Stock Market Responses to COVID-19: The Behaviors of Mean Reversion, Dependence and Persistence

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Abstract

We examine stock market responses during the COVID-19 pandemic period using fractional integration techniques. The evidence suggests that stock markets generally follow a synchronized movement before and the stages of the pandemic shocks. We find while mean reversion significantly declines, the degree of persistence and dependence has been increased in the majority of the stock market indices in whole sample analysis covering the period of 02.08.2019 and 09.07.2020. 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 678.3 million and 6.78 million persons as of February 17, 2023. Currently, the US is the mostly affected, with highest number of detected cases of COVID-19, and the highest number of deaths. Brazil, India, Russia, Mexico, Peru, UK, Italy, Germany, France, Indonesia, Iran, and Colombia are the next countries to the US in terms of the total number of COVID-19 induced deaths.[2] Developing countries from different regions are also top of the death list in global pandemic. Since the time of announcement of the pandemic on 11 March[3], 2020, 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. Early studies in emerging COVID-19 finance literature involve comparisons of COVID-19 with the conclusions of 1929 Crash (Shariff, 2020), with global financial crisis of 2008/09 (Yaya et al., 2021), and even an imagined nuclear conflict (Goodell, 2020). Characterized by the skyrocketing uncertainty and fear, the ongoing COVID-19 period seems to change behaviors of economic agents. As a response to Knightian uncertainty, advanced/developing countries' monetary authorities' generously support real/financial industries through various tools (i.e., Baker et al., 2020; IMF, 2020). COVID-19 pandemic was an external shock that triggered crisis that slowed down global economic and financial markets (UNCTAD, 2020; Vittuari et al., 2021).

Stock market reactions to this global uncertainty have interesting characteristics. While the global stock market crash is clearly 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

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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] https://www.worldometers.info/coronavirus/#countries
[3] Available at: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19 (accessed on: 24.10.2020).

showed a simultaneous collapses and increases during February and March 2020. In this respect, declines in global stock markets started during 05.02.2020 and 20.02.2020 periods and then rebounds were observed during 17.03.2020 and 23.03.2020 periods (see Zhao, Rasoulinezhad and Sarker, 2023).

Motivated by this almost simultaneous crash-rebound movements 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 02.08.2019 and 09.07.2020. In the emerging COVID-19 finance literature, the present paper is the first to investigate these behaviors by using fractional integration techniques. 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 pandemic for COVID-19. By doing so, the paper aims to analyze the stock market responses to global pandemic in the intersections of mean reversion and the degree of persistence and dependence. Thus, the main objective of the paper is to investigate the statistical features of the most important stock market prices in the world, focusing on issues such as the degree of dependence and the hypothesis of mean reversion . In specific, 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.

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 conclusion.

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/US election), and climate change. However, there is no comparable global health crisis comparable to COVID-19 except Spanish Flue during first quarter of 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 SARS negatively impacted the main stock indices associated with the 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 SARS epidemic did weaken the long-run relationship between China and the four markets. They further discuss that stockholders and policy makers should be concerned about the influence of catastrophic epidemic diseases on the financial integration of stock market in Asia.

Despite mostly regional effects of SARS, COVID-19 outbreak results in a 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 1918 influenza epidemic coincided with the start of a mild recession from which the economy rebounded quickly and US 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, COVID-19 global pandemic created significant impacts on financial markets globally. Because

[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).

it results in a high level of uncertainty in a globally dependent market structure, usual expectation would be stock markets may show some correlated (and perhaps declining) trading behaviours based on a persistent negative sentiment and possibly high level of investors' risk aversion. But both data and evolving literature of stock markets 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 US' decision on March 12 to severely restrict travel from the 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 have dropped more than 30% from their peak (Gormsen and Koijen, 2020). 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 US 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 a simple regression analysis. Results show that stock markets reacted more to the growth of the number of cases of the pandemic than the growth in deaths. Liu et al. (2020) evaluates 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 majority of authors have focused on multiple countries, some authors have examined singular countries. For example, Baker et al. (2020) discuss that discussions of with the economic policy uncertainty 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 US stock markets. Al-Wadhi et al. (2020) examine China and find that a contagious disease such as COVID-19 specifically infection and death rates has a negative impact on stock returns.

Some authors have examined the role of sentiments in explaining stock return during the COVID-19 pandemic. In this respect, Haroon and Rizvi (2020) examine the role of sentiment 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 early period of the crisis. Global policy measures generally imply a 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 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, US Federal funds rate were lowered by 150bp to 0-0.25bp as of March 15, 2020[5] and 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

[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).

has spread across the European Union (EU) with a severe impact. To date, national liquidity measures, including schemes approved by the European Commission under temporary flexible EU State Aid rules amounted to over €3 trillion. Like US and other big economies, EU also supports European economies through various instruments such as low interest rates and asset purchase programs. China also has 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 general economy and stock market. In this respect, Topcu and Gulal (2020) find that 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 short-term growth expectations. There is an also ongoing debate in the emerging literature on the efficiency of policy measures in 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 has 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 COVID-19 pandemic itself and 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 COVID-19 crisis may create further uncertainties in the

[7] Available at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 (accessed on 20 October, 2020).

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 market 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 U.S. 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 U.S. 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 suggest multiple breakpoints such as Wieland (2020) and Santamaria and Hortal (2020).

Recent papers have examined the impact of COVID–19 on select markets, Abuzayed et al (2021) examine the systemic distress risk spillover between the global stock market and individual stock markets in countries which were most impacted by the COVID–19 pandemic. There findings reveal that developed markets in Europe and North America transmitted and received more marginal extreme risk to and from the entire global market than the Asian markets. Some authors have examined herding behavior during the covid pandemic, Bouri et al (2021) sought to understand the role of coronavirus pandemic on investor herding on global stock markets. The findings in their paper show a strong association herd formation in stock markets and COVID–19 induced market uncertainty, the results also find the herding effect of COVID–19 induced market uncertainty is strong in emerging stock markets as well as European markets particularly Portugal, Italy, Ireland Greece and Spain.

Cheng et al (2022) investigates the role of the COVID–19 pandemic and how it affects the connectedness network of stock market volatility in 19 countries around the world. Results in this work show that the COVID–19 pandemic strengthens the overall volatility connectedness and the global connectedness level is high throughout 2020. The results highlight that China is disconnected from the global volatility connectedness network until late November 2020. Li et al (2022) study the empirical link between COVID–19 fear and the stock market volatility. The results in this study show that the stock market performance and GDP growth decreased significantly through average increases during the pandemic. From an emerging market perspective, Rakshit and Neog (2022) examines the impact of exchange rate volatility, oil price return and COVID-19 cases on the stock market return and volatility for selected emerging market economies. The findings of this paper shows a negative relationship exchange rate volatility and the stock market returns in Brazil, Chile, India, Mexico and Russia during the COVID-19 pandemic while there is a positive relationship between oil price and stock market returns across all countries in the study during the pandemic.

The above-mentioned papers invetigating on the effects of COVID-19 on stock markets employ mostly 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 a number of general stock indices from across the world.

3. Data and Modelling Strategies

3.1 Data

The paper investigates selected stock markets indices behaviors during the period of 02.08.2019 and 09.07.2020. According to Seligmann et al. (2020), this period may involve both first and some parts of second waves of COVID-19. We also observed the behaviors before and during COVID-19 period. In this respect, our before (during) COVID-19 analysis period covers the period of 02.08.2019 and 10.03.2020 (02.08.2019 and 09.07.2020). The data consists of 247 daily price information for 41 stock markets in Africa, America, Asia, Europe and Oceania. In these world regions/continents, we selected our sample based on (i) the least/most effected from COVID-19 according to total deaths and total cases[2], (ii) having relatively sizable stock market, (iv) geographical variations by continents. To define the least/most effected from COVID-19, we compared the number of COVID-19 cases and deaths by using from Johns Hopkins Coronavirus Resource Center,[3] Worldometer[4] and WHO[5] data as of 9 July 2020. We used IMF/WFE data to define importance of stock market in the selected country. Daily stock market indexes were retrieved from Bloomberg. To decide geographical variations, we followed the transmission path of COVID-19, which started in China, effective in greater Europe including Turkey and then reached US and other countries. Table 1 presents the list of the 41 countries considered with their respective stocks in this paper. Note, in a case where a country has more than one stock market, only a stock market index is listed. In Africa, only two country's stocks, i.e. South Africa and Egypt were included. In America (North, central and south), the seven countries included were: the US, Brazil, Mexico, Canada, Chile,

[2] Available at: https://www.worldometers.info/coronavirus/ (accessed on 9 July, 2020).
[3] Available at: https://coronavirus.jhu.edu/data/cumulative-cases (accessed on 9 July, 2020).
[4] Available at: https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/ (accessed on 9 July).
[5] Available at: https://covid19.who.int/ (accessed on 23 April, 2020).

Colombia, Argentina. In Asia, the 16 country's stocks were listed. These were stocks from India, Turkey, Pakistan, China, Indonesia, Bangladesh, Saudi Arabia, Philippines, Japan, Isreal, South Korea, Greece, Qatar, Malaysia, Singapore and Taiwan. In Europe, the fourteen countries listed were: the UK, Italy, France, Spain, Peru, Russia, Belgium, Germany, Netherlands, Sweden, Switzerland, Romania, Poland, and Slovakia. In Oceania, only Australia was included. Obviously, COVID-19 pandemic affected impacted the economies of Asian and American countries more than any other countries in the globe, probably due to large land mass and international migration tendencies among countries in the two continents.

Since COVID-19 crisis had influenced major global stocks considered before the crisis was declared a pandemic on 11 March 2020, we therefore partitioned the series into two subsamples based on the time of influence of the crisis on the individual stocks. We investigate the behaviors selected stock market during pre-COVID-19 period (02.08.2019 and 10.03.2020), and whole sample involving COVID-19 period (02.08.2019 and 09.07.2020). Table 1 also presents the standard abbreviations and stocks definition for the 41 stock markets. Due to lack of data, Iran was excluded from the list (also see, Zhang et al., 2020). As the time of data collection, the US was highly affected by the COVID-19 pandemic and DJIA stocks index was used to represent US stock market in proxy. Table 1 also displayed ranking of countries by total number of deaths as of 9 July 2020. In Africa, South Africa was more impacted by COVID-19 pandemic than Egypt. In America, The US recorded highest number of COVID-19 induced deaths, while Argentina recorded the least number from among American countries. In Asia, highest number of deaths was recorded in India as at the time of data collection, while Taiwan recorded the least number from the group. In Europe, the UK recorded the highest number of deaths, while Slovakia recorded the lowest number of deaths. In the overall, the US recorded highest number of deaths among the 41 countries, while Taiwan ranked the least in 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 observed from January to March 2020 in all the stocks indices. The COVID-19 induced stocks crash dates were heterogeneous across stocks as reported in Table 4, while crash dates were found around mid-March 2020 in nearly all cases.

[INSERT FIGURE 1 ABOUT HERE]

3.2 Modelling Strategies

We use fractional integration methods that belongs to the category of long memory processes, which are characterized because produce 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. Thus, the main advantage of fractional integration is its flexibility, that allows us to consider a wide range of alternative modelling approaches like anti-persistence ($d < 0$); short memory ($d = 0$) versus long memory ($d > 0$); stationarity ($d < 0.5$) versus nonstationary ($d \geq 0.5$) process; unit roots ($d = 1$), etc. In this context, classical ARMA and ARIMA models become particular cases of the I(d) approach when $d = 0$ and 1 respectively. Basic references here are Granger (1980), Granger and Joyeux (1980) and Hosking (1981).

The estimation of the differencing parameter is conducted via Whittle function in the frequency domain by using a simple version of a testing procedure developed in Robinson (1994). Using this approach we do not to a priori differentiate the series in case of nonstationarity since the method is valid for any real d. Using alternative approaches like

Sowell (1992) or even semiparametric methods (Geweke and Porter-Hudak, GPH, 1982) essentially produced the same results.

4. Empirical Results

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

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

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 table 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 refers 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 was 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 all cases; however, we can observe some differences across the indices. For example, there are total 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 imply 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 which 8 of them are significantly below 1 and thus showing mean reverting behavior. Those indexes 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). Moreover, this method accommodates very well in fractionally integrated processes and its log spectral function approximates the one of AutoRegressive structures. The first thing we observe here is that the time trend is never required, and focusing on d. We observe that there is a single case (MEXBOL with 0.95) showing reversion to the mean ($d < 1$). Therefore, in the rest of the cases we cannot reject the null hypothesis of a unit root (i.e., $d = 1$). More importantly, in this sub-sample, there are 24 indices where d is significantly higher than 1 which imply 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), FBMLLCI (1.14).

[INSERT TABLES 2 AND 3 ABOUT HERE]

According to the results reported so far, for Table 2 and Table 3, mean reversion is observed in 12 (1) of the indices (index) if the errors are uncorrelated (autocorrelated). For these series, shocks will have transitory effects disappearing in the long run though taking 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 comparing the impact of mean reversion. Interestingly, only MEXBOL index shows mean reverting behavior in both uncorrelated (autocorrelated) errors.

In Table 4, we record the impact dates of stocks crash and stock gain dates with values of stock index on these dates. While stock market crashes started in 19.02.2020 in 9 stock markets[8] and generally happened during 05.02.2020 and 20.02.2020, stock market gain started in 18.03.2020, 19.03.2020, and 23.03.2020 in 10, 6, and 18 stock markets respectively and generally happened during 17.03.2020-23.03.2020. It seems that news of fiscal stimuli and further monetary policy actions boost stock markets globally (Gormsen and Koijen, 2020) specifically after CARES act of 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 main reason of stock market increases in the US and elsewhere. Second, the increases in stock markets suggest that sharp decline has lasted either around one or almost 2 months in global stock markets. Interestingly, very close crash and gain starting dates of Shanghai Stock Exchange Composite Index (SHCOMP), which are 05/03/2020 and 23/03/2020, suggest that Chinese stocks started to increase very fast. Third, above crash dates may suggest that using official pandemic announcements of WHO, which is 11 March, 2020 would have led to biased results in the stock market mean reversion and persistence estimates.[9]

[8] 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.

[9] 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) (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).

[INSERT TABLE 4 ABOUT HERE]

In Table 5 and 6, we present the results of 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 41indexes show mean reversion and d is significantly below 1 (such as below in 0,90)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, 38 out of 41 indexes show mean reversion and d is significantly below 1 (such as below in 0,90) 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 data pre-COVID and with the whole sample period. We observe that for the case of no autocorrelation, there is an increase in the value of d in 23 out of the 41 cases presented, changing from mean reversion (in pre-COVID) to lack of it (in the full sample) in the cases of BET, COLCAP and PCOMP. Focussing now on the case of autocorrelation, we also observe an increase in the estimated value of d in 39 out of the 41 cases. Mean reversion occurs in 34 cases with the pre-COVID data; in all these cases this property disappears when using the whole sample period.

[INSERT TABLE 7 ABOUT HERE]

5. Conclusion

This paper investigates mean reversion, the degree of persistence and the degree of dependence during the period of 02.08.2019 and 09.07.2020 which is involving first and some parts of second waves of COVID-19 global health crisis.

We first report a strong and widespread mean reversion in pre-COVID-19 period (02.08.2019 and 10.03.2020) in both uncorrelated and also autocorrelated samples. Second, whole sample (02.08.2019 and 09.07.2020) analysis involving 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., 2015a; 2015b, 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 whole sample analysis. Third, the results for the whole sample period involving pre-COVID period also suggest a strong increase in the degree of dependence in the data with the moving from transitory to permanent shocks in a larger number of cases. This evidence implies an increasing homogeneity for the degree of dependence in whole sample. Finally, the evidences available do not suggest a specific geographic focus for the mean reversion and degree of persistence/dependence.

Therefore, it is particularly apparent that after this sanitary crisis, it has been an increase in the degree of persistence/dependence in the majority of the stock market indices. This increasing and time-varying symmetry implies the increasing integration among stock markets which may result a decline in the benefits of diversification. Interestingly, while 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 COVID-19 period, we do not report consistency of our findings with previous papers. However, this paper related to existing empirical studies in some extent. The evidence of substantially increasing persistency 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 the further rational behaviors is still an open debate. We suggest that investors and policy-makers should be careful on the limitations of the fiscal/monetary policy actions due to ongoing uncertainties in 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, unique persistence profile (Gil-Alana and Payne, 2020) of each index, the determinants of dependency among stock markets, and the role of irrationality in the delayed crashes and a relatively early rebounds in global stock markets would be promising subjects. In addition, the presence of non-linear deterministic structures, as those on Chebyshev polynomials in time (Cuestas and Gil-Alana, 2016), Fourier functions (Gil-Alana and Yaya, 2021) or neural networks (Yaya et al., 2021) can be employed in the analysis of these or alternative stock prices data. Also, the large list of stocks could be partitioned into developed and developing economies in order to check for differences in stocks reactions to COVID-19 induced shocks as in Zhao, Rasoulinezhad and Sarker (2023) but we were limited by data availability at the time of data gathering.

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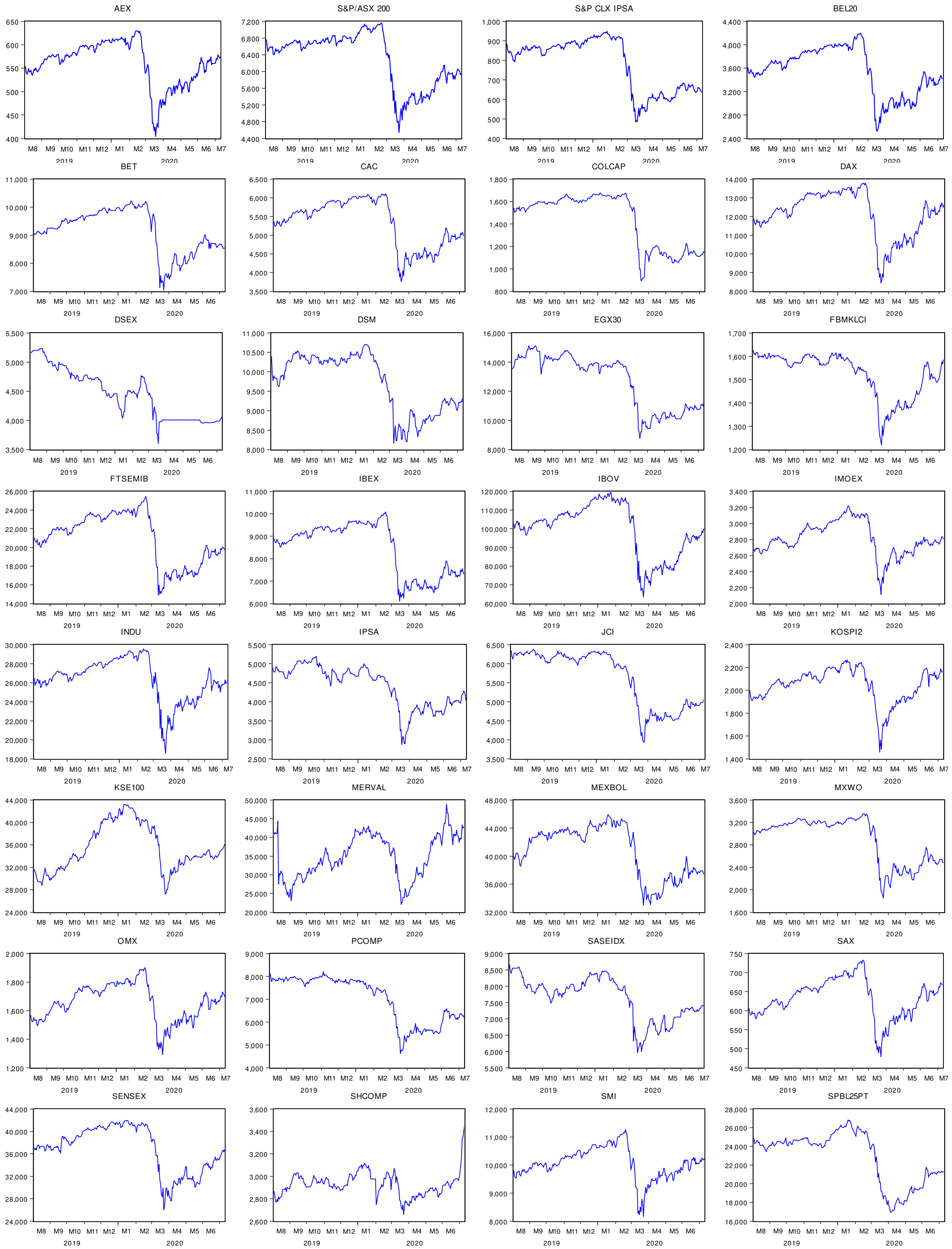
Table 1: Information on Sample Stock Market Indexes

Ranking by Total No. of Deaths as of 9 July 2020	Country	Abbreviation	Definition
Africa			
1	South Africa	TOP40	Johannesburg Stock Exchange Africa Top40 Tradeable Index
2	Egypt	EGX30	Egyptian Exchange EGX 30 Price Index
America			
1	US	DJIA Index	The Dow Jones Industrial Average Index
2	Brasil	IBOV	Ibovespa Brasil Sao Paulo Stock Exchange Index
3	Mexico	S&P_BMV	S&P Bolsa Mexicana de Valores Index
4	Canada	S&P/TSX Composite Index	S&P/Toronto Stock Exchange Composite Index
5	Chile	S&P CLX IPSA	The Indice de Precio Selectivo de Acciones
6	Colombia	COLCAP Index	Colombia Stock Exchange (BVC) (25 most liquid stocks)
7	Argentina	S&P Merval	MERcado de VALores Index of Buenos Aires Stock Exchange
Asia			
1	India	BSE Sensex	Bombay Stock Exchange Sensex 30 Index
2	Turkey	BIST 100 Index	Borsa Istanbul 100 index
3	Pakistan	KSE 100 Index	Karachi Stock Exchange KSE-100 Index
4	China	SHCOMP	Shanghai Stock Exchange Composite Index
5	Indonesia	JCI	Jakarta Stock Exchange Composite Index
6	Bangladesh	DSE30	Bangladesh Dhaka Stock Exchange 30 Index
7	Saudi Arabia	SASEIDX	Tadawul All Share Index
8	Philippines	PCOMP	Philippines Stock Exchange PSEi Index
9	Japan	TPX	Tokyo Stock Exchange Tokyo Price Index TOPIX
10	Israel	TA-35	Tel Aviv Stock Exchange 35 Index
11	South Korea	KOSPI	Korea Stock Exchange Index
12	Greece	Athens General Composite	Athens Stock Exchange General Index
13	Qatar	DSM	Qatar Exchange Index
14	Malaysia	FBMKLCI	FTSE Bursa Malaysia Kuala Lumpur Composite (KLCI) Index
15	Singapore	STI	Straits Time Index
16	Taiwan	TWSE	Taiwan Stock Exchange Weighted Index
Europe			
1	UK	UKX	Financial Times Stock Exchange
2	Italy	FTSEMIB	FTSE Milano Indice di Borsa Index
3	France	CAC 40 Index	Cotation Assistée en Continu 40 Index (Euronext Paris)
4	Spain	IBEX	Índice Bursátil Español Exchange 35 Index
5	Peru	S&P/BVL	Peru General Index

6	Russia	IMOEX	Moscow Exchange Russia Index
7	Belgium	BEL20	Euronext Brussels 20 Index
8	Germany	DAX	Deutsche Boerse AG German Stock Index DAX
9	Netherlands	AEX	Euronext Amsterdam AEX Index
10	Sweden	OMX	The OMX Stockholm 30 Index
11	Switzerland	SMI	Swiss Market Index
12	Romania	BET	Bucharest Stock Exchange Trading Index
13	Poland	WIG30	Warsaw Stock Exchange WIG 30 Index
14	Slovakia	SAX	The Slovak share index
Oceania			
1	Australia	S&P/ASX 200 Index	S&P Australian Stock Exchange 200 Index


AEX
S&P/ASX 200
S&P CLX IPSA
BEL20
BET
CAC
COLCAP
DAX
DSEX
DSM
EGX30
FBMKLCI
FTSEMIB
IBEX
IBOV
IMOEX
INDU
IPSA
JCI
KOSPI2
KSE100
MERVAL
MEXBOL
MXWO
OMX
PCOMP
SASEIDX
SAX
SENSEX
SHCOMP
SMI
SPBL25PT

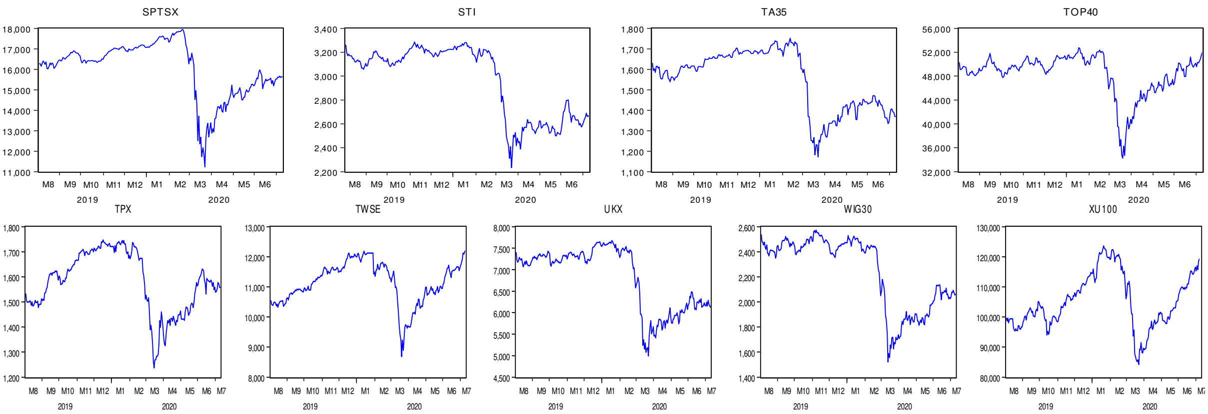


Figure 1: Stock indices movement

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.