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Abstract

We examine stock market responses during the COVID-19 pandemic period using fractional integration techniques by considering the data spanning from August 2nd 2019 to July 9th 2020. The evidence suggests that stock markets generally follow a synchronized movement before and during the stages of the pandemic's shocks. We find that, while mean reversion significantly declines, the degree of persistence and dependence has been increased in the majority of the stock market indices- in the full sample analysis. This outcome implies increasing integration and possibly declining benefits of diversification for the global stock portfolio management.

Keywords: Coronavirus; stock markets; fractional integration; long memory; mean reversion

JEL Classification: C12; C22; F31

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1. Introduction

First detected in Wuhan City, China on 31 December 2019,[1] the number of worldwide Coronavirus (COVID-19) cases and deaths reached 42.5 million and 1.15 million persons as of October 24, 2020. Currently, the United States (US) is the most affected, with the highest number of detected cases of COVID-19, and the highest number of deaths. Brazil, India, Mexico, UK, Italy, Spain, France, and, Peru are the next countries to the US in terms of both detected total cases and the number of deaths.[2] Developing countries from different regions are also on the top death list of the global pandemic. Since the time of announcement of the pandemic on 11 March 2020,[3] global economies have been affected seriously in which oil prices, stocks, and other assets began to crash due to expected loss in profits by investors as a result of lockdown imposed in many countries of the world. Earlier studies in emerging COVID-19 finance literature involve comparisons of COVID-19 and 1929 Wall Street Crash (Shariff et al. 2020) and even an imagined nuclear conflict (Goodell, 2020). Characterized by the skyrocketing uncertainty and fear, the ongoing COVID-19 period seems to change the behaviors of economic agents. As a response to this, Knightian uncertainty, advanced/emerging countries' monetary authorities' generously support real/financial industries through various tools (i.e., Baker et al., 2020; IMF, 2020).

Stock market reactions to this global uncertainty have interesting characteristics while the global stock market crash is observable in the initial period of the shock, the recent market boom seems less connected to economic realities but probably quantitative easing measures (i.e., see, Topcu and Gulal, 2020). Moreover, global stock markets have generally shown simultaneous collapses and increases during February 2020 and March 2020. In this respect,

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[1] Available at: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19 (accessed on: 24.10.2020).
[2] Available at: https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1? (accessed on: 24.10.2020).
[3] Available at: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19 (accessed on: 24.10.2020).

declines in global stock markets generally started between the dates of February 5th, 2020 and February 20th, 2020, and then rebounds were observed during the dates between March 17th, 2020, and March 23rd, 2020.

Motivated by this almost simultaneous crash-rebound movement of global stock markets, this paper examines the structure of the stock markets by looking at the mean reversion, the degree of persistence, and dependence of the stock price index series from a fractional viewpoint over the period of August 2nd, 2019 and July 9th, 2020. We partitioned the series into two subsamples by using the date of 11 March 2020 which is WHO's (The World Health Organization) official declaration of a pandemic for COVID-19. By doing so, the paper aims to analyze the stock market responses to the global pandemic in the intersections of mean reversion, the degree of persistence, and the degree of dependence. Specifically, the paper asks whether selected stock markets show (i) delayed vs. immediate (ii) symmetrical vs. asymmetrical, and (iii) (un) integrated responses to the COVID-19 shock. We also investigate (iv) whether stock market behaviours are time-varying during different phases of the crisis. In the emerging COVID-19 finance literature, the present paper is the first to investigate these behaviours by using fractional integration techniques.

This paper is structured as follows. In the second section, we provide a literature review. Section 3 involves data and modelling strategies. Section 4 involves the empirical evidence from the results obtained, while the last section is reserved for the conclusions.

2. Literature Review

The studies on market integration, dependence, and persistence in stock markets focused on the role of various triggering local/global events such as financial crisis (i.e. Russian Crisis/ Global Financial Crisis), political shocks (i.e. Brexit/ the US election), and climate change. However, there is no comparable global health crisis comparable to COVID-19 except the

Spanish Flu which was experienced during the first quarter of the twentieth century; it is better to ask first whether stock markets had experienced weaken or strengthen relationships during health crises periods. For example, Nippani and Washer (2004) find no evidence that Severe Acute Respiratory Syndrome (SARS) negatively impacted the main stock indices associated with Canada, Hong Kong, Indonesia, the Philippines, Singapore, and Thailand. The only countries that appear to have been impacted by SARS[4] are China and Vietnam. China appears to have been affected in the short event window as compared with the S&P 1200 global index. Chen et al. (2018) find the existence of a time-varying cointegration relation in the aggregate stock price indices, and the SARS epidemic did weaken the long-run relationship between China and other Asian markets. They further discuss that stockholders and policymakers should be concerned about the influence of catastrophic epidemic diseases on the financial integration of the stock market in Asia.

Despite most regional effects of SARS, the COVID-19 outbreak results in sudden and serious supply/demand shocks with substantial heterogeneity in size, to the different sectors of the global economy (Siu and Wong, 2004; Brinca et al., 2020). Baker et al. (2020) underline that no previous infectious disease outbreak, including the Spanish Flu, has impacted the stock market as forcefully as the COVID-19 pandemic. Even Velde (2020) underlines that the 1918 influenza epidemic coincided with the start of a mild recession from which the economy rebounded quickly and the stock market did quite well during the epidemic. Goodell (2020) underlines that the COVID-19 pandemic is causing a direct global destructive economic impact that is present in every area of the globe. Despite previous regional/global health shocks, the COVID-19 global pandemic created significant impacts on financial markets globally. Because it results in a high level of uncertainty in a globally dependent market structure, the usual

[4] The World Health Organisation (WHO) database shows that the SARS infection period was from 2002/11/1 to 2003/8/7. This disease first appeared in Guangdong Province, China in November 2002. The disease then spread to 37 countries, infected more than 8,422 people, and claimed 916 lives (Chen et al., 2018).

expectation would be that stock markets may show some correlated (and perhaps declining) trading behaviours based on a persistent negative sentiment and possibly a high level of investors' risk aversion. But both data and evolving literature of stock market behaviors during COVID-19 periods suggest some interesting patterns.

None of the stock markets responded strongly to the outbreak in China or the lockdown of Wuhan, China, on January 23. However, once it is apparent that the outbreak spread to Italy, South Korea, and Iran, around February 20, stock markets declined sharply. In response to the decision on March 12 to severely restrict travel from the European Union (EU) and decisions by governments in the EU to impose lockdowns to various degrees, stock markets around the world declined by 10% or more. By March 18, stock markets had dropped more than 30% from their peak (Gormsen and Koijen, 2020). Le et al. (2020) show that the connectivity of tail-dependency networks among equities and commodities has increased the most during the pandemic period compared to other asset groups, showing a higher tail contagion effect for these specific assets. By using a quantile regression approach for the daily returns of 10 major sectors of the US, daily S&P500 returns and daily Google Search Index for coronavirus, Azimli (2020) find that following the COVID-19 outbreak, the degree of dependence between returns and market portfolio has increased in the higher quantiles, lowering the benefits of diversification.

By using daily data up to 27 March 2020 for 12 countries, Zhang et al. (2020) find that the outbreak results in substantial increases of volatility in global markets, and global stock markets linkages display clear different patterns before and after the pandemic announcement. Their evidence also shows that regional market integration/collaboration is likely to appear but the stock market has failed to take a leading role in the world before/after the crisis became global. Ashraf (2020) examines the stock market of 64 countries affected by the COVID-19 pandemic from January 22, 2020, to April 17, 2020, using simple regression analysis. Results show that stock markets reacted more to the growth of the number of cases of the pandemic than to the growth in deaths. Liu et al. (2020) evaluate the short-term impact of the coronavirus outbreak on 21 leading stock market indices in major affected countries over the period from 21 February 2019 to 18 March 2020. Their results indicate that the stock markets in major affected countries and areas fell quickly after the virus outbreak and investor's fear sentiment is proved to be a complete mediator and transmission channel for the COVID-19 outbreak's effect on stock markets. Moreover, they also provide evidence that countries in Asia experienced more negative abnormal returns as compared to other countries.

While the majority of authors have focused on multiple countries, some authors have examined singular countries. For example, Baker et al. (2020) discuss that with the economic policy uncertainty, the COVID-19 volatility surge began in the fourth week of January, intensified from the fourth week of February, and began tapering in the fourth week of March in the stock markets. Al-Wadhi et al. (2020) examine China and find that a contagious disease such as COVID-19, specifically the infection and death rates of the diseases have had a negative impact on stock returns.

Some authors have examined the role of sentiments in explaining stock returns during the COVID-19 pandemic. In this respect, Haroon and Rizvi (2020) examine the role of sentiment in employing COVID-19 related news and its effects on stock markets during the COVID-19 pandemic. Findings in the paper show that hysteria generated by news outlets during the COVID-19 pandemic increases volatility in the equity markets. This negative sentiment is related to many factors, with also policy uncertainties during the early period of the crisis. Global policy measures generally imply powerful combat against the pandemic. For example, as a response to seriously contracting economy (annualized rate of 31.7 percent in 2020 Q2), the US issued the Coronavirus Aid, Relief and Economy Security Act (CARES Act) on March 19, 2020, which may provide an estimated US$2.3 trillion (around 11% of GDP) financial help to the US economy. Moreover, the US Federal funds rate was lowered by 150bp to 0-0.25bp as of March 15, 2020,[5] and the purchase of Treasury and agency securities in the amount as needed.[6] On the other hand, since the first reported cases on January 24, 2020, COVID-19 has spread across the European Union (EU) with a severe impact. To date, national liquidity measures, including schemes approved by the European Commission under the temporary flexible EU State Aid rules amounted to over €3 trillion. Like the US and other big economies, the EU also supports European economies through various instruments such as low-interest rates and asset purchase programs. China has also been announced an estimated RMB 4.6 trillion (or 4.5 percent of GDP) of discretionary fiscal measures.[7] However, emerging literature reveals that policy responses would be less effective for vitalizing the general economy and stock market. In this respect, Topcu and Gulal (2020) find that the outcomes of extensive policy measures of monetary policy authorities have begun to offset the distorting impact of COVID-19 on the emerging stock markets by mid-April 2020. However, Gormsen and Koijen (2020) argue that on March 24, S&P 500 rallies almost 10% following news of fiscal stimuli and further monetary policy actions, but news about fiscal stimulus around March 24 boosts the stock market and long-term growth but did little to increase the short-term growth expectations. There is an also ongoing debate in the emerging literature on the efficiency of policy measures in the real economy (i.e., see, Chetty et al., 2020) and financial markets. Igan et al. (2020) argue that rebounded stock indices in the US and Europe have stood in stark contrast with the deterioration in economic indicators. The emergence of this disconnect between markets and the real economy coincided with announcements of unprecedented monetary policy actions. Sharif et al. (2020) discuss that the COVID-19 pandemic itself and

[5] Available at: https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm (accessed on 21 October, 2020).
[6] Available at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 (accessed on 20 October, 2020).
[7] Available at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 (accessed on 20 October, 2020).

related regulatory response to this crisis are sources of geopolitical risk. The relevant uncertainty is primarily related to the long-term path of the US economy and how the Federal Reserve will react to the pandemic. Zhang et al. (2020) argue that policy responses to the COVID-19 crisis may create further uncertainties in the global financial markets and non-conventional policy interventions, such as the US' unlimited QE, create further uncertainty and may cause long-term problems.

Another discussion about the emerging COVID-19 finance literature is about defining the breaking date for the market crash. In this respect, there are some indicative discussions about the dates of COVID-19 related market stock crashes. For example, Giglio et al. (2020) indicate that after one of the longest and most-pronounced stock market booms on record during 2009-2019, the US stock market experienced a sudden crash starting on Monday, February 24th, 2020. By March 11th, 2020, the S&P 500 index had dropped 19.2% from its previous high. Baker et al. (2020) discuss that news related to COVID-19 developments is overwhelmingly the dominant driver of large daily US stock market moves since 24 February 2020 and from 24 February to 24 March 2020, there were 22 trading days and 18 market jumps – more than any other period in history with the same number of trading days. Zhang et al. (2020) use WHO's announcement of a pandemic, used as a breaking point to separate the sample. Akhtaruzzaman et al. (2020) suggest that there is a structural break in hedge ratios on December 31, 2019, when the first confirmed case of COVID–19 is reported by the WHO. Some empirical applications such as Wieland (2020) and Santamaria and Hortal (2020) suggest multiple breakpoints.

The above-mentioned papers investigating the effects of COVID-19 on stock markets employ simple analysis in understanding the impact of the pandemic on general stocks. Our paper contributes to the literature on the impact of COVID-19 on general stocks by employing long-range dependence and fractional integration techniques to better understand the role of the pandemic in several general stock indices from across the world.

3. Data and Modelling Strategies

3.1 Data

The paper investigates selected stock market indices during the period from August 2nd, 2019 to July 9th, 2020. According to Seligmann et al. (2020), this period involves both the first and some parts of the second waves of COVID-19. We also observed the behaviours of selected stock market indices before/during the COVID-19 period. In this respect, taking into account the date of WHO's announcement of the pandemic on 11 March, 2020,[8] our before (during) COVID-19 analysis period involves the period of August 2nd, 2019 and March 10th, 2020 (August 2nd, 2019 and July 9th, 2020). The data consists of 247 daily price information for 41 stock markets. To improve possible heterogeneity in the data, we select our sample based on (i) the least/most affected from COVID-19 according to total deaths and total cases[10], (ii) having a relatively sizable stock market, (iv) geographical variations. To define the least/most affected from COVID-19, we compare the number of COVID-19 cases and deaths by using John Hopkins Coronavirus Resource Center[11], Worldometer[12], and WHO[13] data as of 9 July 2020. We use IMF/WFE data to define the size and relative importance of the stock market in the selected country. Daily stock market indexes were retrieved from Bloomberg. To decide geographical variations, we follow the transmission path of COVID-19, which began in China, and spread to greater Europe including Turkey, and then reached the US and other countries.

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[8] Available at: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19 (accessed on: 24.10.2020).
[10] Available at: https://www.worldometers.info/coronavirus/ (accessed on 9 July, 2020).
[11] Available at: https://coronavirus.jhu.edu/data/cumulative-cases (accessed on 9 July, 2020).
[12] Available at: https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/ (accessed on 9 July 2020).
[13] Available at: https://covid19.who.int/ (accessed on 23 April, 2020).

Since the COVID-19 crisis had influenced major global stock markets before the official pandemic announcement of WHO, on 11 March 2020, we partitioned the series into two subsamples to observe the possible response patterns of stock markets. Therefore, we investigate the behaviors of the selected stock market during the pre-COVID-19 period (August 2^{nd}, 2019 and March, 10^{th}, 2020), and the whole sample involving the COVID-19 period (August 2^{nd}, 2019 and July 9^{th}, 2020). Table 1 presents the information on respective stocks, with standard abbreviations and stocks definition. Altogether, 41 stock markets were considered, Iran was excluded because of a lack of data. As of the time of data collection, the US was highly affected by the COVID-19 pandemic and Dow Jones Industrial Average (DJIA) stocks index was used to represent the US stock market in the proxy. Table 1 also displayed the ranking of countries by the total number of deaths as of 9 July 2020, in which the US recorded the highest number of deaths, and Taiwan ranked the least in the number of COVID-19 deaths in the world.

[INSERT TABLE 1 ABOUT HERE]

Time plots of the 41 stock indices are displayed in Figure 1, where sharp descends were found around January-March 2020 in all the stock indices. The COVID-19 induced stocks crash dates are heterogeneous across stocks as reported in Table 4 below.

[INSERT FIGURE 1 ABOUT HERE]

3.2 Modelling Strategies

We use fractional integration methods that belong to the category of long memory processes, which are characterized by a high level of dependence between the observations even if they are far distant in time. Using fractional integration, a large variety of model specifications can be examined, including nonstationary, though mean-reverting processes if the differencing parameter is constrained in the interval [0.5, 1). In such a case, shocks will have long-lasting effects though disappearing in the long run. On the other hand, if the differencing parameter is 1 or above 1, shocks will have a permanent nature, lasting forever.

This methodology seems to be very appropriate in our context in the sense that by allowing for fractional degrees of differentiation we permit a richer degree of flexibility in the dynamic specification of the model, allowing for short memory patterns (d = 0); stationary long memory processes (0 < d < 0.5); nonstationary and mean reversion (0.5 ≤ d < 1); unit roots (d = 1), or even explosive patterns (d ≥ 1). Besides, the differencing parameter d may be taken as a measure of the degree of persistence or dependence between the data, the higher the value of this parameter is, the higher the level of dependence between the observations is.

4. Empirical Results

In the empirical analysis, we consider a fractional integration framework based on Robinson's (1994) parametric method. This method uses the standard linear model of the form:

$$y_t \;=\; \beta_0 \;+\; \beta_1 t + x_t; \qquad (1 - L)^d x_t \;=\; u_t, \qquad t \;=\; 0,\, 1, \ldots, \tag{1}$$

where y_t is each of the observed time series; β_0 and β_1 are unknown coefficients and x_t is supposed to be I(d). We report the results in terms of the estimated values of d for the three standard cases in the unit root literature of: i) no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$ in (1)), ii) an intercept ($\beta_1 = 0$ in (1), and iii) an intercept with a linear time trend (β_0 and β_1 unknown), marking in bold in the tables the selected model for each series, based on the t-values of the estimated coefficients on the d-differenced series. We display in Table 2 the results based on white noise errors, while those in Table 3 refer to the case of autocorrelated disturbances.

Starting with those based on white noise errors in Table 2, we observe that the time trend is required in a single case (DSEX index) and though not reported in the table, the trend-coefficients were significantly negative. In the rest of the cases, the intercept is sufficient to describe the deterministic part. If we focus on the estimated values of d, we observe that they are high and close to 1 in most of the cases; however, we can observe some differences across the indices. For example, there are 23 cases where the estimated d is higher than 1. Among these cases, the estimated d is significantly higher than 1 in seven stock markets which implies a high degree of persistence. Those cases are: COLCAP (1.15), KSE100 (1.14), SPBL125PT (1.12), TPX (1.11), TWSE (1.08), JCI (1.10), MXWO (1.09). On the other extreme, in another 12 indices, d is found to be below 1 (in which 8 of them are significantly below 1), and thus showing mean-reverting behavior. Those indices are: DSEX (0.89), INDU (0.87), MERVAL (0.91), SPTSX (0.91), SASEIDX (0.92), AS51 (0.93), DSM (0.93), IBOV (0.93) and also MEXBOL (0.99), PCOMP (0.99), SENSEX (0.97), and SMI (0.98). For the remaining indices, the I(1) null hypothesis of a random walk cannot be rejected, supporting thus the hypothesis of market efficiency at least in its weak form.

Table 3 displays the results with autocorrelated errors. Here, we use the model of Bloomfield (1973) for u_t in (1) which is fairly general and does not impose conditions on the coefficients over the stationarity property (see, Gil-Alana, 2001). The first thing we observe here is that the time trend is never required, and focusing on d, we observe that there are two cases (MEXBOL with 0.95 and DSM with 0.93) showing mean reversion (i.e. $d < 1$). Therefore, in the rest of the cases, we cannot reject the null hypothesis of a unit root (i.e., $d = 1$). More importantly, there are 24 indices where d is significantly higher than 1, which implies a high degree of persistence. Those indexes are TSEMIB (1.31), AS51(1.30), COLCAP (1.30), IBEX (1.29), MXWO (1.27), SPTSX (1.27), BET (1.26), IBOV (1.25), XU100 (1.25), IMOEX (1.24), IPSA (1.23), SPBL125PT (1.22), TWSE (1.22), CAC (1.20), INDU (1.20), TA35 (1.20), KOSPI2 (1.20), STI (1.19), TOP40 (1.18), DAX (1.18), BEL20 (1.16), AEX (1.17), AS (1.15) and FBMLLCI (1.14).

[INSERT TABLES 2 AND 3 ABOUT HERE]

According to the results reported so far, mean reversion is observed in 12 (2) of the indices in Table 2 (Table 3), if the errors are uncorrelated (autocorrelated). For these series, shocks will have transitory effects disappearing in the long run though taking a long time to disappear completely. Thus, the effect of the COVID-19 crisis will be less problematic in these indices compared with the remaining cases. Taken into account there are 7 (24) indices where d is significantly higher than 1 if the errors are uncorrelated (autocorrelated), we may conclude that the degree of persistence seems to have a more widespread permanent effect compared to the impact of mean reversion.

In Table 4, we record the impact dates of stock crashes and stock gain dates with values of the stock index on these dates. While stock market crashes started on February 19th, 2020 in 9 stock markets[14] and generally happened during February 5th, 2020 and February 20th, 2020, stock market gain started on March 18th, March 19^{th,} and March 23rd, 2020 in 10, 6, and 18 stock markets, respectively, and generally happened during March 17th, 2020 to March 23rd, 2020. It seems that news of fiscal stimuli and further monetary policy actions boost stock markets globally (Gormsen and Koijen, 2020), specifically after the CARES act of the US as of March 19, 2020, and lowered US Federal funds rate to 0-0.25bp as of March 15, 2020. This picture implies several interesting points. First, policy interventions generally seem to be the main reason for stock market increases in the U.S and elsewhere. Second, the increases in stock markets suggest that a sharp decline has lasted either around one or almost 2 months in global stock markets. Interestingly, a very close crash and gain in dates of the Shanghai Stock Exchange Composite Index (SHCOMP), which are March 5th, 2020 and March 23rd, 2020,

[14] We may speculate that the Covid-19 connected stock market declines might start due to declines in the leading US stock market indexes. In this respect DJIA, Nasdaq and S&P500 indexes were the highest in 19 Feb, 2020 and started to a historical decline in 20 Feb, 2020.

suggest that Chinese stocks started to increase very fast. Third, the above crash dates may suggest that using the official pandemic announcements of WHO, which is 11 March 2020 would have led to biased results.[15]

[INSERT TABLE 4 ABOUT HERE]

In Table 5 and 6, we present the results of mean reversion, dependence, and persistence for pre-COVID-19 samples, in each stock market for both white noise and Bloomfield autocorrelated disturbances. In the case of uncorrelated/white noise disturbances in Table 5, 31 out of 41 indexes show mean reversion and d is statistically significantly below 1 in 15 cases, namely in BET (0.78), INDU (0.77), PCOMP (0.79), MERVAL (0.83) COLCAP (0.81), SMI (0.85), IBOV (0.86), AEX (0.86), SENSEX (0.86), CAC (0.86), FTSEMIB (0.87), JCI (0.87), AS51 (0.89), SHCOMP (0.89), and FBMLLCI (0.89). In the case of autocorrelated disturbances based on Bloomfield (1973) in Table 6, mean reversion was now found in more cases compared to the autocorrelated error disturbance cases in Table 5 namely, 37 out of 41 indexes show mean reversion and d is significantly below 1 in 27 cases such as in MXWO (0.55), MEXBOL (0.56) IBEX (0.59), SMI (0.60), AEX (0.59), CAC (0.61), AS51 (0.63), UKX (0.67), and BEL20 (0.68).

[INSERT TABLES 5 AND 6 ABOUT HERE]

Table 7 summarizes the results in terms of the value of d with the pre-COVID data and with the whole sample period. From pre-COVID to whole sample results, there is an observable

[15] In a broader perspective, all previous COVID-19 related dates may result in false empirical observations such as 8 December, 2019 (the date of first COVID-19 case when a resident in Wuhan City, China), 20 January, 2020 (the first confirmed covid-19 case in the US), 31 January, 2020 (the US restricted some entries from China), 14 February, 2020 (the first European COVID-19 death is announced, in France), 29 February, 2020 (the first coronavirus death is recorded in the US and travel restrictions are announced), and 17 March, 2020 (in the US, the acceleration of the death started in March 17 with 17 deaths, reached 271 deaths in March 24, 2020) (for the dates, see, https://www.weforum.org/agenda/2020/04/coronavirus-spread-covid19-pandemic-timeline-milestones/; for the covid-19 related death statistics, see: https://covid19.who.int/ ; https://covid19.who.int/region/amro/country/us (accessed on 23 April, 2020).

increase in the value of d for the majority of indexes in both the cases of no autocorrelation and autocorrelation. Focusing on the case of autocorrelation, for example, we observe an increase in the estimated value of d in 39 out of the 41 cases. Mean reversion occurs in 37 cases with the pre-COVID data; in all these cases, this property disappears when using the whole sample period. Thus, the irruption of the COVID-19 has produced a substantial increase in the degree of persistence in the majority of the series, moving from mean reversion to lack of it.

[INSERT TABLE 7 ABOUT HERE]

5. Conclusions

This paper investigates mean reversion, the degree of persistence, and the degree of dependence during the period from August 2nd, 2019 to July 9th, 2020, which involves the first and some parts of the second waves of the COVID-19 global health crisis. We first report a strong and widespread mean reversion in the pre-COVID-19 period (August 2nd, 2019, and March 10th, 2020) in both uncorrelated and also autocorrelated samples. Second, the whole sample (August 2nd, 2019 and July 9th, 2020) analysis involving the COVID-19 period suggests that mean reversion significantly declines in all error types. As the time-varying feature of the investigated sample, many series that were mean-reverting, with the sample ending before the crisis has shown to be non-mean reverting with the data including the coronavirus period. This evidence implies how heterogeneity moves (i.e. see Westerlund and Narayan, 2015, Phan et al., 2015, Rizvi and Arshad, 2018) after the shock period. Moreover, we also find that the degree of persistence seems to have a more widespread permanent effect comparing the impact of mean reversion in the whole sample analysis. Third, the results for the whole sample period involving the pre-COVID period also suggest a strong increase in the degree of dependence in the data, moving from transitory to permanent shocks in a larger number of cases. This evidence implies an increasing homogeneity for the degree of dependence in the whole sample.

Finally, the available evidence does not suggest a specific geographic focus for the mean reversion and the degree of persistence/dependence.

Therefore, it is particularly apparent that after this pandemic, there has been an increase in the degree of persistence/dependence in the majority of the stock market indices. This increasing and time-varying symmetry imply the increasing integration among stock markets which may result in a decline in the benefits of diversification (see, Azimli, 2020). Also, this further means that stock markets become more efficient after the initial COVID-19 pandemic shocks, and that arbitrage profits making are not available to market participants (see Gil-Alana et al., 2018). Interestingly, while the SARS epidemic did weaken the long-run relationships among some regional stock markets due to probably its mostly relatively local and transitory characteristics (see, Chen et al., 2018), COVID-19 may support a stronger long-run relationship and connectedness among stock markets probably due to its global feature and leading monetary authorities' extensive supports.

Because this is the first study on the degree of persistence and dependence among stock markets during the COVID-19 period, we do not report the consistency of our findings with previous papers. However, this paper relates to existing empirical studies to some extent. For example, our evidence is in line with those of Le et al. (2020) and Azimli (2020) in terms of the increasing degree of dependence between different asset returns during the COVID-19 outbreak. The evidence of substantially increasing persistence in the stock market indices may imply an increasing inefficiency suggesting that trend trading strategies can be used to generate abnormal profits (see, Caporale et al., 2018) in the stock markets. It seems that extensive policy measures of central banks did stabilize the financial panic, but whether these policies will contribute to further rational behaviors is still an open debate. We suggest that investors and policy-makers should be careful about the limitations of the fiscal/monetary policy actions due to ongoing uncertainties in the real economy and interconnectedness among global stock markets (Gormsen and Koijen, 2020; Zhang et al., 2020; Sharif et al., 2020).

As the future research direction, the unique persistence profile (Gil-Alana and Payne, 2020) of each index, the determinants of dependence among stock markets, and the role of irrationality in the delayed crashes and relatively early rebounds in global stock markets would be promising subjects.

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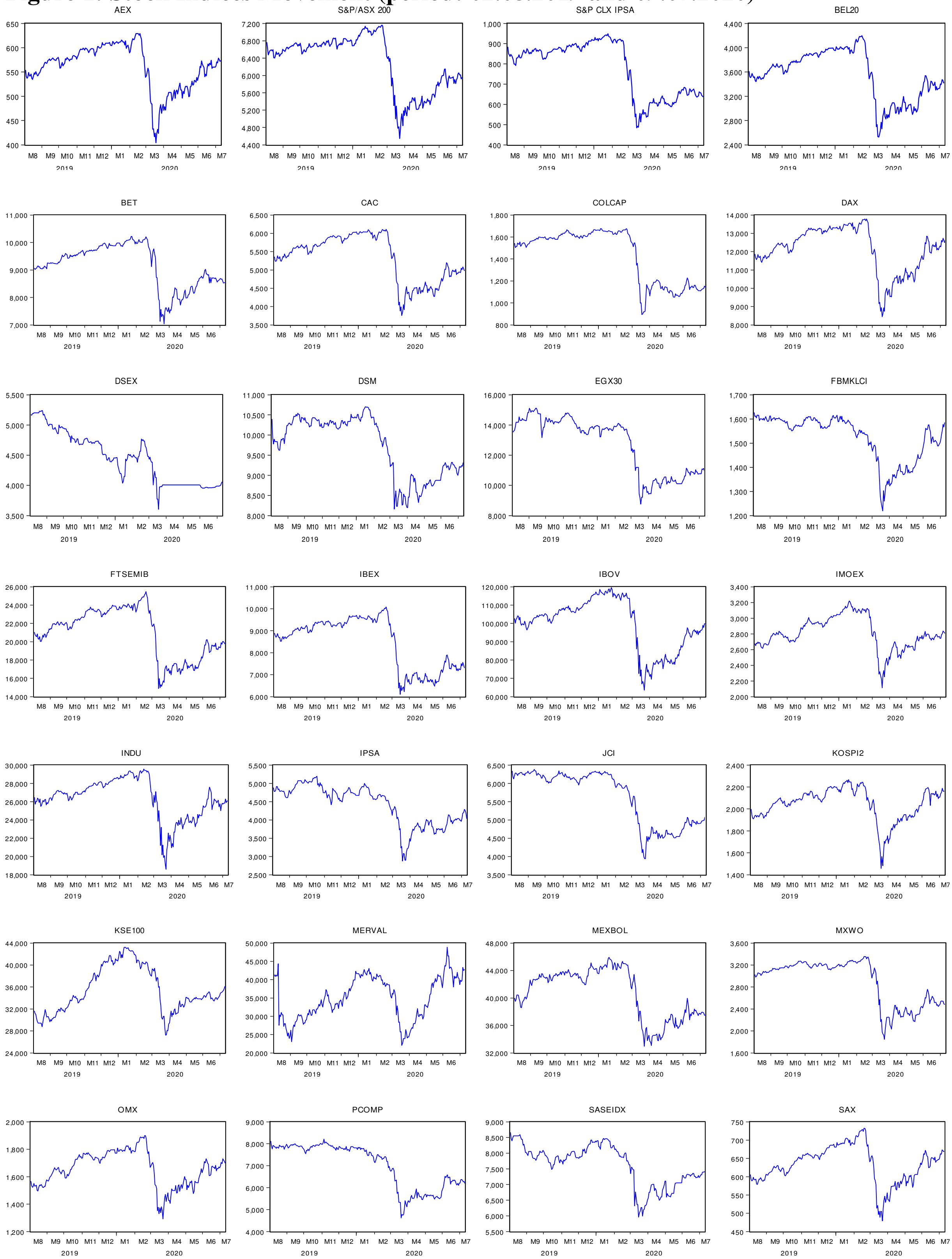
Table 1: Information on Sample Stock Market Indexes

Ranking by Total No. of Deaths as of 9 July 2020	Region/ Country	Abbreviation	Definition
1	US	DJIA Index	The Dow Jones Industrial Average Index
2	Brasil	IBOV	Ibovespa Brasil Sao Paulo Stock Exchange Index
3	UK	UKX	Financial Times Stock Exchange
4	Italy	FTSEMIB	FTSE Milano Indice di Borsa Index
5	Mexico	S&P_BMV	S&P Bolsa Mexicana de Valores Index
6	France	CAC 40 Index	Cotation Assistée en Continu 40 Index (Euronext Paris)
7	Spain	IBEX	Índice Bursátil Español Exchange 35 Index
8	India	BSE Sensex	Bombay Stock Exchange Sensex 30 Index
10	Peru	S&P/BVL General	Peru General Index
11	Russia	IMOEX	Moscow Exchange Russia Index
12	Belgium	BEL20	Euronext Brussels 20 Index
13	Germany	DAX	Deutsche Boerse AG German Stock Index DAX
14	Canada	S&P/TSX Composite Index	S&P/Toronto Stock Exchange Composite Index
15	Chile	S&P CLX IPSA	The Indice de Precio Selectivo de Acciones
16	Netherlands	AEX	Euronext Amsterdam AEX Index
17	Sweden	OMX	The OMX Stockholm 30 Index
18	Turkey	BIST 100 Index	Borsa Istanbul 100 index
19	Pakistan	KSE 100 Index	Karachi Stock Exchange KSE-100 Index
21	Colombia	COLCAP Index	Colombia Stock Exchange (BVC) (25 most liquid stocks)
22	China	SHCOMP	Shanghai Stock Exchange Composite Index
23	South Africa	TOP40	Johannesburg Stock Exchange Africa Top40 Tradeable Index
24	Egypt	EGX30	Egyptian Exchange EGX 30 Price Index
25	Indonesia	JCI	Jakarta Stock Exchange Composite Index
27	Bangladesh	DSE30	Bangladesh Dhaka Stock Exchange 30 Index
28	Saudi Arabia	SASEIDX	Tadawul All Share Index
29	Switzerland	SMI	Swiss Market Index
30	Romania	BET	Bucharest Stock Exchange Trading Index
32	Argentina	S&P Merval	MERcado de VALores Index of Buenos Aires Stock Exchange
35	Poland	WIG30	Warsaw Stock Exchange WIG 30 Index
37	Philippines	PCOMP	Philippines Stock Exchange PSEi Index
40	Japan	TPX	Tokyo Stock Exchange Tokyo Price Index TOPIX
59	Israel	TA-35	Tel Aviv Stock Exchange 35 Index
62	South Korea	KOSPI	Korea Stock Exchange Index
71	Greece	Athens General Composite	Athens Stock Exchange General Index
76	Qatar	DSM	Qatar Exchange Index
80	Malaysia	FBMKLCI	FTSE Bursa Malaysia Kuala Lumpur Composite (KLCI) Index
86	Australia	S&P/ASX 200 Index	S&P Australian Stock Exchange 200 Index
123	Slovakia	SAX	The Slovak share index
124	Singapore	STI	Straits Time Index
163	Taiwan	TWSE	Taiwan Stock Exchange Weighted Index

Figure 1: Stock Indices Movement (period: 02.08.2019 and 09.07.2020)



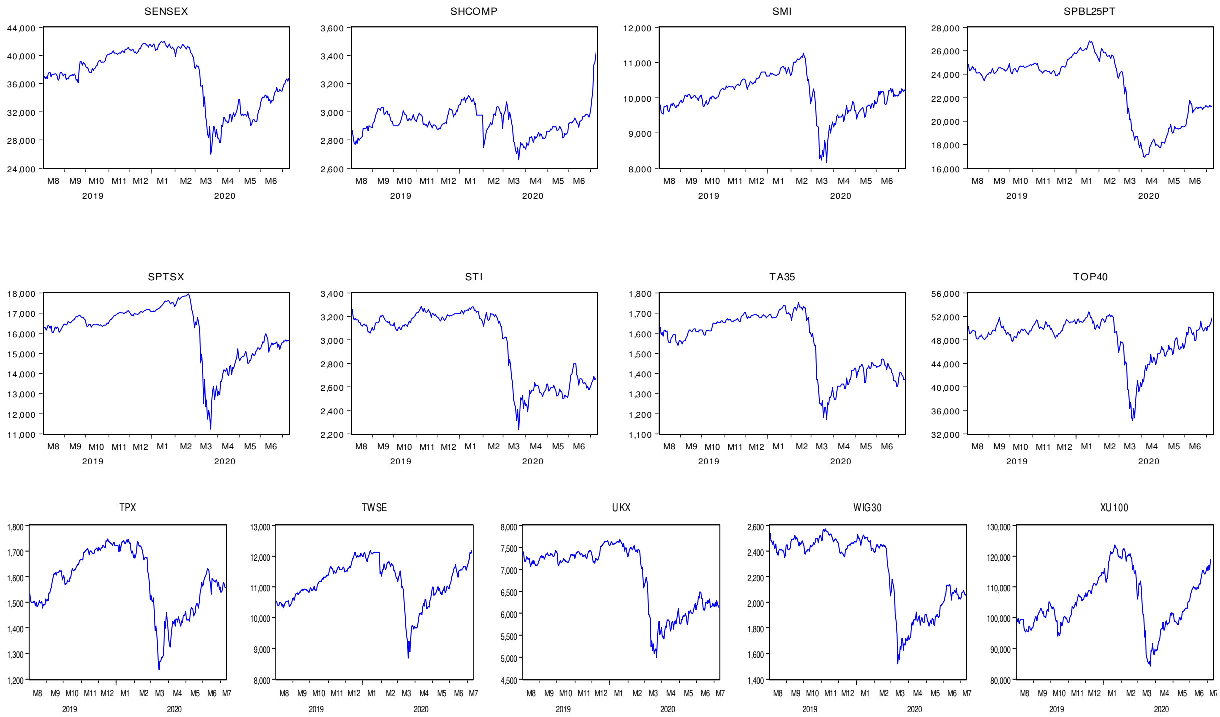

SENSEX
SHCOMP
SMI
SPBL25PT
SPTSX
STI
TA35
TOP40
TPX
TWSE
UKX
WIG30
XU100

Table 2: Estimation of fractional d based on uncorrelated (white noise) errors in the full sample (period: 02.08.2019 and 09.07.2020)

Series	No terms	An intercept	A linear time trend
AEX	0.98 (0.90, 1.08)	**1.05 (0.98, 1.14)**	1.05 (0.98, 1.14)
AS51	0.98 (0.90, 1.09)	**0.93 (0.88, 1.10)**	0.93 (0.88, 1.10)
ASE	0.98 (0.90, 1.08)	**1.04 (0.97, 1.12)**	1.04 (0.97, 1.12)
BEL20	0.98 (0.90, 1.09)	**1.06 (0.98, 1.15)**	1.06 (0.98, 1.15)
BET	0.98 (0.91, 1.09)	**1.02 (0.95, 1.11)**	1.02 (0.95, 1.12)
CAC	0.98 (0.90, 1.08)	**1.04 (0.97, 1.14)**	1.04 (0.97, 1.14)
COLCAP	0.98 (0.90, 1.08)	**1.15 (1.07, 1.25)**	1.16 (1.07, 1.25)
DAX	0.98 (0.90, 1.08)	**1.06 (0.98, 1.14)**	1.06 (0.98, 1.14)
DSEX	0.99 (0.91, 1.09)	0.89 (0.81, 0.99)	**0.89 (0.81, 0.99)***
DSM	0.98 (0.91, 1.09)	**0.93 (0.86, 1.03)**	0.93 (0.86, 1.03)
EGX30	0.99 (0.91, 1.09)	**1.01 (0.94, 1.11)**	1.01 (0.94, 1.11)
FBMLLCI	0.98 (0.91, 1.09)	**1.06 (0.98, 1.16)**	1.06 (0.98, 1.16)
FTSEMIB	0.98 (0.90, 1.09)	**1.02 (0.96, 1.10)**	1.02 (0.96, 1.10)
IBEX	0.98 (0.90, 1.09)	**1.02 (0.95, 1.10)**	1.02 (0.95, 1.10)
IBOV	0.98 (0.90, 1.09)	**0.93 (0.87, 0.99)***	0.93 (0.87, 0.99)
IMOEX	0.98 (0.90, 1.09)	**1.03 (0.96, 1.11)**	1.03 (0.96, 1.11)
INDU	0.98 (0.90, 1.08)	**0.87 (0.81, 0.94)***	0.87 (0.81, 0.94)
IPSA	0.98 (0.90, 1.09)	**1.04 (0.96, 1.14)**	1.04 (0.96, 1.14)
JCI	0.98 (0.90, 1.09)	**1.10 (1.02, 1.21)**	1.10 (1.02, 1.21)
KOSPI2	0.98 (0.90, 1.09)	**1.00 (0.93, 1.08)**	1.00 (0.93, 1.08)
KSE100	0.98 (0.90, 1.09)	**1.14 (1.06, 1.25)**	1.14 (1.06, 1.25)
MERVAL	0.98 (0.90, 1.08)	**0.91 (0.84, 0.98)***	0.91 (0.84, 0.98)
MEXBOL	0.98 (0.90, 1.09)	**0.99 (0.92, 1.09)**	0.99 (0.92, 1.09)
MXWO	0.98 (0.90, 1.09)	**1.09 (1.01, 1.19)**	1.09 (1.01, 1.19)
OMX	0.98 (0.90, 1.08)	**1.00 (0.92, 1.09)**	1.00 (0.92, 1.09)
PCOMP	0.98 (0.90, 1.08)	**0.99 (0.93, 1.08)**	0.99 (0.93, 1.08)
SASEIDX	0.98 (0.90, 1.09)	**0.92 (0.86, 1.00)**	0.92 (0.86, 1.00)
SAX	0.98 (0.90, 1.09)	**1.04 (0.97, 1.14)**	1.04 (0.97, 1.14)
SENSEX	0.99 (0.91, 1.09)	**0.97 (0.91, 1.05)**	0.97 (0.91, 1.05)
SHCOMP	0.99 (0.91, 1.09)	**1.02 (0.94, 1.12)**	1.02 (0.94, 1.12)
SMI	0.99 (0.91, 1.09)	**0.98 (0.90, 1.08)**	0.98 (0.90, 1.08)
SPBL125PT	0.98 (0.90, 1.08)	**1.12 (1.06, 1.20)**	1.12 (1.06, 1.20)
SPTSX	0.98 (0.91, 1.09)	**0.91 (0.85, 0.98)***	0.91 (0.85, 0.98)
STI	0.98 (0.90, 1.08)	**1.00 (0.93, 1.08)**	1.00 (0.93, 1.08)
TA35	0.98 (0.90, 1.08)	**1.00 (0.93, 1.07)**	1.00 (0.93, 1.07)
TOP40	0.98 (0.90, 1.08)	**1.00 (0.93, 1.09)**	1.00 (0.93, 1.09)
TPX	0.98 (0.90, 1.08)	**1.11 (1.03, 1.22)**	1.11 (1.03, 1.22)
TWSE	0.98 (0.90, 1.09)	**1.08 (1.00, 1.17)**	1.08 (1.00, 1.17)
UKX	0.98 (0.90, 1.08)	**1.00 (0.93, 1.09)**	1.00 (0.93, 1.09)
WIG30	0.98 (0.90, 1.08)	**1.05 (0.98, 1.15)**	1.05 (0.98, 1.15)
XU100	0.98 (0.90, 1.08)	**1.06 (0.99, 1.14)**	1.06 (0.99, 1.14)

In bold, the selected models for each series. *: Evidence of mean reversion at the 5% level.

Table 3: Estimation of fractional d based on autocorrelated errors in the full sample (period: 02.08.2019 and 09.07.2020).

Series	No terms	An intercept	A linear time trend
AEX	0.97 (0.83, 1.14)	**1.17 (1.02, 1.41)**	1.17 (1.02, 1.41)
AS51	0.97 (0.82, 1.14)	**1.30 (1.14, 1.49)**	1.30 (1.14, 1.49)
ASE	0.96 (0.82, 1.13)	**1.15 (1.02, 1.33)**	1.15 (1.02, 1.33)
BEL20	0.97 (0.83, 1.15)	**1.16 (1.00, 1.38)**	1.16 (1.00, 1.38)
BET	0.97 (0.84, 1.13)	**1.26 (1.09, 1.50)**	1.26 (1.09, 1.50)
CAC	0.97 (0.84, 1.15)	**1.20 (1.04, 1.41)**	1.19 (1.04, 1.41)
COLCAP	0.97 (0.84, 1.15)	**1.30 (1.10, 1.57)**	1.30 (1.10, 1.57)
DAX	0.96 (0.83, 1.13)	**1.18 (1.04, 1.38)**	1.18 (1.04, 1.38)
DSEX	0.96 (0.84, 1.13)	**1.01 (0.84, 1.23)**	1.01 (0.84, 1.23)
DSM	0.97 (0.83, 1.14)	**0.93 (0.82, 1.07)**	0.93 (0.81, 1.07)
EGX30	0.97 (0.83, 1.14)	**1.02 (0.90, 1.18)**	1.02 (0.90, 1.19)
FBMLLCI	0.97 (0.84, 1.14)	**1.14 (0.97, 1.37)**	1.14 (0.97, 1.37)
FTSEMIB	0.97 (0.84, 1.15)	**1.31 (1.16, 1.59)**	1.31 (1.16, 1.60)
IBEX	0.97 (0.84, 1.11)	**1.29 (1.13, 1.54)**	1.29 (1.13, 1.54)
IBOV	0.98 (0.84, 1.15)	**1.25 (1.12, 1.43)**	1.25 (1.12, 1.43)
IMOEX	0.97 (0.84, 1.15)	**1.24 (1.06, 1.47)**	1.24 (1.06, 1.47)
INDU	0.97 (0.84, 1.15)	**1.20 (1.05, 1.42)**	1.21 (1.05, 1.42)
IPSA	0.97 (0.84, 1.13)	**1.23 (1.03, 1.55)**	1.23 (1.03, 1.55)
JCI	0.97 (0.84, 1.13)	**1.04 (0.93, 1.23)**	1.04 (0.92, 1.23)
KOSPI2	0.97 (0.84, 1.15)	**1.20 (1.05, 1.42)**	1.20 (1.05, 1.43)
KSE100	0.98 (0.83, 1.14)	**1.07 (0.94, 1.22)**	1.07 (0.94, 1.22)
MERVAL	0.96 (0.83, 1.14)	**1.06 (0.94, 1.22)**	1.06 (0.94, 1.23)
MEXBOL	0.96 (0.83, 1.14)	**0.95 (0.86, 1.08)**	0.95 (0.86, 1.08)
MXWO	0.97 (0.83, 1.14)	**1.27 (1.07, 1.61)**	1.27 (1.08, 1.60)
OMX	0.97 (0.84, 1.14)	**1.03 (0.91 1.20)**	1.03 (0.91, 1.20)
PCOMP	0.97 (0.83, 1.15)	**1.17 (1.01, 1.39)**	1.17 (1.01, 1.39)
SASEIDX	0.97 (0.83, 1.15)	**1.16 (1.01, 1.38)**	1.16 (1.01, 1.39)
SAX	0.97 (0.84, 1.14)	**1.11 (0.97, 1.28)**	1.11 (0.97, 1.28)
SENSEX	0.96 (0.84, 1.13)	**1.09 (0.97, 1.27)**	1.09 (0.97, 1.27)
SHCOMP	0.98 (0.85, 1.15)	**1.12 (0.92, 1.34)**	1.12 (0.92, 1.34)
SMI	0.97 (0.84, 1.14)	**1.00 (0.86, 1.16)**	1.00 (0.86, 1.16)
SPBL125PT	0.97 (0.83, 1.14)	**1.22 (1.11, 1.37)**	1.22 (1.11, 1.37)
SPTSX	0.97 (0.84, 1.14)	**1.27 (1.12, 1.49)**	1.27 (1.12, 1.49)
STI	0.97 (0.84, 1.14)	**1.19 (1.04, 1.42)**	1.19 (1.04, 1.42)
TA35	0.97 (0.83, 1.13)	**1.20 (1.07, 1.40)**	1.20 (1.07, 1.40)
TOP40	0.97 (0.84, 1.15)	**1.18 (1.00, 1.39)**	1.18 (1.00, 1.39)
TPX	0.97 (0.83, 1.14)	**1.12 (0.98, 1.30)**	1.12 (0.98, 1.30)
TWSE	0.97 (0.83, 1.14)	**1.22 (1.06, 1.49)**	1.22 (1.06, 1.49)
UKX	0.97 (0.83, 1.14)	**1.06 (0.93, 1.24)**	1.06 (0.93, 1.24)
WIG30	0.97 (0.83, 1.14)	**1.13 (0.99, 1.31)**	1.13 (0.99, 1.31)
XU100	0.97 (0.84, 1.14)	**1.25 (1.10, 1.47)**	1.25 (1.10, 1.47)

In bold, the selected models for each series.

Table 4: Dates of COVID-19 Impact on Stocks

Stock index	COVID-19 Induced Stock Market Crash		COVID-19 Induced Stock Market Gains	
	Date of COVID-19 Stocks Crash	Market Value at This Date	Date of COVID-19 Stocks Gains	Market Value at This Date
MXWO	14/02/2020	3354.47	23/03/2020	1848.18
XU100	05/02/2020	122320.8	23/03/2020	84246.17
TOP40	17/02/2020	52357.57	19/03/2020	34239.3
IMOEX	20/02/2020	3125.1	19/03/2020	2112.64
SHCOMP	05/03/2020	3071.677	23/03/2020	2660.167
TA35	12/02/2020	1751.79	23/03/2020	1171.21
JCI	14/01/2020	6325.41	24/03/2020	3937.632
AEX	14/02/2020	629.23	18/03/2020	404.1
SMI	19/02/2020	11263.01	23/03/2020	8160.79
DAX	19/02/2020	13789	18/03/2020	8441.71
FTSEMIB	19/02/2020	25477.55	18/03/2020	15120.48
CAC	19/02/2020	6111.24	18/03/2020	3754.84
IBEX	19/02/2020	10083.6	23/03/2020	6230.2
UKX	12/02/2020	7534.37	23/03/2020	4993.89
INDU	12/02/2020	29551.42	23/03/2020	18591.93
TPX	06/02/2020	1736.98	17/03/2020	1268.46
STI	12/02/2020	3223.37	23/03/2020	2233.48
KOSPI2	14/02/2020	2243.59	19/03/2020	1457.64
PCOMP	07/02/2020	7507.2	19/03/2020	4623.42
FBMKLCI	07/02/2020	1554.49	19/03/2020	1219.72
TWSE	14/02/2020	11815.7	19/03/2020	8681.34
IBOV	12/02/2020	116674.1	23/03/2020	63569.6
SENSEX	12/02/2020	41565.9	23/03/2020	25981.24
SPBL25PT	11/02/2020	25829.62	06/04/2020	16918.7
MEXBOL	12/02/2020	45338.37	23/03/2020	32964.22
SASEIDX	14/01/2020	8474.81	23/03/2020	5990.23
DSEX	17/02/2020	4768.14	18/03/2020	3603.95
SPTSX	20/02/2020	17944.06	23/03/2020	11228.49
DSM	05/02/2020	10297.54	01/04/2020	8195.02
MERVAL	20/01/2020	43054.01	18/03/2020	22087.13
BEL20	17/02/2020	4198.31	17/03/2020	2528.77
WIG30	12/02/2020	2451.46	23.03.2020	1625.44
AS51	20/02/2020	7162.494	23/03/2020	1625.44
SAX	19/02/2020	732.67	23/03/2020	478.95
KSE100	05/02/2020	40884.25	25/03/2020	27228.8
COLCAP	19/02/2020	1676.29	18/03/2020	894.03
EGX30	06/02/2020	14105.86	18/03/2020	8756.7
ASE	14/02/2020	922.3	18/03/2020	487.35
IPSA	06/02/2020	4699.52	18/03/2020	2876.03
OMX	19/02/2020	1900.282	23/03/2020	1292.274
BET	19/02/2020	10204.97	23/03/2020	7038.95

Table 5: Estimation of fractional d based on uncorrelated (white noise) errors in pre-COVID-19 sample (period: 02.08.2019 and 10.03.2020)

Series	No terms	An Intercept	A Linear Time Trend
AEX	0.97 (0.87, 1.11)	0.86 (0.73, 1.07)	**0.86 (0.70, 1.07)**
AS51	0.97 (0.87, 1.11)	**0.89 (0.76, 1.09)**	0.88 (0.72, 1.09)
ASE	0.97 (0.87, 1.11)	**0.97 (0.83, 1.15)**	0.97 (0.82, 1.15)
BEL20	0.97 (0.87, 1.11)	0.92 (0.80, 1.11)	**0.91 (0.76, 1.11)**
BET	0.97 (0.87, 1.11)	0.78 (0.68, 0.97)	**0.79 (0.66, 0.97)***
CAC	0.97 (0.87, 1.11)	0.86 (0.73, 1.04)	**0.86 (0.73, 1.04)**
COLCAP	0.97 (0.87, 1.11)	0.81 (0.70, 0.96)	**0.81 (0.70, 0.96)***
DAX	0.97 (0.87, 1.11)	0.91 (0.79, 1.08)	**0.91 (0.78, 1.08)**
DSEX	0.98 (0.87, 1.12)	**1.05 (0.93, 1.20)**	1.05 (0.93, 1.20)
DSM	0.97 (0.87, 1.11)	**1.00 (0.86, 1.18)**	1.00 (0.86, 1.18)
EGX30	0.98 (0.87, 1.11)	**1.06 (0.91, 1.28)**	1.06 (0.91, 1.27)
FBMLLCI	0.97 (0.87, 1.11)	**0.89 (0.79, 1.03)**	0.89 (0.79, 1.03)
FTSEMIB	0.97 (0.87, 1.11)	0.87 (0.76, 1.02)	**0.86 (0.74, 1.02)**
IBEX	0.97 (0.87, 1.11)	0.93 (0.79, 1.13)	**0.93 (0.78, 1.13)**
IBOV	0.97 (0.87, 1.11)	0.86 (0.76, 0.99)	**0.85 (0.74, 0.99)***
IMOEX	0.97 (0.87, 1.11)	1.03 (0.92, 1.17)	**1.03 (0.92, 1.17)**
INDU	0.97 (0.87, 1.11)	0.77 (0.68, 0.91)	**0.73 (0.60, 0.90)***
IPSA	0.97 (0.87, 1.11)	**1.00 (0.86, 1.19)**	1.00 (0.86, 1.19)
JCI	0.97 (0.85, 1.12)	**0.87 (0.74, 1.06)**	0.87 (0.74, 1.06)
KOSPI2	0.97 (0.86, 1.11)	**1.01 (0.88, 1.19)**	1.01 (0.87, 1.19)
KSE100	0.97 (0.87, 1.11)	**1.07 (0.96, 1.22)**	1.07 (0.96, 1.22)
MERVAL	0.97 (0.87, 1.11)	**0.83 (0.75, 0.94)***	0.83 (0.74, 0.94)
MEXBOL	0.97 (0.87, 1.11)	**0.95 (0.80, 1.15)**	0.95 (0.81, 1.15)
MXWO	0.97 (0.87, 1.11)	**1.04 (0.88, 1.25)**	1.04 (0.89, 1.25)
OMX	0.97 (0.87, 1.11)	0.99 (0.86, 1.15)	**0.98 (0.86, 1.15)**
PCOMP	0.97 (0.87, 1.11)	**0.79 (0.68, 0.96)***	0.80 (0.69, 0.96)
SASEIDX	0.97 (0.85, 1.12)	**1.04 (0.93, 1.21)**	1.04 (0.93, 1.21)
SAX	0.97 (0.87, 1.11)	0.93 (0.82, 1.10)	**0.92 (0.78, 1.10)**
SENSEX	0.97 (0.87, 1.12)	0.86 (0.73, 1.07)	**0.86 (0.72, 1.07)**
SHCOMP	0.97 (0.87, 1.11)	**0.89 (0.78, 1.03)**	0.89 (0.78, 1.03)
SMI	0.97 (0.87, 1.11)	0.85 (0.72, 1.06)	**0.82 (0.66, 1.06)**
SPBL125PT	0.97 (0.87, 1.12)	**1.06 (0.92, 1.26)**	1.06 (0.92, 1.26)
SPTSX	0.97 (0.87, 1.11)	0.99 (0.88, 1.16)	**0.99 (0.87, 1.16)**
STI	0.97 (0.87, 1.11)	**0.94 (0.83, 1.08)**	0.94 (0.83, 1.08)
TA35	0.97 (0.87, 1.11)	**0.91 (0.77, 1.11)**	0.90 (0.75, 1.11)
TOP40	0.97 (0.87, 1.11)	**0.97 (0.83, 1.15)**	0.97 (0.83, 1.15)
TPX	0.97 (0.86, 1.11)	0.94 (0.85, 1.06)	**0.94 (0.85, 1.06)**
TWSE	0.97 (0.87, 1.11)	0.90 (0.79, 1.05)	**0.89 (0.78, 1.05)**
UKX	0.97 (0.87, 1.11)	**0.96 (0.81, 1.17)**	0.96 (0.81, 1.17)
WIG30	0.97 (0.87, 1.11)	**0.91 (0.79, 1.06)**	0.91 (0.79, 1.06)
XU100	0.97 (0.86, 1.11)	0.98 (0.88, 1.12)	**0.98 (0.86, 1.13)**

In bold, the selected models for each series. *: Evidence of mean reversion at the 5% level.

Table 6: Estimation of fractional d based on autocorrelated errors in pre-COVID-19 sample (period: 02.08.2019 and 10.03.2020)

Series	No terms	An Intercept	A Linear Time Trend
AEX	0.93 (0.77, 1.17)	0.59 (0.50, 0.77)	**0.52 (0.33, 0.79)***
AS51	0.93 (0.77, 1.16)	0.63 (0.51, 0.84)	**0.49 (0.28, 0.82)***
ASE	0.94 (0.78, 1.18)	**0.80 (0.62, 1.09)**	0.78 (0.38, 1.09)
BEL20	0.93 (0.76, 1.17)	0.68 (0.56, 0.88)	**0.56 (0.34, 0.88)***
BET	0.93 (0.76, 1.17)	0.65 (0.58, 0.84)	**0.58 (0.43, 0.83)***
CAC	0.93 (0.78, 1.17)	0.61 (0.52, 0.80)	**0.60 (0.52, 0.83)***
COLCAP	0.93 (0.77, 1.16)	0.67 (0.51, 0.94)	**0.71 (0.53, 0.95)***
DAX	0.93 (0.77, 1.17)	0.71 (0.60, 0.94)	**0.69 (0.52, 0.94)***
DSEX	0.93 (0.77, 1.17)	**1.25 (0.90, 1.84)**	1.25 (0.92, 1.83)
DSM	0.93 (0.75, 1.17)	**0.95 (0.70, 1.21)**	0.95 (0.69, 1.21)
EGX30	0.93 (0.76, 1.20)	**0.63 (0.44, 0.86)***	0.63 (0.36, 0.87)
FBMLLCI	0.93 (0.76, 1.18)	**0.92 (0.71, 1.18)**	0.93 (0.74, 1.19)
FTSEMIB	0.94 (0.76, 1.18)	0.69 (0.56, 0.94)	**0.66 (0.45, 0.93)***
IBEX	0.94 (0.77, 1.17)	0.59 (0.49, 0.79)	**0.49 (0.28, 0.77)***
IBOV	0.93 (0.77, 1.18)	0.74 (0.63, 0.92)	**0.68 (0.51, 0.91)***
IMOEX	0.94 (0.77, 1.17)	0.97 (0.77, 1.23)	**0.97 (0.77, 1.22)**
INDU	0.93 (0.77, 1.17)	0.69 (0.58, 0.86)	**0.57 (0.32, 0.86)***
IPSA	0.93 (0.79, 1.17)	**0.74 (0.57, 1.02)**	0.74 (0.50, 1.02)
JCI	0.91 (0.73, 1.18)	**0.70 (0.52, 0.96)***	0.71 (0.52, 0.96)
KOSPI2	0.93 (0.77, 1.17)	0.86 (0.63, 1.28)	**0.86 (0.54, 1.28)**
KSE100	0.92 (0.77, 1.17)	1.01 (0.86, 1.27)	**1.01 (0.82, 1.26)**
MERVAL	0.90 (0.72, 1.19)	**1.01 (0.85, 1.21)**	1.01 (0.84, 1.20)
MEXBOL	0.94 (0.77, 1.18)	0.56 (0.43, 0.80)	**0.61 (0.44, 0.83)***
MXWO	0.94 (0.78, 1.17)	0.55 (0.40, 0.92)	**0.72 (0.54, 0.94)***
OMX	0.94 (0.78, 1.17)	0.78 (0.64, 1.03)	**0.77 (0.60, 1.03)**
PCOMP	0.93 (0.77, 1.17)	0.68 (0.54, 0.87)	**0.67 (0.51, 0.88)***
SASEIDX	0.91 (0.73, 1.18)	**0.97 (0.82, 1.27)**	0.98 (0.81, 1.28)
SAX	0.93 (0.77, 1.16)	0.75 (0.64, 0.94)	**0.61 (0.31, 0.91)***
SENSEX	0.94 (0.77, 1.17)	0.65 (0.55, 0.81)	**0.59 (0.42, 0.82)***
SHCOMP	0.94 (0.77, 1.17)	**0.83 (0.59, 1.13)**	0.83 (0.62, 1.13)
SMI	0.94 (0.77, 1.17)	0.60 (0.52, 0.73)	**0.39 (0.18, 0.64)***
SPBL125PT	0.93 (0.76, 1.17)	**0.81 (0.68, 1.03)**	0.80 (0.64, 1.03)
SPTSX	0.93 (0.78, 1.17)	0.81 (0.66, 1.03)	**0.77 (0.58, 1.03)**
STI	0.93 (0.76, 1.17)	**0.81 (0.61, 1.02)**	0.81 (0.60, 1.02)
TA35	0.93 (0.77, 1.17)	0.68 (0.55, 0.87)	**0.60 (0.37, 0.87)***
TOP40	0.93 (0.77, 1.17)	0.70 (0.48, 1.01)	**0.67 (0.38, 1.01)**
TPX	0.93 (0.77, 1.17)	**1.09 (0.89, 1.50)**	1.09 (0.89, 1.52)
TWSE	0.93 (0.77, 1.17)	0.84 (0.70, 1.05)	**0.83 (0.67, 1.05)**
UKX	0.93 (0.76, 1.18)	**0.67 (0.51, 0.93)***	0.65 (0.41, 0.93)
WIG30	0.93 (0.77, 1.17)	**0.78 (0.57, 1.01)**	0.79 (0.57, 1.01)
XU100	0.93 (0.77, 1.17)	0.97 (0.79, 1.28)	**0.96 (0.75, 1.28)**

In bold, the selected models for each series. *: Evidence of mean reversion at the 5% level.

Table 7: Summary of results (full sample period: 02.08.2019 and 09.07.2020; subsample period: 02.08.2019 and 10.03.2020)

Series	No Autocorrelation		Autocorrelation	
	Full Sample Period	**Subsample Period**	**Full Sample Period**	**Subsample Period**
AEX	1.05 (0.98, 1.14)	0.86 (0.70, 1.07)	1.17 (1.02, 1.41)	0.52 (0.33, 0.79)*
AS51	0.93 (0.88, 1.10)	0.89 (0.76, 1.09)	1.30 (1.14, 1.49)	0.49 (0.28, 0.82)*
ASE	1.04 (0.97, 1.12)	0.97 (0.83, 1.15)	1.15 (1.02, 1.33)	0.80 (0.62, 1.09)
BEL20	1.06 (0.98, 1.15)	0.91 (0.76, 1.11)	1.16 (1.00, 1.38)	0.56 (0.34, 0.88)*
BET	1.02 (0.95, 1.11)	0.79 (0.66, 0.97)*	1.26 (1.09, 1.50)	0.58 (0.43, 0.83)*
CAC	1.04 (0.97, 1.14)	0.86 (0.73, 1.04)	1.20 (1.04, 1.41)	0.60 (0.52, 0.83)*
COLCAP	1.15 (1.07, 1.25)	0.81 (0.70, 0.96)*	1.30 (1.10, 1.57)	0.71 (0.53, 0.95)*
DAX	1.06 (0.98, 1.14)	0.91 (0.78, 1.08)	1.18 (1.04, 1.38)	0.69 (0.52, 0.94)*
DSEX	0.89 (0.81, 0.99)*	1.05 (0.93, 1.20)	1.01 (0.84, 1.23)	1.25 (0.90, 1.84)
DSM	0.93 (0.86, 1.03)	1.00 (0.86, 1.18)	0.93 (0.82, 1.07)	0.95 (0.70, 1.21)
EGX30	1.01 (0.94, 1.11)	1.06 (0.91, 1.28)	1.02 (0.90, 1.18)	0.63 (0.44, 0.86)*
FBMLLCI	1.06 (0.98, 1.16)	0.89 (0.79, 1.03)	1.14 (0.97, 1.37)	0.92 (0.71, 1.18)
FTSEMIB	1.02 (0.96, 1.10)	0.86 (0.74, 1.02)	1.31 (1.16, 1.59)	0.66 (0.45, 0.93)*
IBEX	1.02 (0.95, 1.10)	0.93 (0.78, 1.13)	1.29 (1.13, 1.54)	0.49 (0.28, 0.77)*
IBOV	0.93 (0.87, 0.99)	0.85 (0.74, 0.99)*	1.25 (1.12, 1.43)	0.68 (0.51, 0.91)*
IMOEX	1.03 (0.96, 1.11)	1.03 (0.92, 1.17)	1.24 (1.06, 1.47)	0.97 (0.77, 1.22)
INDU	0.87 (0.81, 0.94)*	0.73 (0.60, 0.90)*	1.20 (1.05, 1.42)	0.57 (0.32, 0.86)*
IPSA	1.04 (0.96, 1.14)	1.00 (0.86, 1.19)	1.23 (1.03, 1.55)	0.74 (0.57, 1.02)
JCI	1.10 (1.02, 1.21)	0.87 (0.74, 1.06)	1.04 (0.93, 1.23)	0.70 (0.52, 0.96)*
KOSPI2	1.00 (0.93, 1.08)	1.01 (0.88, 1.19)	1.20 (1.05, 1.42)	0.86 (0.54, 1.28)
KSE100	1.14 (1.06, 1.25)	1.07 (0.96, 1.22)	1.07 (0.94, 1.22)	1.01 (0.82, 1.26)
MERVAL	0.91 (0.84, 0.98)*	0.83 (0.75, 0.94)*	1.06 (0.94, 1.22)	1.01 (0.85, 1.21)
MEXBOL	0.99 (0.92, 1.09)	0.95 (0.80, 1.15)	0.95 (0.86, 1.08)	0.61 (0.44, 0.83)*
MXWO	1.09 (1.01, 1.19)	1.04 (0.88, 1.25)	1.27 (1.07, 1.61)	0.72 (0.54, 0.94)
OMX	1.00 (0.92, 1.09)	0.98 (0.86, 1.15)	1.03 (0.91, 1.20)	0.77 (0.60, 1.03)
PCOMP	0.99 (0.93, 1.08)	0.79 (0.68, 0.96)*	1.17 (1.01, 1.39)	0.67 (0.51, 0.88)*
SASEIDX	0.92 (0.86, 1.00)	1.04 (0.93, 1.21)	1.16 (1.01, 1.38)	0.97 (0.82, 1.27)
SAX	1.04 (0.97, 1.14)	0.92 (0.78, 1.10)	1.11 (0.97, 1.28)	0.61 (0.31, 0.91)*
SENSEX	0.97 (0.91, 1.05)	0.86 (0.72, 1.07)	1.09 (0.97, 1.27)	0.59 (0.42, 0.82)*
SHCOMP	1.02 (0.94, 1.12)	0.89 (0.78, 1.03)	1.12 (0.92, 1.34)	0.83 (0.59, 1.13)
SMI	0.98 (0.90, 1.08)	0.82 (0.66, 1.06)	1.00 (0.86, 1.16)	0.39 (0.18, 0.64)*
SPBL125PT	1.12 (1.06, 1.20)	1.06 (0.92, 1.26)	1.22 (1.11, 1.37)	0.81 (0.68, 1.03)
SPTSX	0.91 (0.85, 0.98)*	0.99 (0.87, 1.16)	1.27 (1.12, 1.49)	0.77 (0.58, 1.03)
STI	1.00 (0.93, 1.08)	0.94 (0.83, 1.08)	1.19 (1.04, 1.42)	0.81 (0.61, 1.02)
TA35	1.00 (0.93, 1.07)	0.91 (0.77, 1.11)	1.20 (1.07, 1.40)	0.60 (0.37, 0.87)*
TOP40	1.00 (0.93, 1.09)	0.97 (0.83, 1.15)	1.18 (1.00, 1.39)	0.67 (0.38, 1.01)
TPX	1.11 (1.03, 1.22)	0.94 (0.85, 1.06)	1.12 (0.98, 1.30)	1.09 (0.89, 1.50)
TWSE	1.08 (1.00, 1.17)	0.89 (0.78, 1.05)	1.22 (1.06, 1.49)	0.83 (0.67, 1.05)
UKX	1.00 (0.93, 1.09)	0.96 (0.81, 1.17)	1.06 (0.93, 1.24)	0.67 (0.51, 0.93)*
WIG30	1.05 (0.98, 1.15)	0.91 (0.79, 1.06)	1.13 (0.99, 1.31)	0.78 (0.57, 1.01)
XU100	1.06 (0.99, 1.14)	0.98 (0.86, 1.13)	1.25 (1.10, 1.47)	0.96 (0.75, 1.28)

*: Evidence of mean reversion at the 5% level.