such crises because information about the disease influences investors' behaviour towards the risk they intend to bear.

Relationships between COVID-19 and stock markets were recently analyzed using available data. Sansa (2020) analyzed the impact of COVID-19 pandemic on Shanghai Stock Exchange and Dow Jones between 1st and 25th of March, 2020, but contrary to expectations, a significant positive relationship was confirmed between both stock markets and COVID-19. Zhang *et al.* (2020) observed a significant upward leap of stock market risks and high market volatility due to COVID-19. A statistical analysis of daily data from several countries between February and March 2020 showed that the correlation between stock markets and COVID-19 was low in February and highest in the first week of March when the pandemic peaked in Europe. This suggests that the reaction of stock returns to pandemics could be time-varying.

Some studies have established relationships between COVID-19 and stock markets with the aid of econometric techniques. Aslam *et al.* (2020), for instance, gave a network analysis of the 56 stock indices. Liu *et al.* (2020a) employed both event study mechanism and panel fixed effect regressions to assess 21 leading stock markets. The analysis revealed a negative impact on stock market indices. While market indices in most epicenters dropped after the virus outbreak, many Asian market indices recorded greater severity. Al-Awadhi *et al.* (2020) considered a panel of Chinese companies' stock markets, and reported that as both number of confirmed cases and deaths due to COVID-19 increased, stock returns fell. Al-Qudah and Houcine (2021) investigated the reaction of daily stock returns using panel data from six regions. The event study approach confirmed that daily stock markets reacted negatively to daily increase in the number of COVID-19 cases reported. This negative effect was found to be highest during the early stage of the pandemic. With the aid of the Maki (2012) cointegration technique on time series data, Zeren and Hizarci (2020) investigated the existence of cointegrating relationships between COVID-19 and the daily stock market indices: Cotation Assistée en Continu 40 (CAC40), Deutscher Aktienindex 30 (DAX30), Financial Times Stock Exchange (FTSE), Índice Bursátil Españo Index 35 (IBEX35), Milano Indice di Borsa (MIB), Korea Composite Stock Price Index (KOSPI) and Shanghai Stock Exchange (SSE). Cointegration was found between all the stock markets and deaths due to COVID-19. However, total cases of COVID-19 infections were not cointegrated with FTSE MIB, CAC40, and DAX30, but were cointegrated with SSE, KOSPI and IBEX 35.

COVID-19 caused stock prices to fall sharply, as observed by Yan (2020) in an analysis of a window of fifty trading days, beginning from January 20, 2020 to April 7, 2020. Evidence from Erdem (2020) also showed that COVID-19 has significant negative effects on markets index returns and positive effects on market volatilities. Khan *et al.* (2020) employed pooled ordinary least squares (OLS) regression, t-test and Mann-Whitney test to assess returns on 16 leading stock indices. Through a weekly analysis and comparing the returns of both pandemic and non-pandemic periods, it was evident that the market reacted negatively in both the short and long event window. Harjoto *et al.* (2021a) compared 53 emerging countries with 23 developed countries and found differences between the reactions of their indices, even though the number of fatalities recorded due to COVID-19 between January 14 and August 20, 2020 generally had negative effects on stock returns and also increased market volatility. Ashraf (2020) also confirmed a negative response of stock returns to the growth in the number of COVID-19 confirmed cases between January and April 2020. In other words, as the pandemic peaked in 64 countries, there was a decline in their stock returns. The link between stock market volatility and the pandemic was also analyzed by Baek *et al.* (2020), Bora and Basistha (2020), and Papadamou *et al.* (2020), all of whom found evidence of increased volatility sequel to the increased number of COVID-19 infections.

Researchers continue to find answers to the many questions surrounding the reaction of stock markets to the disease outbreak. Recent empirical indications suggest that other factors which influence investors' behaviour must have triggered the stock markets' negative reactions to the COVID-19 pandemic. For instance, anti-pandemic policies imposed in different countries induced shocks which impacted their financial markets (Baker *et al.*, 2020c; Naidenova *et al.*, 2020). Phan and Narayan (2020) theorized that markets react impulsively to unexpected news, while the release of more information returns the market to stability eventually. The negative stock returns and pronounced impacts of shocks on stocks were attributed to panic and uncertainty associated with the announcement (Salisu *et al.,* 2020; Xu, 2021). Markets' response to COVID-19-related news and uncertainty were asymmetric in some cases (Cepoi, 2020; Xu, 2021) whereby negative news caused decrease in stock returns. Declines in stock returns and the increased volatilities were further aggravated by a high culture of risk aversion, especially immediately after the announcement of a first case of COVID-19 (Fernandez-Perez *et al.,* 2021). Although negative shocks in global stock markets were due to the World Health Organization's announcement on COVID-19, policy response stimulated some positive abnormal returns, especially for US firms (Harjoto *et al.,* 2021b). Thus, the impact of the pandemic on stock markets has been subject to policy response to pessimism and bear markets situations (Topcu & Gulal, 2020). This is however subject to the expectations (Gormsen & Koijen, 2020) and level of trust in both government and citizens, such that the lower the level of trust, the higher the significance of stock volatility (Engelhardt *et al.,* 2021).

According to Rahman *et al.* (2021), in general, the Australian stock market reacted negatively to the announcement of the COVID-19 pandemic. Moreover, smaller, least profitable and value portfolios were the most negatively affected. Also, the response of stock indices to the pandemic outbreak is dependent on the nature of industry being considered as indicated by Liu *et al.* (2020), Mazur *et al.* (2021) and Narayan *et al.* (2022). Mazur *et al.* (2021), in an investigation of stock market performance of some US industries found positive returns for some industries which specialize in consumables, while real estate and tourism industries experienced significant declines in their stock values. Narayan *et al.* (2022) employed a quantile regression and observed that the impact of COVID-19 on stock market returns vary from one sector to another. For instance, while their analysis showed that the health sector and information technology experienced positive stock returns, energy and financial sectors had negative returns. Liu *et al.* (2020) used an event study method to assess the Chinese and Asian stock returns for 10 days succeeding the outbreak of the COVID-19 pandemic in China. Significant positive returns were noticed in the health sector and some industries which specialize in consumables and information technology, whereas, the financial sector, real estate, tourism sector and energy sector suffered significant declines in their stock values.

Izzeldin *et al.* (2021) have proven, from their assessment of stock markets across the group of seven (G7) countries, that the impact of the COVID-19 pandemic is not similar to the impact of previous disease outbreaks, but could be matched to the impact of financial crises. Therefore, with respect to the characteristics and consequences of past disease outbreaks and past global financial crises (Goodell, 2020), we find indications of a global emergency related to human health concerns. The COVID-19 pandemic is either directly or indirectly connected to shocks in the stock markets, but may not follow the same pattern of relationship as previous diseases outbreaks or major global financial crises seen in the past. This therefore suggests the need for more investigation into the pattern of stock markets response to such a large-scale event. Our study significantly differs from previous studies in the choice of econometric techniques adopted. Instead of the conventional cointegration approaches, we adopt a time-varying cointegration analysis which is especially useful for capturing infection patterns that vary with time. We also improve on previous studies by employing the wild bootstrap likelihood ratio test that is capable of generating time-varying results that are robust to non-normality, small sample bias, endogeneity and conditional heteroscedasticity, all common features of the financial time series. Finally, we test the sensitivity of the selected stock markets to the unanticipated outbreak of COVID-19 within an event study set-up. This battery of techniques is sufficient for robust inferences.

3. Methodology

3.1 Time-Varying Cointegration Analyses

Determining the presence of comovements via cointegration tests has become widely accepted since the seminal work of Engle and Granger (1987). Although cointegration is quite appealing as a conceptual framework for modelling comovements and interpreting models containing nonstationary data, it has however been mostly unsuccessful in the practical domain (Park & Hahn, 1999; Cavaliere *et al.,* 2010a; Cavaliere *et al.,* 2018). According to Park and Hahn (1999), more often than not, results obtained from cointegration tests suggest the absence, not the presence, of cointegration. This pattern is mostly caused by empirical model misspecifications resulting from parameter instabilities. These parameter instabilities play an important role in cointegrated models, as they define the long-term comovements between variables and are estimated using data series with relatively long time spans (Park & Hahn, 1999). In summary, relationships between variables are likely to vary with time when studied over a relatively long period (Quintos & Phillips, 1993; Hanson, 2002; Lee *et al.,* 2014; Lv et al., 2021).

To deal with the limitation of the conventional cointegration techniques, this study employs the time-varying cointegration approach proposed by Bierens and Martins (2010) and Martins (2018). This approach considers cointegrating relationships that evolve smoothly over time and is thus useful for modelling comovements that slowly evolve with time. The superiority of this approach over conventional cointegration approaches is in its robustness to parameter instabilities, nonlinearities, regime shifts and time variations. Ho *et al.* (2020) show that time-varying techniques are particularly useful in studying the impacts of COVID-19 due to the fact that as the spread of the disease increased, citizens and governments were forced to change their behaviour. Ho *et al.* (2020) also show that outbreaks of diseases generally display patterns that vary with time. T the number of cases is initially few and far between. The growth rate of infections is however high and increases at an exponential rate till a turning point is reached at which there are no new hosts for the pathogen, either because they are already immune or are already protected from being infected due to policies such as social distancing and wearing of face masks.

Following Bierens and Martins (2010), Chen *et al.* (2018b) and Martins (2018), a time-varying VECM(p) with a drift which extends the Johansen (1988, 1991, 1995) cointegration method in such a way that it accommodates multiple cointegration relationships, is given as follows;

$$\Delta Y_t = \mu + \Pi_t' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \, \Delta Y_{t-j} + \varepsilon_t \quad t = 1, \ldots, T \tag{1}$$

Where Y_t, is a k x 1 vector of variables observed at time t, Δ is a difference operator, μ represents the k x 1 vector of intercepts, $\varepsilon_t \sim N_k[0, \Omega]$ and T refers to the number of observations. The objective is to test the null hypothesis of time-invariant cointegration ($\Pi_t' = \Pi' = \alpha\beta'$) where α and β are fixed k x r matrices with rank r, against the alternative hypothesis of time-varying cointegration ($\Pi_t' = \alpha\beta_t'$) where α is as it was before but β_t''s are time-varying k x r matrices with rank r. For both null and alternative hypotheses, Ω and Γ_j's are fixed k x k matrices and $1 \leq r \leq k$. For this study, r =1, while k = 2.

Based on the assumption that the discrete time β_t function is smooth (detailed explanation can be found in Bierens & Martins, 2010), it can be specified as:

$$\beta_t = \beta_m\left(\frac{t}{T}\right) = \sum_{i=0}^{m} \xi_{i,T}\, P_{i,T}\,(t) \tag{2}$$

For some fixed m < T-1, where the orthonormal Chebyshev time polynomials ($P_{i,T}\,[t]$) are given as $P_{0,T}(t) = 1, P_{i,T}(t) = \sqrt{2}\cos(i\pi\,(t\text{-}0.5)/T$, t =1, 2,⋯,T, i = 1, 2, ⋯, m, and $\xi_{i,T} = \frac{1}{T}\sum_{t=1}^{T} \beta_t\, P_{i,T}\,(t)$ represent unknown k x r matrices. Consequently, VECM(p) model specified in equation (1) can be more conveniently specified as:

$$\Delta Y_t = \mu + \alpha\xi' Y_{t-1}^{m} + \Gamma X_t + \varepsilon_t \tag{3}$$

Where $\xi' = (\xi_0', \xi_1', \ldots, \xi_m')$ represents an r x (m+1)k matrix of rank r and $Y_{t-1}^{m} = (Y_{t-1}', P_{1,T}[t]Y_{t-1}', \; P_{2,T}\,[t]\; Y_{t-1}', \cdots, P_{m,T}[t]\; Y_{t-1}')'$ and
$X_t = (1, \Delta Y_{t-1}', \cdots, \Delta\, Y_{t-p+1}')$.

To test the null of time-invariant cointegration against the alternative of time-varying cointegration as defined by equation (3), Bierens and Martins (2010) introduced an LR test statistic in which under the null hypothesis, the restricted model is of the form $\xi' = (\beta'\; 0_{r,k.m})$ and is asymptotically χ^2_{mkr} distributed. The authors however also discovered that the test suffers from size distortions such that the right null of time-invariant cointegration tends to be over rejected. To deal with this problem, Martins (2018) proposed as alternative, parametric bootstrap implementations of the original LR test and showed that the bootstrap approximation to the finite-sample distribution produces very accurate results. The restricted and unrestricted wild (Cavaliere *et al.,* 2010a, 2012) and the iid (Swensen, 2006) parametric bootstrap versions of the test statistic obtained from equation (3) are therefore estimated in this study.

The wild bootstrap test for time-varying cointegration based on unrestricted residuals is constructed as follows; (i) bootstrap pseudo-disturbances $(\varepsilon_t^b), t = p + 1, \ldots, T$ and $b = 1, \ldots$ Bare obtained from residuals $(\hat{\varepsilon}_t)$ according to $\varepsilon_t^b = \hat{\varepsilon}_t w_t$, where $\{w\}_{t=p+1}^{T}$ is an i.i.d. N(0,1) scalar sequence. (ii) A bootstrap sample $\{\Delta Y_t^b\}_{t=1}^{T}$ is generated recursively from equation (4) with initial values given as $Y_t^b = Y_t, t = 1, \ldots, p$.

$$\Delta Y_t^b = \hat{\mu} + \hat{\Pi}' Y_{t-1}^b + \sum_{j=1}^{p-1} \hat{\Gamma}_j \, \Delta Y_{t-j}^b + \varepsilon_t^b \quad t = 1, \dots, T \tag{4}$$

(iii) The bootstrap likelihood ratio test statistic ($\mathrm{LR}_{m,T}^{b} = T \sum_{j=1}^{r} \ln \left[\frac{1-\hat{\lambda}_{0,j}^{b}}{1-\hat{\lambda}_{m,j}^{b}} \right]$) is generated from the bootstrap sample constructed in step ii. $\hat{\lambda}^{b}$s represents the bootstrap versions of the ordered generalized eigenvalues ($\hat{\lambda}$). (iv) The bootstrap critical values are calculated and the p-values ($p_{m,T}^{b}$) corresponding to the test statistics ($\mathrm{LR}_{m,T}^{tvc}$) are calculated as $p_{m,T}^{b} = 1 - F_{m,T}^{b}(\mathrm{LR}_{m,T}^{tvc})$. (v) Given a particular significance level (δ), the null of standard time-invariant cointegration is rejected if $\tilde{p}_{m,T}^{b} < \delta$.

Swensen's iid version is almost identical to the wild bootstrap, the only difference being that the bootstrap pseudo-disturbances (ε_t^b) are randomly selected with replacement from the residuals ($\hat{\varepsilon}_t$). The restricted alternative of all the three time-varying cointegration approaches are also estimated. The only variation in the restricted versions is that the bootstrap pseudo-disturbances are extracted from the restricted residuals and the bootstrap sample is constructed from the same equation with the estimated coefficients generated under the null hypothesis.

3.2 The Wild Bootstrap Likelihood Ratio (WBLR) Test

To examine the ability of COVID-19 to predict stock market performance in the selected countries, the newly developed WBLR test of Kim and Shamsuddin (2020) is employed. The test produces time-varying results that are robust to non-normality, small sample bias, endogeneity and conditional heteroscedasticity, all common features of the financial time series. WBLR is a time-varying approach which adopts the wild bootstrap LR test with rolling sub-sample windows. The rolling sub-sample windows method gives the opportunity to detect the time-varying (or dynamic) predictive ability of predictors. Moreover, the rolling sub-sample windows method adequately prevents data snooping bias (Hsu & Kuan, 2005) and is also robust to potential structural instabilities and nonlinearities in the time series (Lazăr, Todea & Filip, 2012). The wild bootstrap test is based on the LR test in a restricted vector autoregression (VAR) form of predictive regression in which rate of COVID-19 infections serves as the persistent predictor employed in predicting stock returns in the selected countries.

$$R_t = \alpha_0 + \beta I_{t-1} + \varepsilon_t \tag{5}$$

Where R_t denotes stock markets returns, and I, the rate of change in COVID-19 infections.

To take endogeneity into account, the predictor is expressed thus:

$$I_t = \alpha_1 + \theta I_{t-1} + \gamma_t \tag{6}$$

In equations (5) and (6), it is assumed that I is weakly stationary, θ measures the persistence of the regressor and the null of unpredictability is given as $H_0: \beta = 0$.

The augmented regression method (ARM) employed assumes that the error terms in equations (5) and (6) are linked in the following manner: $\varepsilon_t = \emptyset\gamma_t + e_t$. γ_t and e_t are normally distributed and independent, with fixed variance and mean of zero.

The bias-adjusted estimations of equation (6) is conducted in the following manner:

$$I_t = \hat{\alpha}_1^a + \hat{\theta}^a I_{t-1} + \gamma_t^a \tag{7}$$

Where $\hat{\alpha}_1^a$ and $\hat{\theta}^a$ denote the bias-adjusted estimators for α and θ obtained via the asymptotic formulae of Stine and Shaman (1989), and γ_t^a represents the corresponding residual.

Equation (5) is then further augmented in the following manner:

$$R_t = \alpha_0 + \beta I_{t-1} + \emptyset\gamma_t^a + e_t \tag{8}$$

In equation (8), the least squares (LS) estimator for β is the bias-adjusted ARM estimator. ARM estimators are known to exhibit better small sample properties when compared with traditional least squares estimators (see Amihud *et al.,* 2010; Kim, 2014; Kim & Shamsuddin, 2020). Equations (5) and (6) are treated as a restricted VAR which is estimated via the estimated generalized least squares (EGLS) method instead of the LS method. This choice is due to the superiority of EGLS in addressing endogeneity resulting from contemporaneous correlations between the error terms. The null hypothesis of no predictability ($H_0: \beta = 0$) is tested using the LR test specified thus:

$$LR = T[log(det(\Sigma(H_0))) - log(det(\Sigma(H_1)))] \tag{9}$$

Where T = sample size, det() = matrix determinant, $\Sigma(H_i)$ = EGLS residual covariance matrix for $H_i (i = 0 \text{ or } 1)$. To ensure robustness against small sample bias which often affects LR test, a bootstrap alternative is employed. For a sample $\{(R_t,\ P_t)\}_{t=1}^{T}$, the bootstrap test is conducted over 3 steps. In the first step, the parameters are estimated through EGLS under $H_0: \beta = 0$ in equations (5) and (6). The restricted parameter estimators are given as: $\hat{\alpha}_0, \hat{\alpha}_1^a, 0, \hat{\beta}, \hat{\theta}$, while $\hat{\varepsilon}_t$ and $\hat{\gamma}_t$ represent the residuals under H_0. As a second step, artificial data generation through residual resampling under H_0 is carried out thus:

$$R_t^* = \hat{\alpha}_0 + \hat{\beta} I_{t-1}^* + \hat{\varepsilon}_t^* \tag{10}$$

$$I_t^* = \hat{\alpha}_1 + \hat{\theta} I_{t-1}^* + \hat{\gamma}_t^* \tag{11}$$

Where $(\hat{\varepsilon}_t^*, \hat{\gamma}_t^*)$ are the random resamples obtained from $\{(\hat{\varepsilon}_t, \hat{\gamma}_t)\}_{t=1}^{T}$. $\{(R_t^*, P_t^*)\}_{t=1}^{T}$ is therefore generated recursively from the resampled residuals in a process that takes R_1, P_1 as the initial values. As a final step, the bootstrap LR test statistic is computed with the formula:

$$LR^* = T[log(det(\Sigma^*(H_0))) - log(det(\Sigma^*(H_1)))] \tag{12}$$

Where $\Sigma^*(H_i)$ = EGLS residual covariance matrix obtained from $\{(R_t^*, P_t^*)\}_{t=1}^{T}$ under $H_i (i = 0 \text{ or } 1)$.

The last two steps are repeated G times to generate the bootstrap distribution $\{LR^*(i)\}_{i=1}^{G}$. Bootstrap p-values are then generated as the part of $\{LR^*(i)\}_{i=1}^{G}$ greater than the LR value obtained from equation (12). The H_0 is rejected at a significance level ($\propto$) if the p-value obtained is smaller than $\propto$. The Mammen (1993) wild bootstrap is selected for its ability to strengthen the bootstrap LR test against small sample properties and heteroskedasticity.

3.3 Event Study Analysis

Finally, we examine the sensitivity of the selected stock markets to the unanticipated outbreak of COVID-19 within an event study set-up. The day of the announcement of the first case in each country is taken as the event day. Following Liu *et al.* (2020a) and Wu *et al.* (2021), we set up thirteen event windows to evaluate the effect of the outbreak across different periods. The windows cover a period of thirteen weeks following the event day in each country, made up of 90 working days grouped thus: 1st week/window after the event day (0,6), 2nd week/window after the event day (7,13), 3rd week/window after the event day (14,20), and so on. An estimated window of 80 working days prior to the event day was adopted. To begin with, the natural logarithms of the stock returns are obtained as follows:

$$R_{j,t} = ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) \tag{13}$$

$$R_{m,t} = ln\left(\frac{P_{m,t}}{P_{m,t-1}}\right) \tag{14}$$

In equation (13), $R_{j,t}$ represents the return of a particular j country's stock price index, $P_{j,t}$ represents the closing price of the index at time t and $P_{j,t-1}$ represents the closing price of the index at time t-1. In equation (14), $R_{m,t}$ refers to market returns which is the Standard and Poor's (S&P) Global 1200 index. It is a free-float weighted stock market index covering international equities from 31 countries and accounting for approximately 70% of the world's stock market capitalization. $P_{m,t}$ refers to the closing price of the index at time t, while $P_{m,t-1}$ refers to the closing price at time t-1. To estimate the expected stock returns, the market model is employed. As used in this study, the model considers the past performance of a specific country's stock market and its sensitivity to global market movements reflected by the S&P Global 1200 index. The expected returns are obtained using the ordinary least squares estimation based on the regression model:

$$R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t} \tag{15}$$

Where $\widehat{\alpha}_j$ and $\widehat{\beta}_j$ are the coefficient estimates required to compute the expected returns and abnormal returns as follows:

$$\hat{R}_{j,t} = \hat{\alpha}_j + \hat{\beta}_j R_{m,t} \tag{16}$$

(16)

$$AR_{j,t} = R_{j,t} - \hat{R}_{j,t} \tag{17}$$

where $\hat{R}_{j,t}$ is the expected return and $AR_{j,t}$ is the abnormal return on a particular day (t) within the event window. Abnormal returns are calculated by employing the market model methodology of Dodd and Warner (1983) and Brown and Warner (1985).

The cumulative abnormal return (CAR) over a given window (t_0, t_1) is then calculated thus:

$$CAR_{(t_0,t_1)} = \sum_{t=t_0}^{t_1} AR_{j,t} \tag{18}$$

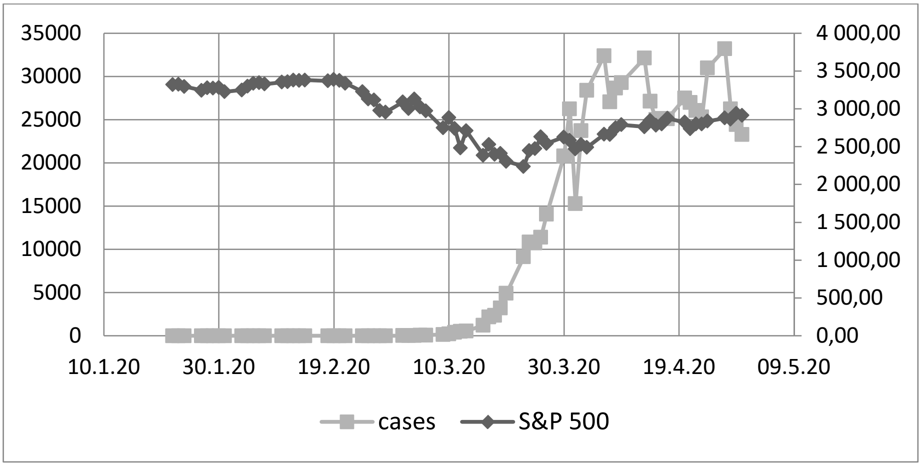
4. Data Analysis and Empirical Results

4.1 Data Description

Data used in this study include the daily stock price indices and returns for the USA (Standards & Poor 500 index), Italy (FTSE MIB), Spain (IBEX 35) and Germany (DAX 30), as well as the number of COVID-19 daily infections recorded in the same set of countries over a period of 90 working days starting from the date of first occurrence of the disease in each of these countries. In the USA, the 90 working days period starts from 22-01-2020. In Italy, it starts from 31-01-2020. In Spain, the period begins on 03-02-2020. In Germany, it begins from 27-01-2020. The selected countries were among the top countries with the most infections as at the time of writing this article. Data on the selected stock price indices are downloaded from www.investing.com, while data on the daily infection rates was obtained from the website of Johns Hopkins University Center for Systems Science and Engineering (HJU CSSE).

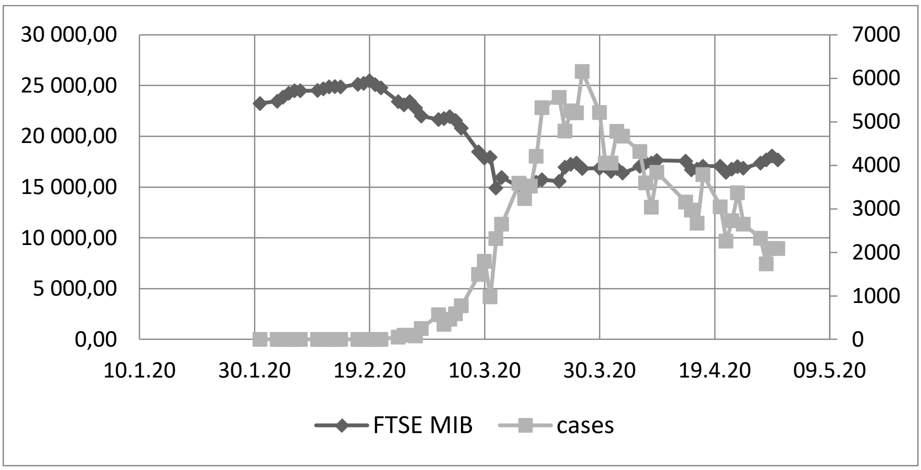
By our compilation, we juxtapose the trend of COVID-19 case confirmations in each of the countries of focus with the trend of stock market indices of these countries in Figures 1 – 4. When the USA recorded hundreds of COVID-19 cases in February, there was a fall in the Standard and Poor's (S&P) 500 index by about 30% between the third week of February and mid-March. Consequent upon economic interventions, the market eventually began to recover in April and the recovery has been sustained, an indication of the resilience of the US stock market to the outbreak. As the markets are forward looking, the reaction of the Federal Reserve was quite aggressive and fast. Some of the important steps taken include the reduction of the federal fund rate, the issuance of forward guidance, the resumption of massive quantitative easing program, and the resumption of the primary dealer credit facility program, amongst others. Seeing this, investors might have been assured in advance that despite the current surge of COVID cases, the economy will do well in the future. Prior to the first reported case of COVID-19 in their respective countries, the Italian, Spanish and German stock markets had good performances. However, the FTSE MIB index fell by approximately 40%, from about 25,000 in the third week of February to 14,800 in mid-March, and the IBEX 35 fell by about 35%, from 9,960 to 6,470 in the same period. By mid-March, thousands of cases were already being recorded in both Italy and Spain. In the same period, DAX 30 also saw a nosedive of about 36% in stock index, plunging from about 13,780 to about 8,740. These European stock indices started a slow recovery from the last week of March 2020, with DAX 30 outperforming the others.

Figure 1 Trends of COVID-19 Infections and Stock Price Performance in USA



Notes: Cases are measured on the primary axis and stock prices are measured on the secondary axis.

Figure 2 Trends of COVID-19 Infections and Stock Price Performance in Italy



Notes: Cases are measured on the secondary axis and stock prices are measured on the primary axis.

Figure 3 Trends of COVID-19 Infections and Stock Price Performance in Spain

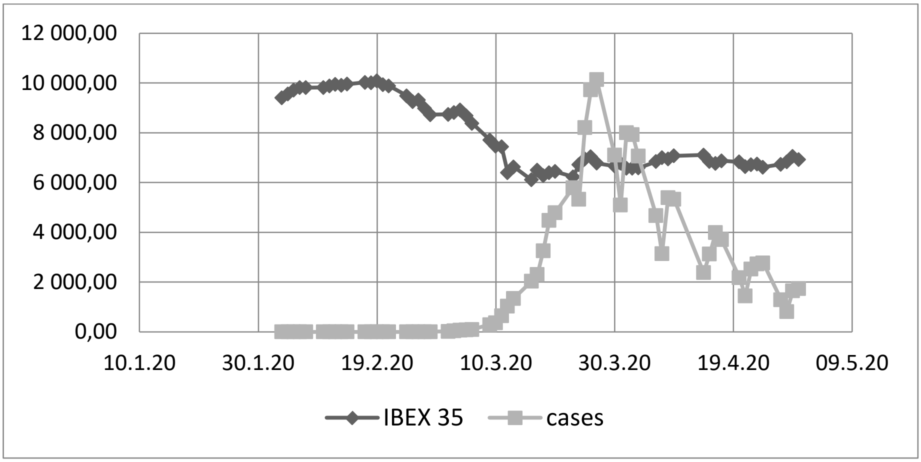
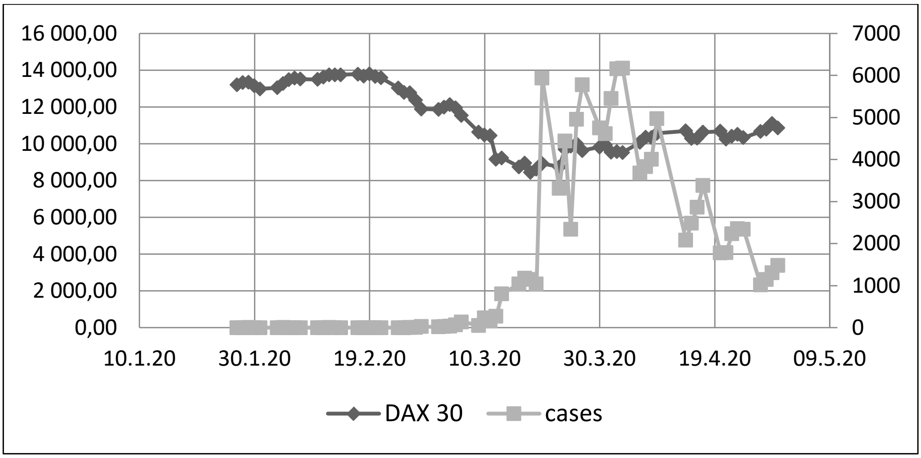


Figure 4. Trends of COVID-19 Infections and Stock Price Performance in Germany



Notes: Cases are measured on the secondary axis and stock prices are measured on the primary axis.

4.2. Time-Varying Cointegration Results

Before performing the time-varying cointegration analysis, we examine the time-series properties of both COVID-19 daily infections and the stock price indices via the Dickey–Fuller generalized least-squares [DF-GLS, Elliott *et al.* (1996)] and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS, 1992) unit root tests. The tests outcomes are presented in Table 1. The conclusion reached on the basis of the results is that both series are I(1) processes in all the selected countries. We thus proceed with the time-varying cointegration analyses.

Table 2 reports the likelihood ratio test statistics for the standard cointegration test of Johansen (1988), the restricted and unrestricted versions of the wild (Rademacher and Mammen) bootstrap time-varying cointegration and Swensen's iid bootstrap time-varying cointegration, with the degree of the Chebyshev time polynomial m. During empirical analyses, for the cointegrating rank r ≤ k, k is set to 2, and r is set to 1. M ranges from 1-13 = T/10, and bootstrap pseudo samples (B) is set to 1000. Following Bierens and Martins (2010) and Martins (2018), we set p to 1 and select the value of m according to the Hannan–Quinn information criterion. On the basis of the outcome of the time-invariant standard cointegration tests, a comovement between stock prices and COVID-19 is detected only in Italy. However, the presence of strong time-varying cointegration was detected in all the selected countries. Based on the computed LR statistics and their corresponding p-values, we are able to reject the null hypothesis of time-invariant cointegration in all the selected countries. These results confirm that there are strong comovements between COVID-19 infections and stock price indices in the USA, Italy, Spain and Germany. The implication of the empirical finding is that there is a strong link between COVID-19 pandemic and stock prices. Therefore, the steadiness of the financial markets is not independent of exogenous factors which have adverse health effects that can influence investors' decisions.

Table 1 Unit Root Test Results

Variable	*Test type*	*Intercept*		*Conclusion*
		Level	*First diff.*	
COVID-19 infections in USA	DF-GLS	-1.163	-4.743***	I(1)
	KPSS	0.922***	0.205	I(1)
Stock price index for USA	DF-GLS	-0.531	-11.800***	I(1)
	KPSS	0.738**	0.164	I(1)
COVID-19 infections in Italy	DF-GLS	-0.055	-4.065***	I(1)
	KPSS	0.903***	0.194	I(1)
Stock price index for Italy	DF-GLS	-0.106	-7.735***	I(1)
	KPSS	0.767***	0.141	I(1)
COVID-19 infections in Spain	DF-GLS	-0.289	-4.344***	I(1)
	KPSS	4.637***	0.205	I(1)
Stock price index for Spain	DF-GLS	-0.112	-3.028***	I(1)
	KPSS	0.806***	0.155	I(1)
COVID-19 infections in Germany	DF-GLS	-0.965	-2.612**	I(1)
	KPSS	0.674**	0.142	I(1)
Stock price index for Germany	DF-GLS	-0.285**	-6.813***	I(0)
	KPSS	0.649**	0.132	I(1)

Notes: (1) *** P < 0.01, ** P < 0.05, * P < 0.1. (2) I(0) = stationarity at level. I(1) = stationarity after first difference.

Table 2 Cointegration Tests

Country	*Approach*	m^*_{HQ}	*STI*	*Wild (Rademacher)*	*Wild (Mammen)*	*Swensen's iid*
USA	Unrestricted	12	(0.509)	✓	✓	✓
	Restricted			✓	✓	✓
Italy	Unrestricted	12	(0.095)	✓	✓	✓
	Restricted			✓	✓	✓
Spain	Unrestricted	11	(0.285)	✓	✓	✓
	Restricted			✓	✓	✓
Germany	Unrestricted	12	(0.166)	✓	✓	✓
	Restricted			✓	✓	✓
China	Unrestricted	13	(0.146)	✓	✓	✓
	Restricted			✓	✓	✓

Notes: (1) STI is the standard time-invariant cointegration (Johansen, 1988) case m=0. (2) Wild (Rademacher) is the bootstrap version based on the Rademacher distribution. (3) Wild (Mammen) is the bootstrap version based on the Mammen (1993) two-point distribution. (4) All 3 tests are under the null hypothesis of time-invariant cointegration distributed as χ2(rmk). (5) ✓ represents significance at 1%. (6) $\mathrm{m}^*_{\mathrm{HQ}}$ represents the value of m selected by the Hannan–Quinn information criterion.

4.3 The WBLR Test Results

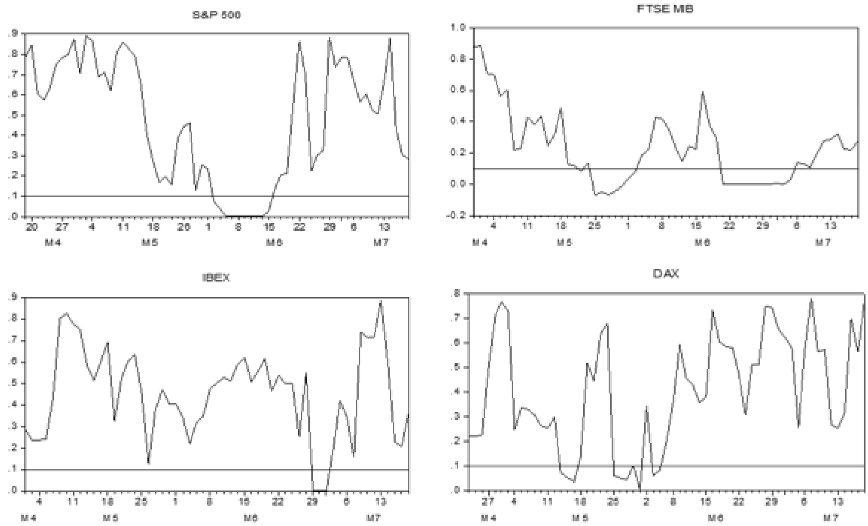
To evaluate the ability of the COVID-19 pandemic to predict stock market performance, we employ the WBLR approach. The test is applied to the pairs of COVID-19 infection rates of change and stock market returns in each of the five most affected countries. The length of the sub-sample window is determined as 60 daily observations in each case[7]. After the wild bootstrap LR test is applied on the first sub-sample period, the window moves forward by one day and the test is reapplied. This process is continued till the end of the sample period, and the wild bootstrap LR test p-values for each sub-sample are obtained as a measure of dynamic predictive ability of changes in the rate of infection for stock market returns. This process enables us to isolate episodes of high degree of predictability (statistical significance).

Figure 5 plots the p-values of the wild bootstrap LR test applied on returns series for $H_0: \beta = 0$, The p-value below the horizontal line indicates the rejection of the null of unpredictability at 10% significance level i.e. returns are statistically predicted. As reflected by the amplitudes of the graphs, the p-values are below the 10% significance line on a few occasions in each of the countries. This is an indication that the rejection of the null hypothesis of no predictability is recorded at one time or the other in all of the countries sampled. This outcome shows that changes in the rate of infection exhibit some degree of predictive power over stock returns across the sampled countries. The implication of this finding is that the response of the selected stock markets to the COVID-19 outbreak is heterogeneous

[7] Kim, Shamsuddin and Lim (2011), Charles *et al.* (2017), and Khuntia and Pattanayak (2018) empirically show that the test results are generally insensitive to changes in window length, thus, different window lengths are not considered.

and stock returns are generally relatively sensitive to the evolution of COVID-19 infections.

Figure 5 Wild Bootstrap LR Test p-values



Notes: The null hypothesis is that changes in the rate of COVID-19 infections do not have the ability to predict stock market returns. Horizontal line represents the 10% significance level.

4.4 Event Study Results on Cumulative Abnormal Returns

Comparisons of the cumulative abnormal returns recorded across the five stock markets over different windows are provided in Table 3. With regards to the S&P 500, significant negative cumulative abnormal returns are detected over the 6th, 9th, 10th and 11th windows [(35,41), (56,62), (63,69), (70,76)]. As for FTSE MIB, significant negative cumulative abnormal returns are recorded in the 4th, 5th, 8th and 11th windows [(21,27), (28,34), (49,55), (70,76)]. Significant positive abnormal returns are however detected in the 12th window (77,83). Concerning IBEX 35, significant negative cumulative abnormal returns occurred in the 4th, 6th and 8th windows [(21,27), (35,41), (49,55)], whereas, significant positive cumulative abnormal returns occurred in the 12th window (77,83). The DAX 30 price index recorded significant negative cumulative abnormal returns in the 4th, 5th, 6th and 7th windows [(21,27), (28,34), (35,41), (42,48)]. Significant positive cumulative abnormal returns were however recorded in the 12th and 13th windows [(77,83), (84,90)].

Overall, the results show that the reaction of the stock markets in the selected countries to the outbreak of COVID-19 pandemic is predominantly negative. The results also suggest to a large extent that the three European Union member countries sampled (Italy, Spain and Germany) are economically integrated as the pattern of the reaction of their stock markets to the outbreak of the pandemic is quite similar. All three of them began to experience significant downturns in their market returns over the fourth event window following the announcement of COVID-19. All three of them also recorded significant upturns in their market returns, for the first time following the outbreak, in the 12th window. The fact that the USA stock market only became significantly negative in the 6th window is an indication that the country's stock market was more resilient to the impact of the outbreak than the other stock markets.

Table 3 Cumulative Abnormal Returns in the Event Windows

Stock price indices	CAR(4th window)	t-statistics
FTSE MIB	-0.169***	-5.241
IBEX 35	-0.033**	-1.967
DAX 30	-0.041**	-2.066
Stock price indices	CAR(5th window)	t-statistics
FTSE MIB	-0.142***	-5.207
DAX 30	-0.100***	-4.111
Stock price indices	CAR(6th window)	t-statistics
S&P 500	-0.032**	-2.040
IBEX 35	-0.064***	-3.097
DAX 30	-0.110***	-5.348
Stock price indices	CAR(7th window)	t-statistics
DAX 30	-0.054***	-2.622
Stock price indices	CAR(8th window)	t-statistics
FTSE MIB	-0.057***	-2.652
IBEX 35	-0.059***	-3.010
Stock price indices	CAR(9th window)	t-statistics
S&P 500	-2.310***	-10.776
Stock price indices	CAR(10th window)	t-statistics
S&P 500	-0.074***	-3.429
Stock price indices	CAR(11th window)	t-statistics
S&P 500	-0.300***	-10.105
FTSE MIB	-0.038**	-1.979
Stock price indices	CAR(12th window)	t-statistics
FTSE MIB	0.055***	2.860
IBEX 35	0.061***	3.378
DAX 30	0.061***	2.694
Stock price indices	CAR(13th window)	t-statistics
DAX 30	0.042**	2.011

Notes: (1) *** P < 0.01, ** P < 0.05, * P < 0.1. (2) the generalized rank t-test that is robust to cross correlation of returns, serial correlation of returns and event-induced volatility is reported.

5. Conclusions

This study contributes to the growing body of literature on the impact of the COVID-19 pandemic in a number of ways. First, we empirically tested for relationships between COVID-19 infections and the performances of S&P 500 (USA), FTSE MIB (Italy), IBEX 35S (Spain), DAX 30 (Germany) and Shanghai Composite Index (China) by using a time-varying cointegration technique then we tested the nature of this relationship through the wild bootstrap likelihood ratio (WBLR) test. Both tests are robust to parameter instabilities, nonlinearities, non-stationarity, regime shifts and time variations that may have characterized the stock market during the study period. The results indicated that there is a strong relationship between COVID-19 infections and stock price indices in all four selected countries. In testing the nature of this relationship, we also confirmed that changes in the rate of COVID-19 infections predict stock returns in the selected countries. We further employed an event study analysis to show that the reaction of the stock markets to the outbreak of the COVID-19 pandemic is predominantly negative in all the sampled countries. Our findings align with that of Iglesias (2022) which concludes the US stock market was the most resilient because the US was the only country that financial markets could trust to positively respond to the pandemic.

Also, as detected through the event study analysis conducted, first, the reaction of the stock markets of the three European Union member countries included in the study to the pandemic is quite similar, suggesting that countries that are regionally and economically integrated are likely to experience relatively similar effects. Second, the results showed the USA stock market to be the most resilient to the impact of the outbreak.

The strong interconnectedness between the stock markets and COVID-19 is due to a number of reasons. First, the COVID-19 pandemic is a black swan event (Ahmad *et al.,* 2021). Black swan events are regarded as occurrences that are possible but unpredictable based on past evidence. Characterized by rarity and disruptive tendencies, black swan events are generally recognized as causes of volatility in stock market returns (Lin & Tsai, 2019). The unpredictable nature of black swan events makes them difficult to adequately prepare for. Second, it is well established that stock markets move with speculations (Mei *et al.,* 2009). One may thus expect that periods following the announcement of the disease would be followed by downturns in stock returns due to fear and uncertainty surrounding the disease. The fear and uncertainty surrounding the COVID-19 pandemic is even further amplified because of its highly contagious nature and the non-negligible mortality rate recorded among those infected (Salisu & Akanni, 2020). Third, the downturn in stock market returns is directly connected with the extreme containment policies instituted to bring the spread of the disease under control (Gu *et al.,* 2022). Travel bans and stay-at-home orders have adversely impacted manufacturing, entertainment, tourism, oil and gas, transportation, agriculture and trade, among others.

It is worthy of mention that this study is an initial analysis of stock market reactions to the COVID-19 pandemic. There are therefore several limitations to our study. For instance, due to the relatively short event window, we were only able to study the short-term impact of the pandemic on stock markets. We were also not able to include control variables. There is also the possibility that stock markets' reactions to the pandemic might be asymmetric in nature; after all, it is widely believed that responsiveness to bad news often outweigh that of good news. This was not accounted for in our study. Moreover, there is likely to be a strong connection between the pandemic-induced fear and the overall impact of the outbreak on the stock market. This was also not explicitly accounted for in our study. We therefore suggest these limitations as potential areas for further empirical research as relevant data become more available. Furthermore, the experience in the early countries may already be priced in within the first window of the European countries. Also, the development on the US market might have played a part in the reactions noticed in the other markets.

LIST OF ABBREVIATIONS

ARM	Augmented regression method
CAC40	Cotation Assistée en Continu 40
CAR	cumulative abnormal returns
COVID-19	Coronavirus Disease 2019
DAX30	Deutscher Aktienindex 30
DF-GLS	Dickey–Fuller generalized least-squares
EGLS	Estimated generalized least squares
ESM	Event-Study Methodology
FTSE	Financial Times Stock Exchange
G7 countries	Group of seven countries
HJU CSSE	Johns Hopkins University Center for Systems Science and Engineering
IBEX35	Índice Bursátil Españo Index 35
KOSPI	Korea Composite Stock Price Index
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LS	least squares
MIB	Milano Indice di Borsa
OLS	Ordinary least squares
SARS	Severe Acute Respiratory Syndrome
S&P	Standard and Poor's
SSE	Shanghai Stock Exchange
VAR	Vector autoregression
WBLR	The wild bootstrap likelihood ratio
WHO	World Health Organization

REFERENCES

Ahmad W, Kutan AM, Gupta S (2021): Black Swan Events and COVID-19 Outbreak: Sector Level Evidence from the US, UK, and European Stock Markets. *International Review of Economics & Finance*, *75:*546-557.

Al-Awadhi AM, Al-Saifi K, Al-Awadhi A, Alhamadi S (2020): Death and Contagious Infectious Diseases: Impact of the COVID-19 Virus on Stock Market Returns. *Journal of Behavioural and Experimental Finance,* 100326.

Alfaro L, Chari A, Greenland AN, Schott PK (2020): *Aggregate And Firm-Level Stock Returns during Pandemics, in Real Time* (No. w26950). National Bureau of Economic Research.

Al-Qudah AA, Houcine A (2021): Stock Markets' Reaction to COVID-19: Evidence from the Six WHO Regions. *Journal of Economic Studies*. (In press). doi: 10.1108/JES-09-2020-0477

Amihud Y, Hurvich CM, Wang Y (2010): Predictive Regression with Order-P Autoregressive Predictors. *Journal of Empirical Finance*, *17*(3):513-525.

Ashraf BN (2020): Stock markets' reaction to COVID-19: Cases or Fatalities?. *Research in International Business and Finance*, *54:*101249.

Aslam F, Mohmand YT, Ferreira P, Memon BA, Khan M, Khan M (2020): Network Analysis of Global Stock Markets at the Beginning of the Coronavirus Disease (Covid-19) outbreak. *Borsa Istanbul Review*, *20(1):*S49-S61.

Atkeson A (2020a): *How Deadly Is COVID-19? Understanding The Difficulties with Estimation of Its Fatality Rate* (No. w26965). National Bureau of Economic Research. doi: 10.3386/w26965

Atkeson A (2020b): *What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios* (No. w26867). National Bureau of Economic Research. doi: 10.3386/w26867

Baek S, Mohanty SK, Mina G (2020): COVID-19 and Stock Market Volatility: An Industry Level Analysis. *Finance Research Letters*, 37:101748.

Baker SR, Bloom N, Davis SJ, Terry SJ (2020a): COVID-Induced Economic Uncertainty (No. w26983). National Bureau of Economic Research. doi: 10.3386/w26983

Baker SR, Farrokhnia RA, Meyer S, Pagel M, Yannelis C (2020b): How Does Household Spending Respond to an Epidemic? Consumption during the 2020 COVID-19 Pandemic (No. w26949). National Bureau of Economic Research. doi: 10.3386/w26949

Baker S, Bloom N, Davis SJ, Kost K, Sammon M, Viratyosin T (2020c): The Unprecedented Stock Market Reaction to COVID-19. *COVID Economics: Vetted and Real-Time Papers, 1*(3).

Barro RJ, Ursúa JF, Weng J (2020): *The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity* (No. w26866). National Bureau of Economic Research. doi: 10.3386/w26866

Barry JM (2004): The Site of Origin of the 1918 Influenza Pandemic and its Public Health Implications. *Journal of Translational Medicine, 2*(1):3. doi: 10.1186/1479-5876-2-3

Bartik AW, Bertrand M, Cullen ZB, Glaeser EL, Luca M, Stanton CT (2020): *How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey* (No. w26989). National Bureau of Economic Research. doi: 10.3386/w26989

Bierens HJ, Martins LF (2010): Time-Varying Cointegration. *Econometric Theory, 26*(5):1453-1490.

Bora D, Basistha D (2020): The Outbreak of COVID-19 Pandemic and Its Impact on Stock Market Volatility: Evidence from a Worst-affected Economy. *Journal of Public Affairs*, in press. Doi:10.1002/pa.2623

Brown SJ, Warner JB (1985): Using Daily Stock Returns: The Case of Event Studies. *Journal of financial economics*, *14*(1):3-31.

Campbell JY, Shiller RJ (1988): The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *Review of Financial Studies, 1*(3):195– 228.

Cavaliere G, De Angelis L, Rahbek A, Taylor AR (2018): Determining the Cointegration Rank in Heteroskedastic VAR Models of Unknown Order. *Econometric Theory*, *34*(2):349-382.

Cavaliere G, Rahbek A, Taylor AR (2010a): Cointegration Rank Testing under Conditional Heteroscedasticity. *Econometric Theory, 26*(6):1719-1760.

Cavaliere G, Rahbek A, Taylor AR (2010b): Testing for Co-Integration in Vector Autoregressions With Non-Stationary Volatility. *Journal of Econometrics*, *158*(1):7-24.

Cavaliere G, Rahbek A, Taylor AR (2012): Bootstrap Determination of the Cointegration Rank in Vector Autoregressive Models. *Econometrica, 80*(4):1721-1740.

Cepoi CO (2020): Asymmetric Dependence Between Stock Market Returns and News during COVID19 Financial Turmoil. *Finance Research Letters*, 36:101658.

Charles A, Darné O, Kim JH (2017): Adaptive Markets Hypothesis for Islamic Stock Indices: Evidence from Dow Jones Size and Sector-Indices. *International Economics*, 151:100-112.

Chen MH, Jang SS, Kim WG (2007): The Impact of the SARS Outbreak on Taiwanese Hotel Stock Performance: an Event-Study Approach. *International Journal of Hospitality Management, 26*(1):200-212.

Chen MP, Lee CC, Lin YH, Chen WY (2018a): Did the SARS Epidemic Weaken the Integration of Asian Stock Markets? Evidence from Smooth Time-Varying Cointegration Analysis. *Economic research-Ekonomska istraživanja, 31*(1):908-926.

Chen PF, Zeng JH, Lee CC (2018b): Renminbi Exchange Rate Assessment and Competitors' Exports: New Perspective. *China Economic Review*, 50:187-205.

Coibion O, Gorodnichenko Y, Weber M (2020): *Labor Markets During the COVID-19 Crisis: A Preliminary View* (No. w27017). National Bureau of Economic Research. doi:10.3386/w27017

Dingel JI, Neiman B (2020): *How Many Jobs can Be Done at Home?* (No. w26948). National Bureau of Economic Research. doi:10.1177/1354816620971981

Dodd P, Warner JB (1983): On Corporate Governance: A Study of Proxy Contests. *Journal of financial Economics*, *11*(1-4):401-438.

Elliott G, Rothenberg TJ, Stock J (1996): Efficient Tests for an Autoregressive Unit Root. *Econometrica, 64*(4):813-36.

Engelhardt N, Krause M, Neukirchen D, Posch PN (2021): Trust and Stock Market Volatility During the COVID-19 Crisis. *Finance Research Letters*, *38:*101873.

Engle RF, Granger CW (1987): Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 251-276.

Erdem O (2020): Freedom and Stock Market Performance during Covid-19 Outbreak. *Finance Research Letters*, 36, 101671.

Fernandes N (2020): Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy. *IESE Business School Working Paper No. WP-1240-E, Available at SSRN: https://ssrn.com/abstract=3557504 or* doi:*10.2139/ssrn.3557504*

Fernandez-Perez A, Gilbert A, Indriawan I, Nguyen NH (2021): COVID-19 Pandemic and Stock Market Response: A Culture Effect. *Journal of Behavioral and Experimental Finance*, *29:*100454.

Fu M, Shen, H. (2020): COVID-19 and Corporate Performance in the Energy Industry. *Energy Research Letters*, *1*(1):12967.

Gil-Alana LA, Monge M (2020): Crude Oil Prices and COVID-19: Persistence of the Shock. *Energy Research Letters*, *1*(1):13200.

Goodell JW (2020): COVID-19 and Finance: Agendas for Future Research. *Finance Research Letters*, *35:*101512.

Gormsen NJ, Koijen RS (2020): Coronavirus: Impact on Stock Prices and Growth Expectations. *The Review of Asset Pricing Studies, 10(4*):574–597.

Gu J, Yue XG, Nosheen S, Shi L (2022): Does More Stringencies in Government Policies during Pandemic Impact Stock Returns? Fresh Evidence from GREF Countries, a New Emerging Green Bloc. *Resources Policy*, *76:*102582.

Guerrieri V, Lorenzoni G, Straub L, Werning I (2020): *Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?* (No. w26918). National Bureau of Economic Research. doi:10.3386/w26918

Guimbeau A, Menon N, Musacchio A (2020): *The Brazilian Bombshell? The Long-Term Impact of the 1918 Influenza Pandemic the South American Way* (No. w26929). National Bureau of Economic Research. doi:10.3386/w26929

Hanson BE (2002): Tests for Parameter Instability in Regressions with I (1) Processes. *Journal of Business & Economic Statistics*, *20*(1):45-59.

Harjoto MA, Rossi F, Paglia JK (2021a): COVID-19: Stock Market Reactions to the Shock and the Stimulus. *Applied Economics Letters*, 28, 795-861. doi:10.1080/13504851.2020.1781767

Harjoto MA, Rossi F, Lee R, Sergi BS (2021b): How Do Equity Markets React to COVID-19? Evidence from emerging and developed countries. *Journal of Economics and Business*, 115, 105966. doi:10.1016/j.jeconbus.2020.105966

Harris, J. E. (2020). *The Coronavirus Epidemic Curve is Already Flattening in New York City* (No. w26917). National Bureau of Economic Research. doi:10.3386/w26917

Hassan TA, Hollander S, van Lent L, Tahoun A (2020): *Firm-level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1* (No. w26971). National Bureau of Economic Research. doi: 10.3386/w26971

Ho P, Lubik TA, Matthes C (2020): *How To Go Viral: A COVID-19 Model with Endogenously Time-Varying Parameters* (No. 20-10). Federal Reserve Bank of Richmond. DOI: doi:10.21144/wp20-10

Hsu PH, Kuan CM (2005): Re-Examining Profitability of Technical Analysis with Data Snooping Check. *Journal of Financial Econometrics*, *3(4):*606-628.

Ichev R, Marinč M (2018): Stock Prices and Geographic Proximity of Information: Evidence from the Ebola Outbreak. *International Review of Financial Analysis, 56:*153-166.

Iglesias EM (2022): The Influence of Extreme Events such as Brexit and Covid-19 on equity Markets. *Journal of Policy Modeling*, In press. doi:10.1016/j.jpolmod.2021.10.005

Izzeldin M, Muradoğlu YG, Pappas V, Sivaprasad S (2021): The Impact of Covid-19 on G7 Stock Markets Volatility: Evidence from a ST-HAR Model. *International Review of Financial Analysis*, *74:* 101671.

Johansen S (1988): Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control, 12*(2-3):231-254.

Johansen S (1991): Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica, 59(6),* 1551-1580.

Johansen S (1995): *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press on Demand. doi:10.1093/0198774508.001.0001

Jordà O, Singh SR, Taylor AM (2020): Longer-run Economic Consequences of Pandemics (No. w26934). National Bureau of Economic Research.

Khan K, Zhao H, Zhang H, Yang H, Shah MH, Jahanger A (2020): The Impact of COVID-19 Pandemic on Stock Markets: An Empirical Analysis of World Major Stock Indices. *The Journal of Asian Finance, Economics, and Business*, *7*(7):463-474.

Khuntia S, Pattanayak JK (2018): Adaptive Market Hypothesis and Evolving Predictability of Bitcoin. *Economics Letters*, *167:*26-28.

Kim JH (2014): Predictive Regression: An Improved Augmented Regression Method. *Journal of Empirical Finance, 26:*13-25.

Kim JH, Shamsuddin A (2020): A Bootstrap Test for Predictability of Asset Returns. *Finance Research Letters*, *35:*101289.

Kim JH, Shamsuddin A, Lim KP (2011): Stock Return Predictability and the Adaptive Markets Hypothesis: Evidence from Century-Long U.S. Data. *Journal of Empirical Finance*, *18:*868-879.

Kwiatkowski D, Phillips PC, Schmidt P, Shin Y (1992): Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. *Journal of Econometrics, 54*(1-3):159-178.

Lazăr D, Todea A, Filip D (2012): Martingale Difference Hypothesis and Financial Crisis: Empirical Evidence from European Emerging Foreign Exchange Markets. *Economic Systems*, *36*(3):338-350.

Lee CC, Chen MP (2020a): Do Natural Disasters and Geopolitical Risks Matter for Cross-Border Country Exchange-Traded Fund Returns? *North American Journal of Economics and Finance*, 51:101054.

Lee CC, Chen MP (2020b): The Impact of COVID-19 on the Travel & Leisure Industry Returns: Some International Evidence. *Tourism Economics*, forthcoming. doi:10.1177/1354816620971981

Lee CC. Lee CC, Lien D (2019): Do Country Risk and Financial Uncertainty Matter for Energy Commodity Futures? *The Journal of Futures Markets*, 39(3):366-383.

Lee CC, Lee CC, Wu Y (2021): The Impact of COVID-19 Pandemic on Hospitality Stock Returns in China. *International Journal of Finance and Economics*. doi:10.1002/ijfe.2508

Lee CC, Tsong CC, Lee JF (2014): Testing for the Efficient Market Hypothesis in Stock Prices: International Evidence from Non-Linear Heterogeneous Panels, *Macroeconomic Dynamics,* 18(4):943-958.

Lee JW, McKibbin WJ (2004): Estimating the Global Economic Costs of SARS. In *Learning from SARS: preparing for the next disease outbreak: workshop summary* (p. 92). Washington, DC: National Academies Press.

Lewis D, Mertens K, Stock JH (2020): *US Economic Activity during the Early Weeks of the SARS-Cov-2 Outbreak* (No. w26954). National Bureau of Economic Research.

Lin WY, Tsai IC (2019): Black Swan Events in China's Stock Markets: Intraday Price Behaviors on Days of Volatility. *International Review of Economics & Finance*, *59:*395-411.

Liu H, Manzoor A, Wang C, Zhang L, Manzoor Z (2020a): The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environmental Research and Public Health, 17*(8):2800.

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.

Liu L, Wang EZ, Lee CC (2020b): Impact of the COVID-19 Pandemic on the Crude Oil And Stock Markets in the US: A Time-Varying Analysis. *Energy Research Letters*, *1*(1):13154.

Liu M, Choo WC, Lee CC (2020c): The Response of Stock Market to the Announcement of Global Pandemic. *Emerging Markets Finance and Trade*, 56(15): 3562-3577. doi:10.1080/1540496X.2020.1850441

Ludvigson SC, Ma S, Ng S (2020): *COVID-19 and the Macroeconomic Effects of Costly Disasters* (No. w26987). National Bureau of Economic Research. doi:10.3386/w26987

Lv C, Shao C, Lee CC (2021): Green Technology Innovation and Financial Development: Do Environmental Regulation and Innovation Output Matter? *Energy Economics*, 98:105237. doi:10.1016/j.eneco.2021.105237

Maital S, Barzani E (2020): The Global Economic Impact of COVID-19: A Summary of Research Haifa Israel: Samuel Neaman Institute. https://www.neaman.org.il/EN/The-Global-Economic-Impact-of-COVID-19-A-Summary-of-Research

Maki D (2012): Tests for Cointegration Allowing for an Unknown Number of Breaks. *Economic Modelling, 29*(5):2011-2015.

Mammen E (1993): Bootstrap and Wild Bootstrap for High Dimensional Linear Models. *The Annals of Statistics,* 21(1):255-285.

Martins LF (2018): Bootstrap Tests for Time Varying Cointegration. *Econometric Reviews, 37*(5):466-483.

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.

McKibbin WJ, Fernando R (2020): The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. CAMA Working Paper No. 19/2020, Available at SSRN: https://ssrn.com/abstract=3547729. or http://dx.doi.org/10.2139/ssrn.3547729

McKibbin WJ, Sidorenko A (2006): *Global Macroeconomic Consequences of Pandemic Influenza* (p. 79). Sydney, Australia: Lowy Institute for International Policy.

Mei J, Scheinkman JA, Xiong W (2009): Speculative Trading and Stock Prices: Evidence from Chinese AB Share Premia. In *Annals Of Economics And Finance 10-2:225–255*.

Mushir N, Suryavanshi R (2021): Impact of COVID-19 on Portfolio Allocation Decisions of Individual Investors. *Journal of Public Affairs*, e2649. doi:10.1002/pa.2649

Naidenova I, Parshakov P, Shakina E (2020): Idiosyncratic and Systematic Shocks of COVID-19 Pandemic on Financial Markets. *Available at SSRN 3574774.*

Narayan PK, Gong Q, Aliahmed HJ (2022): Is There a Pattern in How COVID-19 Has Affected Australia's Stock Returns?. *Applied Economics Letters*, 29(3):179-182.

Nicola M, Alsafi Z, Sohrabi C, Kerwan A, Al-Jabir A, Iosifidis C, ... & Agha R (2020): The Socio-Economic Implications of the Coronavirus and COVID-19 Pandemic: A Review. *International Journal of Surgery*, 78:185-193. doi:10.1016/j.ijsu.2020.04.018

Nippani S, Washer KM (2004): SARS: A Non-Event for Affected Countries' Stock Markets? *Applied Financial Economics, 14*(15):1105-1110.

Olasehinde-Williams, G., Olanipekun, I., & Özkan, O. (2021). Foreign exchange market response to pandemic-induced fear: Evidence from (a) symmetric wild bootstrap likelihood ratio approach. *The Journal of International Trade & Economic Development*, *30*(7), 988-1003.

Ozili PK, Arun T (2020): Spillover of COVID-19: Impact on the Global Economy. *Available at SSRN 3562570. https://ssrn.com/abstract=3562570* or doi:*10.2139/ssrn.3562570*

Özkan, O., Olasehinde-Williams, G., & Olanipekun, I. (2022). Predicting Stock Returns and Volatility in BRICS Countries during a Pandemic: Evidence from the Novel Wild Bootstrap Likelihood Ratio Approach. *Finance a Uver*, *72*(2), 124-149.

Papadamou S, Fassas A, Kenourgios D, Dimitriou D (2020): Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis. MPRA Paper 100020, University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/100020/1/MPRA_paper_100020.pdf

Park JY, Hahn SB (1999): Cointegrating Regressions with Time Varying Coefficients. *Econometric Theory*, 15(5):664-703.

Pástor Ľ, Veronesi P (2006): Was There a Nasdaq Bubble in the late 1990s? *Journal of Financial Economics*, *81*(1):61-100.

Phan DHB, Narayan PK (2020): Country Responses and the Reaction of the Stock Market to COVID-19—A Preliminary Exposition. *Emerging Markets Finance and Trade*, *56*(10):2138-2150.

Quintos CE, Phillips PC (1993): Parameter Constancy in Cointegrating Regressions. *Empirical Economics*, *18*(4):675-706.

Rahman ML, Amin A, Al Mamun MA (2021): The COVID-19 Outbreak and Stock Market Reactions: Evidence from Australia. *Finance Research Letters*, *38:*101832.

Ramelli S, Wagner A (2020a): What the Stock Market Tells Us about the Consequences of COVID-19. *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever,* 63.

Ramelli S, Wagner AF (2020b): Feverish Stock Price Reactions to COVID-19. Swiss Finance Institute Research Paper No. 20-12, Available at SSRN: https://ssrn.com/abstract=3550274 or doi:10.2139/ssrn.3550274

Salisu AA, Ebuh GU, Usman N (2020): Revisiting Oil-Stock Nexus during COVID-19 Pandemic: Some Preliminary Results. *International Review of Economics & Finance*, *69:*280-294.

Sansa NA (2020): The Impact of the COVID-19 on the Financial Markets: Evidence from China and USA. *Available at SSRN 3562530.*

Schmitt-Grohé S, Teoh K, Uribe M (2020): *COVID-19: Testing Inequality in New York City* (No. w27019). National Bureau of Economic Research.

Shen JH, Long Z, Lee CC, Zhang J (2022): Comparative Advantage, Endowment Structure, and Trade Imbalances. *Structural Change and Economic Dynamics*, 60, 365–375. doi:10.1016/j.strueco.2021.12.012

Shiller RJ (1981): Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *American Economic Review, 71*(3):421–436.

Stock, J. H. (2020). *Data Gaps and the Policy Response to the Novel Coronavirus* (No. w26902). National Bureau of Economic Research.

Stock JH, Watson MW (2005): Implications of Dynamic Factor Models for VAR Analysis. NBER Working Paper 11467, Cambridge MA.

Swensen AR (2006): Bootstrap Algorithms for Testing and Determining the Cointegration Rank in VAR Models 1. *Econometrica, 74*(6):1699-1714.

Topcu M, Gulal OS (2020): The Impact of COVID-19 on Emerging Stock Markets. *Finance Research Letters*, *36:*101691.

Wang EZ, Lee CC (2022): The Impact of Clean Energy Consumption on Economic Growth in China: Is Environmental Regulation a Curse or a Blessing? *International Review of Economics & Finance*, 77, 39-58. doi:10.1016/j.iref.2021.09.008

Wang CW, Lee CC, Chen MC (2022): The Effects of Economic Policy Uncertainty and Country Governance on Banks' Liquidity Creation: International Evidence. *Pacific-Basin Finance Journal*, 71, 101708. doi:j.pacfin.2022.101708

World Health Organisation (2020): Coronavirus Disease 2019 Situation Report-67. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situationreports.

Wu W, Lee CC, Xing W, Ho SJ (2021): The Impact of the COVID-19 Outbreak on Chinese-Listed Tourism Stocks. *Financial Innovation,* 7, Article number: 22. doi:10.1186/s40854-021-00240-6

Xu L (2021): Stock Return and the COVID-19 Pandemic: Evidence from Canada and the US. *Finance Research Letters*, *38:*101872.

Yan C (2020): COVID-19 Outbreak and Stock Prices: Evidence from China. *Available at SSRN 3574374*.

Zeren F, Hizarci A (2020): The Impact of COVID-19 Coronavirus on Stock Markets: Evidence from Selected Countries. *Muhasebeve Finans İncelemeleri Dergisi, 3*(1):78-84.

Zhang D, Hu M, Ji Q (2020): Financial Markets under the Global Pandemic of COVID-19. *Finance Research Letters*, 36:101528.

Zhang X, Zhou H, Lee CC (2022): Systemic Risk of China's Financial Industry During the Spread of the COVID-19 Epidemic and the Breakdown of Crude Oil Negotiation, *Emerging Markets Finance and Trade*, 58:1:56-69.