# Stock Market Efficiency Amidst Fear of COVID-19: A Fractal View on Market Efficiency in Times of Crisis


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**Abstract**

Since the onset of the COVID-19 pandemic, financial markets have witnessed unprecedented movements. The pandemic damaged the performance of financial markets on a global scale and stock markets are in turmoil due to restricted economic activity caused by restrictive measures and the suspension of major events. As it is well documented that sudden and large shocks, e.g. the financial crisis of '07-'09 cause structural changes in financial markets which may also influence market efficiency. With the emergence of the COVID-19 pandemic the question regarding the validity of the Efficient Market Hypothesis (EMH) resurfaced. This study investigates the Efficient Market Hypothesis using MF-DFA methodology on two sub samples separating the pre-COVID-19 and post-COVID-19 periods. While the EMH relies on a variety of assumptions to describe the model, such as independence, normality and linear paradigm among others, stock markets are complex entities which prove to possess several properties such as long-term correlation, fat-tails, volatility clustering, fractal and multifractal properties, and chaos. Using MF-DFA to calculate the Hurst exponent which characterises the autocorrelation function by associating the long memory with persistence this study finds that the included stock market return series are not efficient in both the pre-COVID and COVID-19 period. All return series are found to be of a multifractal nature, both in the pre- and post-COVID-19 period. Based on the multifractality spectra between the pre- and post-COVID periods definitive conclusions of changes in the spectrum could not be drawn.

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# 1 Introduction

Worrying news reports regarding a cluster of pneumonia cases in China marked the end of 2019. These reports evoked memories of the first pandemic of the 21st century, the 2003 SARS epidemic, which was also caused by a novel coronavirus. The SARS outbreak caused widespread panic and disrupted the lives of millions in China and its neighbours, weakened the economy and dampened the stock market. In November 2019 the initial confirmed case of COVID-19, caused by the novel coronavirus SARS-CoV-2, was detected in Wuhan, China. Given that the novel coronavirus can quickly spread among people when they have close contact, even when symptoms do not yet appear and is most contagious in the first few days after the symptoms appear it caused deep alteration of social life and people soon became aware that COVID-19 had the potential to become the worst pandemic in recent history.

The first couple of months after the start of the pandemic the number of cases, and related deaths increased dramatically as the coronavirus rapidly spread to other countries in Asia, Europe and North America. On March 11, 2020 The world Health Organization (WHO) declared COVID-19, a global health pandemic in response to the number of reported cases for the preceding two weeks. At that point in time there were 118,000 confirmed cases and 5,000 deaths worldwide. In the two weeks following this declaration the the number of worldwide confirmed cases increased to 500,000 and in April exceeded one million.

In trying to contain the corona pandemic, or pandemics in general, there is no set of guidelines, policy prescriptions, models nor experts that governments can rely on to contain and deal with the impact. It goes hand in hand with uncertainty in both the medical and economic dimensions. The best practices for the containment of the pandemic come from own experiences, or that of other countries as the pandemic progresses. Medically, the fight against covid-19 is not just about finding a vaccine, or effective treatment preventing serious illness and death but also about understanding it's origins, how it evolves and how it mutates. Not just the medical, health care, side of the pandemic relied on how quickly and with what level of certainty these questions can be answered but they are also detrimental for the stability of the society and economy of countries, and globally. Financial economists are presented the challenge of determining how and to what extent the economy and the financial markets are affected by the unprecedented environment of the the COVID-19 pandemic.

Earlier research on the impact of global health emergencies show that pandemics severely affect the supply side of the economy, cause a decline and change in consumption patterns, cause a slowdown of the economic activity, may trigger higher inflation, decrease investments, trigger a debt crisis and cause a fall in the value of many assets, amongst others (e.g. Smith, Yago, Millar & Coast, 2005; Keogh-Brown & Smith, 2008; Keogh-Brown, Wren-Lewis, Edmunds, Beutels & Smith, 2010).

In contrast to conventional economic downturns, which are characterized by a moderate but accelerating decline in economic activity, the environment of the COVID-19 pandemic differs in that it poses a rare and sudden shock due to it's rapid emergence and global spread. Individuals are shown to experience difficulties forming beliefs regarding the future during major events that occur infrequently. Besides, when individuals update their beliefs, they place disproportionately more weight on the events that occurred more recently (Malmendier & Nagel, 2011). Even more so if these events are particularly salient (Bordalo, Gennaioli & Shleifer, 2012) This might lead individuals to form considerably different beliefs during the unprecedented COVID-19 pandemic period.

Since the onset of the COVID-19 pandemic, financial markets have witnessed unprecedented movements. The pandemic damaged the performance of financial markets on a global scale and stock markets are in turmoil due to restricted economic activity caused by restrictive measures and the suspension of major events. With the emergence of the COVID-19 pandemic the question regarding the validity of the Efficient Market Hypothesis (EMH) resurfaced. It is well documented that sudden and large shocks, e.g. the financial crisis of '07-'09, cause structural changes in financial markets which may also influence market efficiency. Hence recent crisis events are important in testing the Efficient Market Hypothesis proposed by Fama (1965). In the EMH a market in which prices always reflect the available information is considered efficient. Where the EMH, based on the information efficiency is divided in to three forms, weak, semi-strong and strong form efficiency. In the weak form, past information is directly embodied into current prices. As information enters the market randomly, movement of prices must by extension also follow a random pattern. Hence, an efficient market follows a random walk. This random sequences makes it impossible to predict prices or identify a pattern yielding abnormal returns, that is returns above the random walk without changes in its risk. As discussed the COVID-19 pandemic influences investor demand, preferences, risk profile regarding financial assets. This in turn can cause changes to the degree of market efficiency.

The EMH has become the quintessence of modern financial theory in explaining the behaviour of financial markets. It is the foundation for many financial theories in valuing financial instruments and methodological approaches such as the modern portfolio theory (MPT), Sharpe's capital asset pricing model (CAPM), Merton's option pricing model (OPM), Black-Scholes option pricing model and arbitrage pricing theory (APT). However, the EMH and the assumptions underlying it, have been challenged by numerous academics and practitioners both theoretically and empirically. The EMH is shown to not always be confirmed, the level of efficiency is not a constant but varies greatly between different countries and also with time. Additionally, during the '07-'09 global financial crisis market participants in markets that traditionally were considered to be effective, suffered immense losses. This is not novel at all as in times of crisis, changes in market efficiency have been observed before. Although the behaviour of markets in times of crisis in general as well as in a cross-country setting is not thoroughly documented and the 'problem' of market efficiency not solved. Hence the literature regarding market efficiency in crisis times can be improved and exploring stock markets during crisis periods is worthwhile.

While the EMH relies on a variety of assumptions to describe the model, such as independence, normality and linear paradigm among others, stock markets are complex entities which prove to possess several properties such as long-term correlation, fat-tails, volatility clustering, fractal and multifractal properties, and chaos. Leading to a large stream of literature developing the Fractal Market Hypothesis (FMH) contrary to the EMH. Financial markets are shown to be of a multifractal nature. Hence, it is necessary to adopt a paradigm that accurately deals with these characteristics of financial markets. An adequate statistical method for analyzing financial market time-series is with the use of Multifractal Detrended Fluctuation Analysis (MF-DFA), in which a volatility function combined with the scaling or power-law relationship is used to determine the Hurst exponent $h(q)$. Several factors make MF-DFA appealing compared to other methodologies such as its higher statistical certainty compared to wavelet based methods and more reliable detection of mono and multifractality. A comprehensive discussion of procedures for evaluating market efficiency is given in Section 2.8. Using MF-DFA this study presents a reliable multifractal characterization of the multifractal non-stationary time series by observe multifractal properties in the stock market indices enabling the examination of long range memory and characterization of fractal properties which is subsequently employed to quantify market efficiency. The Hurst exponent which characterises the autocorrelation function by associating the long memory with persistence. In case of persistence or positive long memory, past positive increments are positively correlated with future positive increments and vice versa. That is, an increase is more likely to be followed by another increase and a decrease is more likely followed by decrease. On the other hand, with anti-persistence or negative long memory a positive increment is more likely to be followed by a negative increment and vice versa, signifying a higher frequency of switching than expected with a random process. In either case there is a pattern in the fluctuations of returns that could possibly be identified and exploited to obtain abnormal returns, contradicting a random process. In the center of its interval the Hurst exponent signifies the series is not serially correlated and reflects a Brownian motion and can be described by a random walk implying market efficiency. Note that in the EMH an efficient market follows a random walk, hence this demonstrates that the EMH is a special case of the FMH. As such the fractal analysis, and by extension the FMH, expands the meaning of EMH.

A vast body of research studied the market impact of COVID-19, however few studies examine the stock market efficiency in and after COVID-19 times. This study contributes to the existing literature in several ways. First of all, it tries to broaden the investigation, and hopefully the understanding of the impact of unexpected black swan events on the efficiency of financial markets. The efficiency before and after the onset of the COVID-19 pandemic is compared showing the impact, dynamics and evolution of the efficiency. Additionally, it documents how financial markets react to the COVID-19 pandemic in a cross-section of countries encompassing North America, Europe, Central and East Asia and the Pacific. This cross-section setting allows for comparative analysis of how the various economies react concerning the EMH. Furthermore, it tests whether and to what degree financial markets are efficient, and by extension if patterns can be identified that yield abnormal returns.

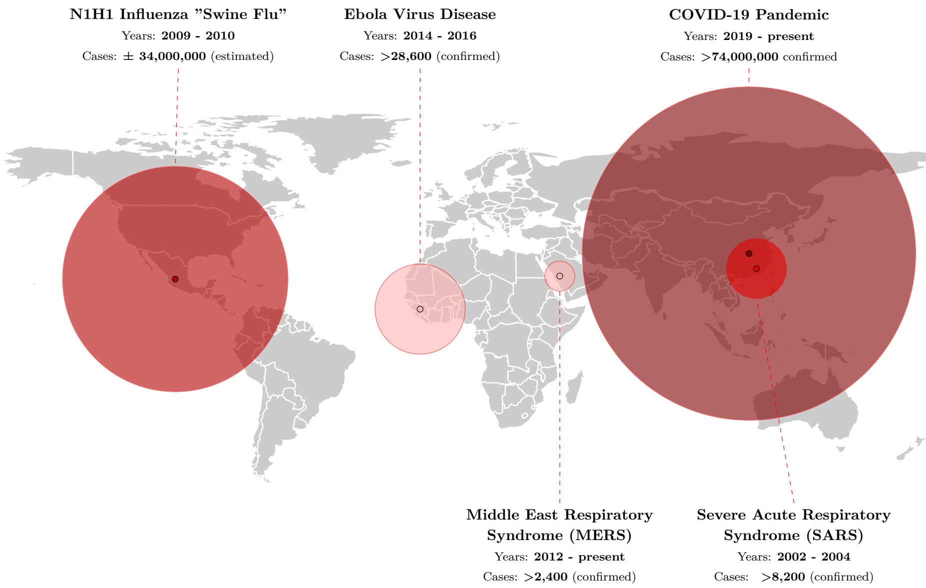
The remainder of this thesis is organized as follows. Section 2 will discuss the theoretical framework with an overview of the most relevant literature on market efficiency, Random walk, the Efficient Market Hypothesis with its assumptions, observed anomalies and the development of fractal finance. Furthermore, discussing procedures for evaluating market efficiency with their advantages and drawbacks in motivating the use of MF-DFA. In Section 3 the research methodology using MF-DFA will be discussed, where first the collected data sample and defined variables will be discussed. After which the applied research methodology is explained. Section 4 describes the empirical results and Section 5 discusses the findings and provides concluding remarks.

## 2 Theoretical Framework

### 2.1 Previous Epidemics and Pandemics

Over the last two decades zoonotic diseases, originating in animals and transmissible to humans, have impacted global health. Major epidemics and pandemics outbreaks characterised by human-to-human transmission have proven to have far-reaching effects with profound implications for global health, economic systems, financial markets and the societal landscape. Fig. 1 gives a graphical overview of the major zoonotic epidemics and pandemics that occurred since the late twentieth century highlighting the locations of the first detected cases, the relative outbreak magnitude and the fatality rate.

**Figure 1.** *Epidemics and pandemics with human to human transmission since the late twentieth century.*




*Note.* The location where the first case is detected are indicated with black circles. The red circles denote the outbreak magnitude measured by the number of human cases.

The Severe Acute Respiratory Syndrome (SARS) pandemic in 2002-2003, originating in China and spreading across continents, showed how a health crisis can adversely impact global trade and supply chains due to the increased globalization. Moreover it demonstrated how quickly such a novel virus can spread. Sectors which are reliant on cross-border activity, such as travel, hospitality and retail are immediately impacted. The Swine Flu pandemic in 2009-2010 once again accentuated the importance of preparedness and swift policy responses in order to mitigate economic disruption of pandemics. The recurring outbreaks of Middle East Respiratory Syndrome (MERS) since 2012, although less pervasive, emphasize the need for understanding the origins, evolution and how such mutations of such diseases which transfer from animal to human. These earlier global health emergencies have contributed to our understanding the health, societal and economic implications during epidemics and pandemics. Financial markets and investor behaviour during previous epidemics and pandemics are affected market returns, market volatility and investor decision making through changed risk factors, financial disruption and increased volatility.

## 2.2 COVID-19

On December 31 2019 the Chinese office of the WHO was informed of the detection of a cluster of pneumonia cases in Wuhan, China. On January 14 2020 the WHO reports that there is no clear evidence suggesting that the virus can easily transmits between humans for which the WHO relies on information supplied by the Chinese government. Furthermore it notes that investigations into the full extend is still being evaluated as Wuhan is a major domestic and international transport hub. The WHO recommends public health measures and surveillance for novel corona viruses apply but does not recommend any specific health measures for travelers. On January 23, transport in Wuhan and surrounding areas is severely restricted. It wasn't until 30 January that the WHO declared a Public Health Emergency of International Concern (PHEIC). On 11 February the novel coronavirus was named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and the disease it causes is named COVID-19. On 22 February the Italian government reports clusters of COVID-19 cases in Lombardy. Since members of European Union (EU) are heavily connected it is considered that the virus could be present anywhere in Europe. On 25 February the Center for Disease Control and Prevention (CDC) in the United States warned for corona outbreaks in the US. On 11 March the WHO declared covid-19, a global health pandemic in response to the number of reported cases for the preceding two weeks. It wasn't until this point that most countries in the world implemented lockdowns in order to contain the spread of the coronavirus.

The COVID-19 pandemic differs from earlier global health emergencies in a number of ways. The genetic sequence of the novel coronavirus causing COVID-19 is different than that of earlier pandemics resulting in little insight into its origins and characteristics. Transmission rate of COVID-19 is higher than SARS and MERS (Xie et al., 2020). Case fatality is also found to be lower compared to previous pandemics. Even though it resulted in many more deaths than both of these prior outbreaks combined (Mahase, 2020). The COVID-19 pandemic put greater emphasizes on the importance social distancing, mask-wearing, and vaccination in reducing the impact on public health than was the case during earlier pandemics. In the globalized world we live in today a highly contagious virus which can spread between persons through small droplets which are spread when a person with COVID-19 coughs or exhales can spread much faster and lead to a pandemic. In a normal world, people in urbanized communities do not normally keep more than 1 meter distance from other people and as such the virus is not likely to be contained soon. Additionally, the elderly population is uniquely affected. Older people have a significantly higher risk of developing severe illness from COVID-19. Communities which have a higher population of elderly people are more prone to higher death tolls.

A growing body of research examined the effect of covid-19 on the global economy. The pandemic caused a slowdown in economic growth for countries worldwide as it triggered the sharpest downturn in the world economy since the Great Depression. Global GPD declined by 3.0 percent in 2020 (International Monetary Fund, 2020). The labor market is strongly affected. It is estimated that up to 80 percent of the total workforce, that is nearly 2.7 billion workers, were affected by the pandemic. Coibion, Gorodnichenko and Weber (2020) estimate that unemployment dramatically increased and that the number of job losses are much larger than over the entire great recession. They also note that many of the individuals losing their jobs will not actively look to find new ones. In 2020 global poverty and inequality increased significantly, the largest increase over the least 30 years (Mahler, Yonzan & Lakner, 2022). Moreover, The economic fallout resulted in the disruption of global supply chains, as the demand fell dramatically due to the fact that the majority of customers were in lockdown (Lawreniuk, 2020). Besides, COVID-19 had a significant impact on the local economy. The pandemic caused great challenges and difficulties to many small-business owners, many of which were forced to shut down temporarily or even permanently Zhai and Yue (2022). Their findings suggest that the impact on the local economy and societies are not evenly distributed. The tourism industry is also significantly impacted. The by various countries imposed travel bans, border closures and stay at home orders placed tourism on hold as the travel plans for the majority of tourists either got postponed, changed destinations, or cancelled. Which entailed an undeniable devastating impact on the tourism industry which was more serious than the impact of the SARS (Lee & Chen, 2022). The authors also note that the impact of the pandemic varies across different sub sectors and businesses such as the aviation industry, restaurants and recreational services. The lockdowns not only affected the leisure industry but also resulted in decreased production, a supply side shock, which gave rise to shortages of goods and services. As factories were forced to shut down this had a negative effect on, amongst other, manufacturing and retail industries (Guerrieri, Lorenzoni, Straub & Werning, 2020). Moreover, The economic fallout resulted in the disruption of supply chains, as the demand fell dramatically due to the fact that the majority of customers were in lockdown (Lawreniuk, 2020). The disrupted supply chains resulted in higher unemployment rates, Lawreniuk (2020) highlights Cambodia's garment sector labor market shock where approximately one third of the entire workforce were laid off. The effects of the pandemic to the workforce do not seem to be uniform. Borjas and Cassidy (2020) examined the effects on the labor market in the United States, finding increased unemployment primarily among less skilled workers. Older workers seem to be more affected by the pandemic compared to other ages groups, and woman also have higher unemployment rates than men across all age groups (Bui, Button & Picciotti, 2020). Compared to previous recessions the unemployment rates among older workers are greater than the rates during the Great Recession and the early 1980s recession (Bui et al., 2020). While new entrants to the labor market also face great challenges due to the pandemic disrupting education and (work-based) training (Wu, Yong & Lee, 2022).

The pandemic also sent shock waves throughout international financial markets. Some research focused on the effect of covid-19 on the banking sector. Banks are particularly vulnerable in times characterised by high levels of uncertainty. The pandemic significantly impacted the financial performance, risks and practices of the banking sector. The pandemic slowed the growth of bank loans and the more a country is affected by the pandemic, the weaker the bank lending is ( olak & Öztekin, 2021). Financial performance and stability of banks are significantly negatively impacted by the pandemic (Elnahass, Trinh & Li, 2021). Underpricing of Initial Public Offerings in COVID-19 times is significantly higher than in the precovid period, and the level of underpricing increases if fear related to covid-19 increases in the Chines market(Lobregt, 2022). Stock market indices in the United States the S&P 500 index fell by as much as 30 percent from mid-February to late March. In the first 100 days the pandemic diminished earnings by 30 percent in the Chinese stock markets (Ali, Alam & Rizvi, 2020). The ten major markets around the world declined and the effects of the pandemic on capital markets could be as large as the financial crisis of 1929 Ruiz Estrada, Koutronas and Lee (2020). Islamic stock markets seem to be less negatively impacted and hence perform better during the pandemic (Shear & Ashraf, 2022). Empirical evidence indicates that COVID-19 adversely affected stock markets globally. Ali et al. (2020) further note that as the epicenter of the coronavirus moved from China to Europe and the US, the Chinese market stabilized as opposed to the global markets which experienced great declines in later phases of the pandemic.

The covid-19 pandemic gave rise to fear of the unknown among a large part of the world population. During the corona pandemic governments, businesses and individuals had to react without having a choice or the information on how to best react. Various countries implemented non pharmaceutical government interventions on an unprecedented scale, such as quarantines, social restrictions, traffic restrictions, teleworking, and stay-at-home orders also known as lockdowns, which were advocated by medical experts as well as economists. These non-pharmaceutical interventions are found to have had a significant impact on reducing the transmission of the covid-19 hence preventing infections and deaths (Flaxman et al., 2020). Although the lockdown interventions reduced the transmission of the coronavirus and hence positively affect the public health dimension, it is important to note that these lockdowns also severely affected the society and the economy of countries all over the world as it contributed to the fear of what was about to come.

This uncertainty can cause unusual price reactions and gives rise to overreaction and underreaction theories. e.g. panic and fear among investors can cause them to sell in response to the crisis. Section 2.5 provides a more detailed description on those theories. Given the high level of uncertainty, especially in the first stages, of crises periods, tend to cause market participants to overreact which results in the collapse of asset prices in theses early stages and bounce back in a later stage. Fetzer, Hensel, Hermle and Roth (2021) documents a vast increase in economic anxiety when the covid-19 virus spread to the US. Furthermore they find that people overestimated the mortality rate and contagiousness of the virus.

## 2.3 Investment behaviour

In what way investors evaluate asset prices is key to understanding and examining financial markets reactions to new information. The following paragraphs will look into how investor behaviour, i.e. financial decisions, influence asset prices. Starting from the perspective of the traditional finance constant growth model followed by the behavioural finance scenario-based approach.

According to the Constant Growth Model (CGM) the stock price is a function of the dollar value of the first expected dividend, the required rate of return the investor seeks in order to compensate for the risk, and the expected growth rate (Gordon, 1959). The expected first dividend is positively related to the stock price whereas the required rate of return and the expected growth rate are negatively related to the stock price. The value of the first dividend changes as the economic environment changes.

When economic activity slows down, businesses reduce their production, which causes them to let employees go, which in turn decreases individuals income and hence less consumption. Firms are expected to have less profits, which they pay dividends from, causing the expected

growth rate to decrease. For investors to participate in the stock market during these times the returns need to increase, causing asset prices to decrease. In addition, the fact that the investors health is at risk causes the investor to be more risk averse increasing their required rate of return (Decker & Schmitz, 2016).
Considering the case of a epidemic or pandemic. During a global health emergency the by government imposed restrictions in an attempt to slow the spread, especially social distancing and lockdowns, cause the economy to slow down. This slowdown causes dividends to decrease, the expected growth rate to decrease. The investors required rate of return increases due to both the environment being riskier and the investor being more risk adverse due to the greater health risk. These factors combined cause the stock price to decrease.

The basis for the scenario-based approach comes from the idea that for each financial decision a rational investor examines a number of different outcome scenarios when evaluating asset prices. A rational investor aims to achieve the highest possible return with the lowest possible risk. The return is dependent on the occurrence of certain financial conditions and the risk can be measured by the standard deviation of the return.
The scenarios include both favourable conditions, such as economic growth and technological innovation, but also the worst scenarios of for example global health pandemics and wars. For each scenario the investor determines the probability with which the scenario, in his view, is expected to happen in the real world. The sum of probability of all n-scenarios times the expected return under the n-th scenario lead to an expected return for each scenario and also a corresponding standard deviation. The behaviour of the market can be viewed as the aggregation of the perceptions of all investors. So the perceptions of investors shapes the behaviour of the market.
The release of new information leads investors, and thus the stock market, to evaluate the probabilities and expected returns under the different scenarios. The revised scenarios and probabilities influence the market's performance, that is it's return and volatility. The released news can cause a change in the probabilities of the already examined scenarios but also cause including a new scenario in the evaluation. In the case that the released news is not included in the n-scenarios the investor has considered, i.e. the news is not in line with expectations, the expected return and the risk are over- or underestimated. When the news corresponds to a not considered negative scenario the expected returns are overestimated and the risk underestimated.

Considering the case where new information has come to light that leads investors to conclude that a pandemic of epidemic is very likely to happen, as a result the probabilities for a bad scenario are underestimated and have to be increased significantly. Under the bad scenario the expected returns are low and risk is high which might lead to a decline in stock prices and lower stock investment turnover.

## 2.4 Market Efficiency

As discussed in the above Section 2.3, newly available information changes asset prices. If investors are assumed rational at every point in time and asset pricing models are correct, all available information at a certain time is incorporated in the asset prices and the market is said to be efficient. The Efficient Market Hypothesis (EMH) is one of the milestones in modern financial theory and serves as a guiding principle for both practitioners as academics (Fama, 1965). The EMH states that the price of an asset is reflective of all the available information in the market. To illustrate this, suppose that some information, e.g. a future merger between two firms, is widely available to investors. If the stock price does not yet reflect the information regarding the merger, investors are able to trade on it, moving the price until the information is no longer useful in trading. Note however that this does not necessarily imply the unpredictability of stock prices. For example, if the information is that a financial crisis is coming soon investors may sell stocks until the price drops enough so that the current risk is compensated by the expected return.

Fama (1965) categorizes the EMH into three sub hypothesis based on the set of knowledge: Weak-, Semi-strong- and Strong form. In the weak form the current stock price is considered to be a reflection of all past trading information. Implying that past price changes do not follow any pattern or trend and did not have any serial dependencies. Outperforming the market based on technical analysis, using historical price data in an attempt to predict future prices, is not possible due to past prices being incorporated into current prices.

In the semi-strong form all publicly available information is considered to be reflected in the stock price. So in addition to the past trading data, the weak form, all public information such as financial statements, news and other public disclosures are considered to be incorporated into current prices. Outperforming the market with fundamental analysis, analyzing a company's financial and/or economic conditions should not result in above average results.

The most stringent form of the EMH, the strong form, assumes that all information, both from public and private sources, is fully reflected in stock prices. This form implies that even having access to non-public, insider, information won't lead to an investor investors outperforming the market.

The EMH outlines the standard ideal state and operating rules of financial markets. It has become the quintessence of modern financial theory. The modern portfolio theory (MPT), Sharpe's capital asset pricing model (CAPM), Merton's option pricing model (OPM), Black-Scholes option pricing model and arbitrage pricing theory (APT) all have their foundation in the EMH. There is vast empirical literature in favour of the EMH, extenuating that in principle pure logic, rationality assisted with auxiliary assumptions can explain asset prices. In line with this the traditional view even reconciles asset bubbles with the concept of homo economicus. Contrary to the idea that the formation of speculative asset bubbles should not be possible in an efficient market is widespread among specialists, with recent history of capital markets showing they are not uncommon.

While the efficient market hypothesis was widely accepted as the correct explanation of how markets work, the EMH started to get more critique and many began to believe that this exercise lacks plausibility. This gave rise to a more nuanced understanding of the mechanisms of financial markets in which, at least partially, past price patterns and fundamentals can be used to predict future stock prices. Also, many viewed that the role of psychology had to be recognised in finance. The heuristics and biases literature gained popularity among academics as well as practitioners. The foundation of non-rationality was provided by the research of Tversky and Kahneman (1974) in which they break down rationality in terms of a number of psychological mechanisms that shape human action and behaviour. Their contribution shaped the trend in academics towards behavioural finance, paving the way for many subsequent research in this domain. Which both theoretically and empirically challenged the EMH by revealing various behavioral anomalies (e.g. cognitive biases such as overreaction, overconfidence, representative bias) that cast doubts about the validity of the EMH.

## 2.5 Overreaction

The Overreaction Hypothesis (OH) challenges the EMH by arguing that investors overreact to the emergence of new information which causes asset prices to temporarily deviate from their fundamental value and as such asset prices may not always fully reflect all the available information (De Bondt & Thaler, 1985). Overreaction is not such a radical departure from traditional theory. Looking back in history one of the first notions of stock market overreaction was made by Keynes (1973) who argued that “day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and nonsignificant character, tend to have an altogether excessive, and even an absurd, influence on the market”

The paper by De Bondt and Thaler (1985) is the first paper to explicitly reject the EMH due to the behavioural overreaction theory. In this paper De Bondt and Thaler examined the stock market overreaction hypothesis, and concluded that in the U.S. large movements in stock price will be followed by price reversals in the opposite direction. This creates an opportunity for investors to realize abnormal returns by taking advantage of long-term overreactions, as past ”winners” will subsequently have negative returns during the next time period while past ”losers” will subsequently have positive returns in the next time period. Forming a portfolio based on underperforming stocks over the past three to five years will yield significant higher returns in the next three to five years compared to stocks that performed well in that same initial three to five year period.

The theory on the causes of the overreaction evidence firstly stresses irrational perceptions of risk. The emotional reactions of investors often conflict with cognitive assessment of risk. In line with this past losers feel more risky than past winners from an investors point of view. Secondly, people worry about how other people look at them, individuals experience social pressure which may cause them to conform to the general opinion even when they privately disagree. This phenomenon is known as herd behaviour.

The overreaction hypothesis has been examined in both short and long-term. In the case of short-term overreaction, the deviation from fundamental value is contributed by the existing literature to the market reacting to the arrival of new information. Whereas the literature on long-term overreaction describes the deviation from fundamental value arising from waves of optimism and pessimism. De Bondt and Thaler (1985) examined a three to five year period. Jegadeesh (1990) provides empirical evidence support for abnormal returns in the short-term when the ranking and holding period has a duration of one month. Lehmann (1990) finds significant abnormal returns with a one week ranking and holding period. Bremer and Sweeney

(1991) looked at a two day period following an event, characterizing an overreaction event as a decrease in stock price of more than 10 percent in one day.

Furthermore, the overreaction hypothesis has been examined in various contexts. A vast body of research documented and provided evidence for the presence of overreaction in amongst other, the global financial crisis of 2008, the stock market crash of 1987, the east Asian crisis in 1997 and the Russian bond default in 1998. Another range of studies focuses on crisis such as the political crisis in Taiwan, and also terrorist attacks are examined. Such black swan events, composed of economic events, social events, acts of terrorism, natural disasters, pandemics and epidemics have an impact on the investors' mental health and well being. Which in turn impacts it's physiological state and sentiment that affect the investors behaviour in determining asset prices which results in stock price movements and stock market volatility.

In times of crisis, which are characterized by high volatility due to a high level of uncertainty, short-run stock overreaction is commonly observed. During the SARS epidemic in 2002, previous research found that during this public health hazard market volatility increased (Wong, 2008; Chen, Jang & Kim, 2007). In the covid-19 pandemic stock market volatility increased significantly, and reached levels higher than any previous crisis over the last 120 years (Baker et al., 2020). Looking at trade volume and volatility Baig, Butt, Haroon and Rizvi (2021) found that liquidity decreased and volatility increased during the pandemic. Where they note that increases in the number of covid-19 related cases and deaths, lockdowns and negative sentiment increase stock market volatility and illiquidity.

### 2.6 Traditional theoretical view of financial market behaviour and efficiency

The concept of the homo economicus, in which individuals are described as completely rational striving for their own maximum utility, introduced by John Stuart Mill in the nineteenth century has been fundamental to traditional economic theory. These theories contend that each individual will always make the most profitable and rational choice. They always interpret the available information correctly, calculate probabilities of various scenarios right and do not let emotions distort their decisions. The homo economicus forms the basis for the EMH, as it assumes that market participants are rational and self-interested in their economic decision-making given the available information leads to efficient market outcomes according to the EMH.

Market efficiency had already been anticipated conceptually before Fama (1965) formulated the EMH. In the dissertation submitted by Bachelier (1900) pioneering an option pricing model, he offered a first analysis of mathematical properties to model the stochastic change in stock prices. Bachelier passed over the conventional, fundamental, analysis and attempted to estimate the probabilities of price moves in studying French government bonds as he recognised that trying to understand causes and effects of market movements was futile. Bachelier describes markets as a 'fair game'. Analogous to a simple coin toss, each time the coin is tossed the odds remain 50-50 independent of what happened in the previous toss. Trends of repeated equal outcomes can be observed but with each toss the trend is as likely to continue as it is to end. i.e. Bachelier assumed that there is no market memory. He recognised that past, present and even discounted future events are reflected in market prices, but often show no apparent relation to price changes. i.e. prices move up and down randomly, with each fluctuation being completely independent from the last suggesting there should be no predictable pattern of price movements. This is known nowadays as a Random Walk. A Random Walk can be defined as "a mathematical formalization of a path that consists of a succession of random steps" (Pearson, 1905).

In line with this, if price changes of French government bonds, as in Bachelier's proposal, are depicted as a time series, they exhibit a bell-shaped curve (a normal or Gaussian distribution) with the curve showing a high concentration of small changes clustering in the center and few large changes in the tails. Adding different independent stochastic fields with different distributions will produce a stochastic field that is normally distributed. In terms of financial markets, the distribution describes the price difference of the time series, with zero mean.

Bachelier's insights went unnoticed for many years before getting picked up by economists in the 1960s and 1970s. Economists began to recognise that describing markets with the principals of Brownian motions had various advantages, and Bachelier's ideas of 'fair games' and 'random walks' caught on. Fama developed these concepts into a broader framework by studying market dynamics beyond the independent increments which would later become widely known as the Efficient Market Hypothesis (EMH). Recall from Section 2.4 that, in line with EMH, when prices always fully reflect the available information a market is considered efficient. Since new information enters the market randomly, movement of prices must therefore also be random. The more efficient a market is, the more random the sequence of price changes becomes. That is to say, fluctuations of returns in capital markets are unpredictable. The random sequence of price changes makes it impossible to predict prices and identifying a pattern yielding returns above the random walk model is not possible. i.e. there is no statistical short or long term memory in the prices. Excess returns can thus not be obtained by using any historical, public or inside information in the case of efficient markets.

The EMH relies on a variety of assumptions to describe the model, such as independence, normality and linear paradigm among others. Several scholars cast doubt on the EMH, arguing its underlying assumptions make it challenging to provide guidance for investment practices. The EMH is theoretically challenged by persistent anomalies in financial markets, e.g. the P/E and calendar effects, together with the longstanding contradictions and conflict between fundamental and technical analysis, e.g. historic price movement repetition. The latter case illustrated by the overreaction theories, described in Section 2.5, where observed large movements in stock prices over a certain (historic) period are found to be followed by price reversals in the opposite direction (De Bondt & Thaler, 1985; Lehmann, 1990; Bremer & Sweeney, 1991). With the defined winner-loser investment pattern, the sequence of price changes is not random but exhibits historic price movement pattern. Hence disputing the EMH independence assumption. Regarding the anomalies in financial markets a variety of studies reveal patterns of possible predictability based on past stock price behaviour, which among others include, short-term momentum including underreaction to new information, long-run price reversals, seasonal and day-of-the-week patterns. The literature also documents valuation parameters can be used in future returns predictions such as, the initial dividend yields, short-term interest rates and the term structure of interest rate spreads. Cross sectional patterns based on firm characteristics and valuation parameters are also found to be predictable such as the the size of the firm (Size effect), P/E and P/B ratios (value- and growth stocks).

Others doubt the linear paradigm, the assumption that changes in a series of return rate distribution are of a linear fashion (Mandelbrot, 1970). Furthermore, several studies cast doubt on the normality assumption as actual return data show discrepancies compared to a normal distribution. Actual returns are shown to have the characteristics of fat tails, skewed with higher than expected larger positive or negative returns, and leptokurtosis, higher than expected peaks around the mean.

Due to the failure of the independence and normal distribution of increments assumptions time series with such characteristics do not adhere to Gaussian statistics. Which are the causes of the inability to explain characteristics such as clustering, flights and crashes in financial time series. Amidst the financial crisis of '07-'09, market participants in developed countries experienced significant losses. Those, traditionally efficient markets were considered to be exceptionally crisis resilient according to the EMH, but became the conduits for spreading shocks and contributing to the overall destabilization of the global financial and economic systems. This was neither a unique nor a singular instance. The Dow Jones fell by 7.7% in a single day in 1997, with the probability of such an occurrence is one to 50 billion. During the summer of 2002, over a span of seven trading days the index dipped three times, an event with a probability of one in four trillion. On October 19, 1987, famously known as black Monday, the index plummeted by 29.2% making it one of the worst trading days during the last century. Such an occurrence, according to the standard theoretical financial models, could only happen in less than one out of 1050 cases. (Mandelbrot & Hudson, 2004).

These inconsistencies in assumptions of the EMH led to a stream of literature in which academics try to correct the classical theory to try and formulate a theory which resembles the real market dynamics and behaviour accurately, able to better offer practical guidance and stronger interpretation value. One development of such concept that explain the behaviour of financial markets is the Adaptive Market Hypothesis (AMH). The AMH perceives the EMH as a theorized utopia with no practical application. The AMH can be seen as a compromise between rational expectation theory and behavioural finance and is based on the notion that the behaviour of markets depends on subjective psychological factors and as such is not always determined correctly and predictably. It's foundation formed by the work of Tversky and Kahneman (1974) initiating a concept of alternative finance, in which they break down rationality in terms of a number of psychological mechanisms that shape human action.

Another emerging stream of financial literature proposes a more complex stochastic process underlying market dynamics and behaviour. Based on the notion that many phenomenon and processes in markets as well as nature are inherently complex, irregular and rough instead of smooth. Consequently it can't be described by the imposed smooth understanding of market dynamics as in the EMH. It's criticism is focused on the failure of explaining ubiquitous market properties such as fat tails, long-term correlation, volatility clustering, and multifractality. Dependent on the fact that financial markets posses many properties of fractals led to the application of fractals, fuzzy logic and chaos theory in financial markets. Fractal finance refers to the application of fractal analysis, using fractal geometry, in studying financial markets and analyzing their behavior. The next Section provides further elaboration on the application of fractal geometry, statistical physics and mathematical concepts to economic systems.

## 2.7 A fractal view on financial market behaviour and efficiency

Fractal geometry has been shown to be an efficient tool for describing many effects observed in complex natural and socioeconomic systems as their features, although they can be visually apparent, cannot be accurately described or captured by traditional Euclidean geometry. Mandelbrot (1970) introduced the term ”fractals” as to describe self-similarity and self-affinity properties, i.e. correlations and periodicity, of geometric patterns. A fractal refers to a geometric pattern or shape that if split into parts, each part exhibits a self-replicating pattern that regardless of the level of magnification maintains its complexity, displaying the same intricate details at every level. Although appearing to be rough, messy, chaotic and irregular at first sight, Mandelbrot discovered that their roughness often has a set of rules and parameters to it. Based on this they exhibit a structured ”degree of order” that could be used to describe these patterns more accurately. Fractal structures are found in a variety of phenomena and fractal methodologies have become a widely used tool in a variety of disciplines including economics, biology, medicine, geology, mathematics, physics and computer science.

With the work of (Mandelbrot, 1970) fractal geometry made its introduction into the field of finance offering a perspective on how fractal geometry can be used to describe the self similar and complex patterns of financial markets. Mandelbrot (1970) extensively studied the fat-tails in the distribution of cotton prices and, inspired by the work of Hurst (1951), noticed that financial time series entailed long-range dependency properties. Following Mandelbrot’s studies, the stream of fractal finance gained momentum and applying theories and methodologies originating from statistical physics and mathematics to economic and financial systems contributed to a broader understanding of market behaviour, patterns and underlying mechanism that characterize financial and economic activities. Numerous articles providing evidence in favour of the notion that instead of a smooth description of financial markets as assumed by conventional financial theory, in which prices are modeled by a Brownian motion driven by a Gaussian noise random process, there is a more complex stochastic process underlying market dynamics. Likewise, anomalies in conventional financial theory should not be treated as rare or unremarkable deviations from the ’perfect’ model. For instance in relation to market efficiency the various deviations from the independence, normality- and linear paradigm assumption underlying EMH discussed in Sections 2.5 and 2.6.

A considerable body of subsequent research shows financial markets to be of a multifractal nature, which is empirically documented regarding stock market indices (Mandelbrot, 1999; Ahmed & Abdusalam, 2000; Katsuragi, 2000), foreign exchange markets (Vandewalle & Ausloos, 1998; Bershadskii, 1999), commodity markets (Matia, Ashkenazy & Stanley, 2003), gold markets, cryptocurrency markets (Al-Yahyaee, Mensi, Ko, Yoon & Kang, 2020), traded volumes (Moyano, De Souza & Duarte Queirós, 2006) as well as interest rates (Cajueiro & Tabak, 2007).

## 2.8 Procedures for evaluating the efficiency of stock markets

Following the work of Bachelier (1900) the mainstream literature on financial market efficiency is based on the fundamental assumption of normally distributed stock prices following a random walk. Addressing the issue of market efficiency, according to the EMH all information is reflected in market prices in an efficient market. As new information enters the market randomly, price movements therefore must also be random making it impossible to earn excess returns for a given level of risk. Price information has no memory as prices are uncorrelated between different time periods, i.e. the behaviour of the series in the past has no influence on the behaviour today. Consequently, predicting future prices as well as identifying patterns earning excess returns is impossible. Put differently, fluctuations of returns in capital markets represent a fair game pattern and are therefore unpredictable. Market memory can be tested by observing correlations in the time series, as the presence of (long-range) dependence in the time series contradicts the EMH and suggests the market is not efficient. Whereas the absence of memory points to a market being efficient. Statistically, testing the memory in time series involves using a auto-correlation function.

Traditional methods of testing market efficiency involves the Jarque-Bera (JB) test, to assess the normality of the distribution, the parametric autocorrelation test, measuring the dependency of successive returns, the non-parametric runs test, which tests the randomness in the sequence of returns, the variance ratio test, for determining uncorrelated changes in the series, unit root test, in assessing the stationarity of the time series, and the various variants of ARMA and GARCH processes, for the analysis of seasonality patterns. However, these conventional time series analysis methodologies testing market efficiency using ARMA, GARCH processes or Brownian motion are considered to fall short in representing financial markets. The inadequacy stems from asset prices possessing several fundamental properties including, fat tails, long-term memory, volatility clustering, chaos, and multifractality as a result of stock markets being complex entities. More specifically, the ARMA and GARCH models traditionally used fail to accurately portray the volatility resulting from return fluctuations as they rely on Gaussian (normal) statistics. That is, relying on the notion that the return fluctuations are being generated by a Gaussian noise resulting in Brownian motion time series.

Following Mandelbrot (1970) power-law distributions were incorporated in asset returns. Due to fluctuations in asset prices shown to be more accurately described by a fractional Brownian motion as financial time series exhibit non-linear characteristics such as long-memory and self-similarity, contrary to the EMH (Peters, 1991; Mandelbrot & Stewart, 1998). Using Rescaled Range (R/S) analysis in determining the Hurst exponent (Peters, 1991, 1994) provided evidence of the mono-fractal properties of financial markets as well as long-range memory in returns. The R/S methodology however has it flaws. In case the time series contains short-term memory or the series in non-stationary, R/S produces large estimation errors which often causes the estimation of the Hurst exponent to be inaccurate and by extension their implications regarding market efficiency. Lo (1991)'s modified version of the R/S methodology eliminates the short term memory effect interference by using modified standard errors in the modelling. Both methods however are only effective in analyzing stationary time series with mono-fractal properties. Detrended Fluctuation Analysis (DFA) can be used to analyze non-stationary time series with mono-fractal properties at different time scales Peng et al. (1994).

The DFA methodology was extended by Kantelhardt et al. (2002) to a multifractal analysis (MF-DFA) in order to deal with multifractal properties in time series. MF-DFA is able to describe and quantify the multi-scale and subtle substructures of fractals in complex systems while avoiding spurious detection of long-range dependence, as opposed to conventional prevailing approaches in the existing literature analyzing market efficiency. MF-DFA can be applied to non-stationary time series and calculates the Hurst exponent together with a multifractal spectrum. As financial markets are shown to be of a multifractal nature, with a priori unknown properties, employing a methodology capable of accommodating multiple scaling components in this study is critical to ensure reliable and robust results in assessing market efficiency by avoiding biased measurements of the Hurst exponents.

For a variety of mathematical models, e.g monofractal Brownian motion, bifractal Lévy flights and different multifractal binomial cascades, MF-DFA performs better than the wavelet transform modulus maxima (WTMM) method in properly detecting mono- and multifractal characteristics (Kantelhardt et al., 2002; Oświ cimka, Kwapień & Drożdż, 2006). As WTMM is shown to spuriously suggest multifractality due to biased outcomes of the fractional Brownian motion (Oświ cimka et al., 2006). In addition to the mathematical models with known fractal properties, i.e. the artificial generated signals, the authors applied both methods to actual stock market data and the results indicate WTMM is paired with greater statistical uncertainty compared with MF-DFA.

In summary, given these various methods and the fundamental properties of the financial markets being complex entities, testing market efficiency using traditional methods, such as Brownian motion, ARMA and GARCH processes fail to capture the dynamic and complex nature of stock market returns as widely documented in the literature. Additionally, MF-DFA can capture self-similar patterns and irregularities that ARMA and GARCH models cannot. Regarding fractal based models, even though R/S captures monofractal properties unlike prior methods, it is only effective in analyzing stationary time series. Similarly, DFA can be used to analyze the monofractal scaling properties of nonstationary time series but does not permit quantifying multiple scaling components, i.e. multifractal properties of the series. Compared to other methods incorporating multifractal properties, MF-DFA is shown to have more reliable results compared to WTMM as the wavelet based method comes with higher statistical uncertainty and is more sensitive to the specification of parameters which may result in spuriously suggesting multifractality. All in all, these factors make MF-DFA appealing compared to other methodologies offering reliable multifractal characterization of multifractal time series. As such in this study MF-DFA is applied to observe multifractal properties in the return series enabling the examination of long range memory and characterization of fractal properties which are employed to quantify market efficiency.

MF-DFA has been successfully used to analyze market efficiency in a variety of markets. Miloş, Haţiegan, Miloş, Barna and Boțoc (2020) analyzed the multifractality and efficiency for the stock markets indices of Poland, Czech Republic, Romania, Croatia, Hungary, Bulgaria and Slovenia using MF-DFA. They document evidence of multifractality and inefficiency for these central and eastern European stock markets. Aslam, Ferreira and Mohti (2021) used MF-DFA to investigate the behaviour of the frontier MSCI markets for Croatia, Kenya, Mauritius, Morocco, Nigeria, Romania, Serbia, Slovenia and Tunisia. They show the degree of multifractality in these markets varies, implying dependence in the series of daily stock returns.

The markets of Kenya, Morocco, Romania and Serbia show mean reversion, anti persistent, behaviour where the other markets exhibit persistent behaviour. Mensi, Tiwari and Al-Yahyaee (2019) considered the stock market indices from Greece, Ireland, Portugal, Spain, Italy and the US and show long memory in both the short- and long-term for all these markets where the long memory is more pronounced in the long term. Tiwari, Aye and Gupta (2019) apply the MF-DFA methodology to investigate both the short- and long term multifractal components and efficiency of the developed stock market indices of Canada, France, Germany, Italy, Japan, Switzerland, the UK, and the US and the emerging stock market indices of India and South Africa. Their findings reveal that efficiency varies over time for all analyzed markets. Moreover, the results indicate that although most markets are more efficient in the long term compared to the short-term, they are nonetheless inefficient. Comparing the efficiency of the eleven Organization of Islamic Conference member countries MSCI indices, e.g. Malaysia, Indonesia, Pakistan, Turkey, Jordan, Egypt, Nigeria, Kuwait, UAE, Saudi Arabia and Qatar using MF-DFA Arshad, Rizvi, Ghani and Duasa (2016) find that over the last decade the efficiency of these countries improved. They furthermore note that during times in which the economy is thriving efficiency is higher than in economic bursts. Similarly, Bouoiyour, Selmi and Wohar (2018) find the presence of multifractality in both emerging and developed Islamic stock market indices. Their findings indicate that established Islamic markets are more efficient compared to the emerging Islamic markets.

# 3 Data & Methodology

### Data

The sample considered in this study consists of stock market indices from 21 developed markets. An overview of all included stock market indices can be seen in Table 1. The sample covers the daily period ranging from January 1, 2018 to December 31, 2022. Daily closing prices of the stock market indices are obtained from Refinitiv Eikon. The sample is composed of a cross-section of countries encompassing the regions North America (Canada); Europe (Austria, Switzerland, Spain, Norway, Finland, Denmark, Sweden, Ireland, Italy, United Kingdom, France, Portugal, Belgium, Netherlands, Germany) and, East Asia (Japan, Singapore, Hong Kong) and the Pacific (Australia, New Zealand). All countries in the sample are high-income economies.[1] The sample also includes several countries considered among the most affected, i.e. hard-hit, by the COVID-19 pandemic according to the WHO. More specifically Spain, the United Kingdom (UK), Italy, France, and Germany.

The daily stock market returns cover the period before and after the onset of the COVID-19 pandemic. The first day considered in the sample is January 1, 2018 whereas it was on 31 December, 2019 that the Chinese office of the WHO was informed of the detection of a cluster of pneumonia cases in Wuhan, China. As the sample extends to the end of 2022 it encompasses a period of two years since the detection of these initial cases.

[1] According to the Word Bank a high-income economy refers to a country with a gross national income per capita of $13,845 or higher, as determined by the Atlas method.

**Table 1.** *Full Sample Overview*

| Symbol | Stock Market Index | Country | Currency | N |
|---|---|---|---|---|
| AEX | Amsterdam Exchanges Index | Netherlands | Euro | 1281 |
| ATX | Austrian Traded Index | Austria | Euro | 1260 |
| AXJO | S&P/ASX 200 | Australia | Australian Dollar | 1265 |
| BFX | BEL 20 Index | Belgium | Euro | 1281 |
| BVLG | PSI All Share Gross Return Index | Portugal | Euro | 1281 |
| FCHI | CAC 40 Index | France | Euro | 1281 |
| FTMIB | FTSE MIB Index | Italy | Euro | 1270 |
| FTSE | FTSE 100 Index | United Kingdom | British Pound | 1262 |
| GDAXI | Deutsche Boerse DAX Index | Germany | Euro | 1267 |
| GSPTSE | TSX-Toronto Stock Exchange 300 Composite Index | Canada | Canadian Dollar | 1254 |
| HSI | Hang Seng Index | Hong Kong | Hong Kong Dollar | 1232 |
| IBEX | IBEX 35 Index | Spain | Euro | 1279 |
| ISEQ | ISEQ Overall Price Index | Ireland | Euro | 1277 |
| NZ50 | S&P/NZX 50 Index Total Return | New Zealand | New Zealand Dollar | 1252 |
| OMXC20 | OMX Copenhagen 20 Index | Denmark | Danish Krone | 1248 |
| OMCH25 | OMX Helsinki 25 Index | Finland | Euro | 1256 |
| OMXSPI | OMX Stockholm PI | Sweden | Swedish Krona | 1257 |
| OSEAX | Oslo SE All-share Index | Norway | Norwegian Krone | 1256 |
| SSMI | Swiss Market Index | Switzerland | Swiss Franc | 1257 |
| STI | FTSE Straits Times Index | Singapore | Singapore Dollar | 1268 |
| TOPX | TOPIX Stock Price Index | Japan | Japanese Yen | 1217 |

## Methodology

The investigation of market efficiency in this study consists of multiple stages. In the first stage, stock market returns are calculated. The second stage involves applying a change-point test to determine breakpoints in the time series data since there are assumed to be different dynamics in the market before and after the onset of the COVID-19 pandemic. If significant changes in the signal are identified the signal is divided into multiple sub-intervals, and further analysis will be performed independently on these sub-intervals to determine if the pre- and post COVID-19 period is characterised by different multifractal properties and the change in market efficiency.

In the third stage, multifractal detrended fluctuation analysis (MF-DFA) is utilized to investigate the market efficiency. This approach allows for a comprehensive understanding of the data by analyzing different parts of the logarithmic return signal, with their own distinct characteristics. It provides valuable insights into the structure, and potential trends or patterns, underlying the signal. MF-DFA is preferred over other methodologies applied in the literature regarding the analysis of market efficiency due to a variety of factors as discussed more extensively in Section 2.8. MF-DFA is performed independently on each of the sub-intervals separated by the breakpoints. The analysis is implemented in MATLAB guided by (Ihlen, 2012).

***Stage 1:*** **Stock Market Returns**

The initial stage involves calculating stock market returns. Let $P_{i,t}$ be the price of index $i$ at the end of period $t$, $t = 1, \ldots, N$. Given that the sample comprises close prices with daily frequency, the time unit for period $t$ is measured in days. The simple return of the index over that period $t$, $R_{i,t}$ , is given by:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}. \tag{1}$$

The standard deviation, $SD_i$, of the return on the index for the examined period is given by:

$$SD_i = \frac{\sum_{N}^{i-1}(R_i - \overline{R}_i)}{N-1} \tag{2}$$

Where $\overline{R}_i$ is the mean return during the examined period. $\overline{R}_i = \frac{\sum_{i=1}^{N} R_{i,t}}{N}$.

The logarithmic return on index $i$ over period $t$ is calculated by taking the logarithm of the simple return on index $i$ over period $t$, $R_{i,t}$. We define the logarithmic return of the $i$-th index over period $t$, $R^L_{i,t}$, as:

$$R^L_{i,t} = \ln\big(P_{i,t}\big) - \big(\ln P_{i,t-1}\big). \tag{3}$$

***Stage 2:*** **Change-point detection testing**

The sample covers the period before and after the onset of the COVID-19 pandemic. During this period the world economy experienced exceptional economic conditions prior to the declaration of the global health crisis followed by a gradual recovery. As it is well known that sudden large shocks cause structural changes to the financial markets, and for this reason there are hypothesised to be different dynamics in the market during these different time periods. By employing a change point test, a break point is identified where the characteristics of the time series change significantly rejecting the self-similarity of the two sub sample periods. That is, the break point is a time-instant at which the characteristics of the signal, the logarithmic return series, changes significantly. If such a point can be identified, the sample of index returns $r_i$ is divided in two separate time series separating the pre- and post crisis periods: $r_{pre} = (r_1, \ldots, r_{h-1})$ and $r_{post} = (r_h, \ldots, r_N)$.

In this study we examine a single change point before performing separate MF-DFA analysis on the two intervals allowing the examination of the structural break, the COVID-19 pandemic, on the fluctuations of the return series and market efficiency. In case the scaling dynamics and behaviour remain consistent and they do not differ between the pre- and post period, the periods exhibit similar multifractal properties and the self-similarity cannot be rejected. The dynamics are compared by the power-law scaling of the signal using MF-DFA. In case of observed consistent dynamics in the sub periods the performed analysis can be characterised as conventional or standard MF-DFA analysis, simply put as if the change point were not identified. This due to the specifics of the MF-DFA methodology as is illustrated in the third stage discussing the MF-DFA methodology, more specifically in the second step.

As discussed earlier, on the 31st of December 2019 the WHO was informed of a pneumonia of COVID-19 cases in China. However, it wasn't until 30 January that the WHO declared COVID-19 a public health emergency. Hence, separating the series simply on the first day of 2020, as is done in several studies in the the existing literature investigating the effect of

COVID-19, might not mark the break between the pre- and post crisis period accurately. Additionally the date might not be uniform for all indices. In determining the abrupt structural change in the signal more formally the change-point detection test developed by (?, ?) is employed for each separate return series. ? change point test is a single step and non parametric test. Hence, it is not dependent or making any assumptions about the distribution of the underlying signal. It is based on penalized contrast and can be utilized to detect a wide range of changes in the time series estimating the number of change points and their location. For each return series the time-instant at which the standard deviation changes significantly, using (?, ?)'s change point test, the log return series are classified into two separate time series. Additionally, to check the determined change points, the local Hurst exponents are calculated to investigate their evolution over time. This is done for all scales used in the MF-DFA analysis ranging from 4 to $\frac{N}{4}$.

### *Stage 3:* Multifractal Detrended Fluctuation Analysis (MF-DFA)

In the third stage the multifractal detrended fluctuation analysis (MF-DFA) methodology is utilized, The MF-DFA, proposed by (Kantelhardt et al., 2002) represents the multifractal properties of financial time series and is most powerful in detecting multifractality in time series and is able to measure and rank market efficiency. MF-DFA picks the average volatility in the time series for each interval as a statistical point that is further used in order to calculate the volatility function. The generalized Hurst exponent is determined based on the power law of volatility functions.

Let the time series $\{r(i)|i = 1, 2, \ldots, N\}$ be a possible non-stationary time series of stock market returns during the examined period. Following (Kantelhardt et al., 2002) the procedure consists of five steps:

*Step 1:* The first step of the MF-DFA includes constructing the local trend function or 'profile', $Y(i)$, using integration after subtracting its average, $\overline{r}$, from the time series, $r(i)$, as follows:

$$Y(i) = \sum_{i=1}^{j} (r(i) - \overline{r}) \,, \quad i = 1, \ldots, N \tag{4}$$

where $r(i)$ is a time series with finite length $N$ and $\overline{r}$ is the average of the whole time series

$$\overline{r} = \sum_{i=1}^{N} \frac{r(i)}{N} \,. \tag{5}$$

*Step 2:* In the second step, the profile, $Y(i)$ is divided into $N_s = \text{int}(N/s)$ non-overlapping sub-time periods (segments) with boxes of size $s$, where int$[y]$ is the largest integer that is no larger than $y$. The length of the whole series, $N$, may not be an integer multiple of $s$ and consequently a short part of the profile $Y(i)$ at the end of the sample remains uncovered. To overcome this segments are obtained by covering the series from both ends. Hence, $2N_s$ segments are obtained altogether:

$$S_v = \{Y\big((v-1)s+j\big)|j=1,2,\dots,s\}, \qquad v=1,2,\dots,N_s \tag{6a}$$
$$S_v = \{Y\big(N-(v-N_s)s+j\big)|j=1,2,\dots,s\}, \qquad v=N_s+1,N_s+2,\dots,2N_s\ . \tag{6b}$$

*Step 3:* The third step involves estimating the linear trend for each of $2N_s$ segments with the least-squares fit of the series for each segment $v$, $v=1,2,\dots,N_s$ and for $v=N_s+1,N_s+2,\dots,2N_s$. The local detrended fluctuation function in the $v$th box is

$$F^2(s,v)=\begin{cases}\dfrac{1}{s}\displaystyle\sum_{j=1}^{s}\Big\{Y\Big[(v-1)s+j\Big]-\hat{Y}_v^m(j)\Big\}^2, & v=1,2,\dots,N_s \quad (7a)\\[2ex] \dfrac{1}{s}\displaystyle\sum_{j=1}^{s}\Big\{Y\Big[N-(v-N_s)s+j\Big]-\hat{Y}_v^m(j)\Big\}^2, & v=N_s+1,N_s+2,\dots,2N_s \quad (7b)\end{cases}$$

where $\hat{Y}_v^m(i)$ is the fitting polynominal with order $m$ in segment $v$. In general, linear ($m=1$), quadratic ($m=2$), or cubic ($m=3$) polynomials can be used. In this paper a linear polynomial is used to avoid overfitting and in addition facilitate calculation, hence $m=1$.

*Step 4:* In the fourth step the $q-$th order fluctuation function is obtained by averaging over all segments obtained from Eq. (6) in Step 2. Where $q$ can take any real value in Eq. (8a) except zero. According to L' Hôspital's rule for $q=0$ we have Eq. (8b). The $q-$th order fluctuation function is

$$F_q(s)=\begin{cases}\left[\dfrac{1}{2N_s}\displaystyle\sum_{v=1}^{2N_s}\Big(F^2(s,v)\Big)^{\frac{q}{2}}\right]^{\frac{1}{q}}, & q\neq 0 \quad (8a)\\[2ex] \exp\left[\dfrac{1}{4N_s}\displaystyle\sum_{v=1}^{2N_s}\ln\Big(F^2(s,v)\Big)\right], & q=0\ . \quad (8b)\end{cases}$$

The parameter $q$ helps distinguish between segments that have small and large fluctuations. Small fluctuations are enhanced for every $q$, $q\in[-\infty,0)$. Whereas for every $q$, $q\in(0,\infty]$, large fluctuations are enhanced.

*Step 5:* The fifth step involves calculating the scaling or power-law relationship, i.e. the scaling component in the fluctuation function for any fixed $q$, from Eq. (8). Varying the values of segment size, $s$, we can determine the power-law relation between the fluctuation function, $F_q(s)$, and the size scale, $s$, as

$$F_q(s)\sim s^{h(q)} \tag{9}$$

where the slope of $\ln\big(F_q(s)\big)\sim\ln s$ is the $q-$th order generalized Hurst exponent, $h(q)$. By taking the logarithms of both sides of Eq. (9) the relationship between log-log of $F_q(s)$ and $s$ for each value of s can be written as

$$\log\big(F_q(s)\big)=h(q)\cdot\log(s)+c\ , \tag{10}$$

where $c$ is a constant.

The time series is said to be monofractal when $h(q)$ does not depend on $q$, and multifractal when $h(q)$ does depend on $q$. For $q = 2$, $h(2)$ is identical to the Hurst exponent (Kantelhardt et al., 2002; Calvet & Fisher, 2002). The Hurst exponents are used to calculate the market efficiency (or inefficiency). If $h(q) > 0.5$ the existence of positive autocorrelation, persistent behaviour, is implied and an increase (decrease) is more likely to be followed by an increase (decrease). A value closer to 1 indicates larger and more abrupt changes. Whereas a value of $h(q) < 0.5$ implies the presence of negative autocorrelation, a change of the trend (anti-persistent behaviour), and an increase (decrease) is more likely to be followed by a decrease (increase). If $h(q) = 0.5$ the series is not correlated and exhibits characteristics that reflects a Brownian time series. Ergo, it can be described by a random walk process (Peters, 1994).

The Hurst exponent estimated from Eqs. (9) and (10) can also be expressed as a function of the Renyi exponent, $\tau(q)$, and applying the Legendre transformation the multi-fractal spectrum, $f(q)$ can be obtained:

$$\tau(q) = qh(q) - 1, \tag{11}$$

$$\alpha = \frac{d}{dq}\tau(q), \tag{12}$$

$$f(\alpha) = \alpha(q)q - \tau(q) = q\big[\alpha - h(q)\big] + 1. \tag{13}$$

where $f(\alpha)$ is the multifractal spectrum and $\alpha$ the singularity strength or Hölder exponent. The degree of multifractality, $\Delta h$, and the width of the multifractal spectrum, $\Delta\alpha$, are defined as

$$\Delta h = \max\big(h(q)\big) - \min\big(h(q)\big), \tag{14}$$

$$\Delta\alpha = \max(\alpha) - \min(\alpha), \tag{15}$$

with $\Delta\alpha$ reflecting the heterogeneity of the probability distribution and complexity of the whole fractal structure, under the condition of constant scale. For $\Delta\alpha = 0$ the data is completely evenly distributed and as $\Delta\alpha$ gets larger, the more uneven the distribution. A larger $\Delta h$ value indicates a stronger degree of multifractality.

**Parameter Choice**

Note that the fluctuation functions $F_q(s)$ in Eq. (8) are dependent on the choice of the segment size, $s$, and the $q-$th order. Evidently, choosing the right parameters in performing MF-DFA involves careful consideration.

*q-order*: to capture both large and small fluctuations, $q$ should consist of positive and negative values in order to capture multifractality. Besides, it's crucial for $|q|$ to have sufficient magnitude to cover as much of the singularity spectrum as possible, on the other hand an excessively large $|q|$ causes the estimated multifractal spectrum, $f(\alpha)$ in Eq. (13), to be less stable. Accordingly, in this study different scenarios for $q$ are analyzed, $[-10; 10]$, $[-5; 5]$, and $[-2; 2]$, where $|q|$ is limited to 10. A step size for $q$ is chosen that allows for a smooth visualization of the singularity spectrum.

*Segment size, s:* from a statistical point of view, the minimum and maximum segment sizes should be chosen so that they provide a numerical stable estimation of the fluctuation functions $F^2(s, v)$ and $F_q(s)$. The minimum segment size, $s_{min}$, should be large enough to prevent errors in the local fluctuation function , $F^2(s,v)$, and it should also be larger than the polynomial order, $m$. The maximum segment size, $s_{max}$, should be such that it provides a sufficient number of segments for computing the $q-$th order fluctuation function, $F_q(s)$. A commonly employed guideline is $s_{max} < \frac{N}{4}$ to ensure that the time series sample has sufficient segments. Furthermore, choosing a range of $s$ on a base 2 logarithmic scale that has equal spacing between the scales is beneficial for the stabilization of the regression that estimates the $q$-order Hurst exponent, represented by the log-log of $F_q(s)$ and $s$. In finance literature a range of $[2; 64]$ is widely used for short-range dynamics, $[64; 256]$ for medium range dynamics and $[256; 1024]$ and above for long range dynamics. Accordingly, in this study an analysis will be performed by altering the different ranges of $s$ to investigate the dynamics, and choose the range that results in stable fluctuation functions.

# 4 Empirical Results and Discussion

## 4.1 Descriptive Statistics

The descriptive statistics of the considered full sample of logarithmic stock market returns are presented in Table 2. The mean of the return differs among the return series, where the OMXC20 series has the highest mean and HSI the lowest. Furthermore, the minimum and maximum returns depict there are large fluctuations in the returns. Turning to the distributions of the return series, the Quantile-Quantile plots, as can be seen in Appendix A. where the quantiles of the return series are displayed versus the theoretical quantile values from a standard normal distribution indicate the series do not follow a normal distribution. The absolute skewness values for all series are larger than zero as shown in Table 2. This indicates there is there is evidence that the distributions of the returns are asymmetric. The HSI index exhibits positive skewness. While all other series in the sample display negative skewness, indicating a bias towards the left side of the distribution. The kurtosis values for all series are well above the critical value for a normal distribution of 3, ranging from 5.44 for OMXC20 index to 41.15 for GSPTSE. Indicating that the returns series have a higher concentration compared to a normal distribution. All series show notable levels of skewness and kurtosis indicating asymmetric, leptokurtic distributions, with high peaks and fat-tails. Looking at the Jarque-Bera test, the two sided test of composite normality, the value of the test statistic is significantly beyond the critical value for all series indicating there is strong evidence against the null hypothesis of normally distributed data, rejecting the normal distribution hypothesis. The Augmented Dickey-Fuller test rejecting the a unit root, indicating that the time series are stationary.

**Table 2.** *Full Sample Descriptive Statistics and Tests.*

| | **min** | **max** | **mean** | **sd** | **Kurt** | **Skew** | **JB** | **ADF** | **N** |
|---|---|---|---|---|---|---|---|---|---|
| AEX | -0.11376 | 0.08591 | 0.00018 | 0.01196 | 13.88 | -0.88 | 6478.62** | -36.01** | 1281 |
| ATX | -0.14675 | 0.10206 | -0.00008 | 0.01499 | 17.95 | -1.18 | 12024.55** | -33.09** | 1260 |
| AXJO | -0.10203 | 0.06766 | 0.00012 | 0.01105 | 16.71 | -1.29 | 10259.64** | -41.98** | 1265 |
| BFX | -0.15328 | 0.07361 | -0.00006 | 0.01267 | 23.98 | -1.65 | 24073.63** | -34.67** | 1281 |
| BVLG | -0.10935 | 0.08578 | 0.00030 | 0.01175 | 14.03 | -0.83 | 6637.62** | -34.72** | 1281 |
| FCHI | -0.13098 | 0.08056 | 0.00016 | 0.01300 | 16.48 | -1.01 | 9920.00** | -35.90** | 1281 |
| FTMIB | -0.18541 | 0.08549 | 0.00006 | 0.01466 | 28.30 | -2.10 | 34802.57** | -37.52** | 1270 |
| FTSE | -0.11512 | 0.08667 | -0.00002 | 0.01129 | 17.58 | -1.09 | 11424.71** | -36.85** | 1262 |
| GDAXI | -0.13055 | 0.10414 | 0.00006 | 0.01349 | 15.53 | -0.65 | 8374.24** | -36.48** | 1267 |
| GSPTSE | -0.13176 | 0.11294 | 0.00014 | 0.01149 | 41.15 | -1.77 | 76695.77** | -41.63** | 1254 |
| HSI | -0.06567 | 0.08693 | -0.00035 | 0.01450 | 6.35 | 0.19 | 583.24** | -35.03** | 1232 |
| IBEX | -0.15151 | 0.08225 | -0.00016 | 0.01307 | 21.90 | -1.34 | 19415.23** | -36.75** | 1279 |
| ISEQ | -0.10465 | 0.06710 | 0.00001 | 0.01369 | 9.68 | -0.67 | 2466.53** | -35.00** | 1277 |
| NZ50 | -0.07947 | 0.06937 | 0.00025 | 0.00871 | 14.35 | -0.62 | 6795.32** | -33.01** | 1252 |
| OMXC20 | -0.07821 | 0.04098 | 0.00047 | 0.01199 | 5.44 | -0.46 | 354.37** | -35.20** | 1248 |
| OMXH25 | -0.10679 | 0.06665 | 0.00016 | 0.01246 | 10.18 | -0.76 | 2823.27** | -34.11** | 1256 |
| OMXSPI | -0.11805 | 0.07014 | 0.00025 | 0.01254 | 11.31 | -0.91 | 3791.48** | -35.14** | 1257 |
| OSEAX | -0.09832 | 0.05842 | 0.00032 | 0.01207 | 11.19 | -1.12 | 3774.45** | -36.50** | 1256 |
| SSMI | -0.10134 | 0.06780 | 0.00010 | 0.01015 | 14.93 | -0.94 | 7633.54** | -36.10** | 1257 |
| STI | -0.07637 | 0.05895 | -0.00004 | 0.00933 | 12.81 | -0.60 | 5161.29** | -36.84** | 1268 |
| TOPX | -0.05769 | 0.06640 | 0.00001 | 0.01117 | 6.06 | -0.15 | 480.95** | -33.85** | 1217 |

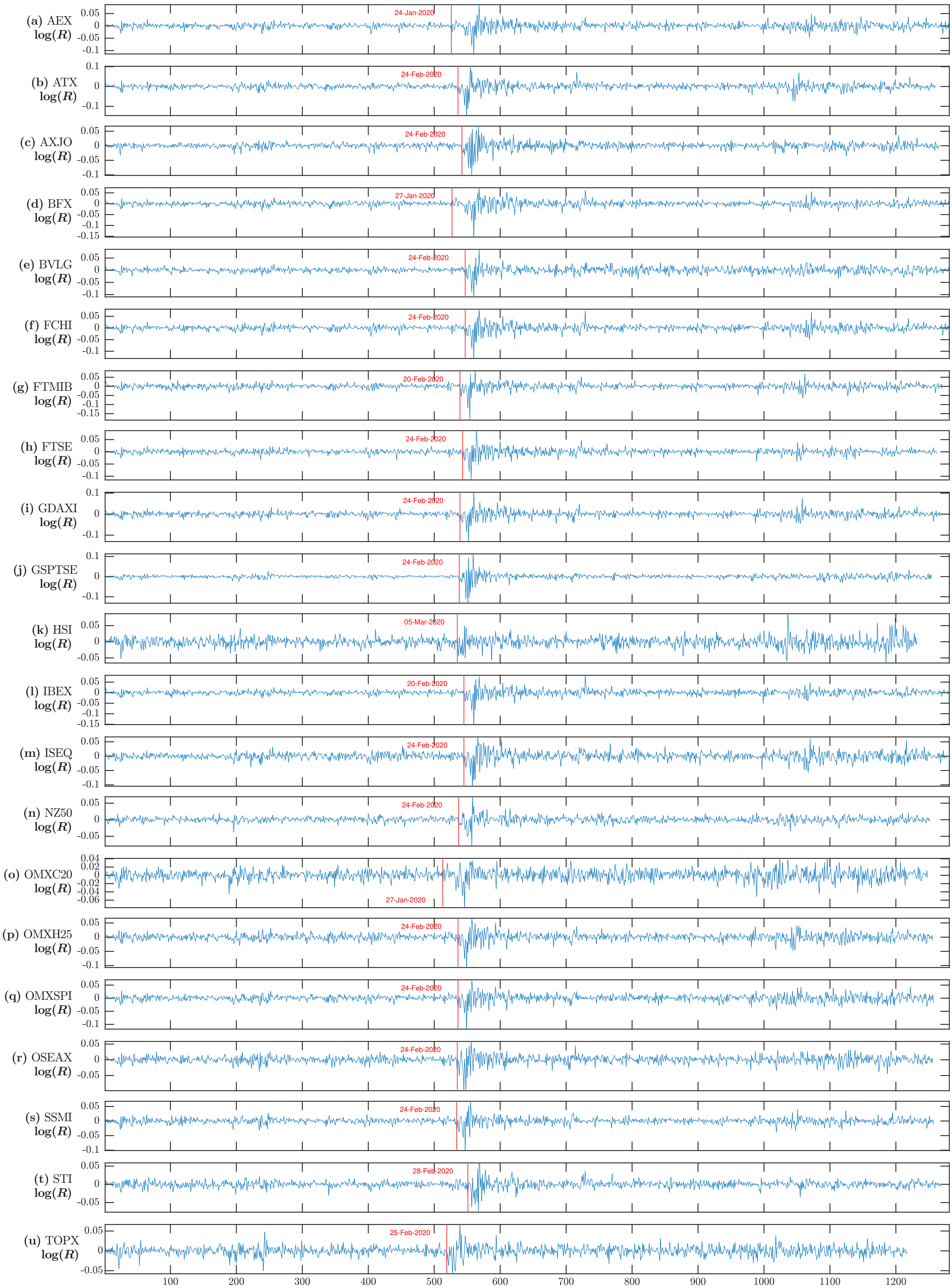
*Note.* The abbreviations Skew, Kurt, JB and ADF in the header row refer to Skewness, Kurtosis, Jarque–Bera and Augmented Dickey-Fuller statistics, respectively. ** $p < 0.01$, indicating rejection of the null at the 1%.

### 4.2 Change Point Detection

In order to determine if the fluctuation mechanism and dynamics of the stock market indices are affected by the COVID-19 pandemic the sample is divided in two periods. The time instance separating the period before and after the onset of the COVID-19 pandemic is determined with the use of (Lavielle, 2005)'s change point test. The logarithmic return series with the classified pre- and post-COVID-19 period samples based on the standard deviation are illustrated in Fig. 2 with the red line indicating the identified change point.
The initial analysis of the change point return series involves the exploration of estimating multiple change points, subsequently reducing the number of change points gradually to obtain a single change point marking the COVID-19 period. In addition to fluctuating the threshold with the objective of eliminating false detected changes. For the HSI index in determining a single change point the estimated time-instant at which the variance changed the most was estimated around observation 1100, that is June 2022. Similarly, for the STI index the estimated point was located in the beginning of 2021. When allowing the examination of multiple change points the points 535 for HSI and 551 for STI were also identified as point on which the variation changed significantly. As the objective of the estimation of the change points is to partition the sample in a pre- and post covid period, dividing the sample was done based on the latter. Looking at the logarithmic return series in Fig. 2 all series seem to exhibit a similar pattern of high peaked volatility in between the 500-th and 600-th observation. This is consistent with the timeline reported in other literature regarding the effects of the pandemic, supporting the determined change points.

The descriptive statistics of the separated sample periods are shown in Table 3, in Panel A. the pre-COVID-19 period before the change point and in Panel B. the COVID-19 period after the change point. The logarithmic returns in the pre-COVID-19 period show considerably smaller minimum and maximum returns. The standard deviation is much higher in the COVID-19 period. Looking at the distribution of the series, the kurtosis values before the change point are much smaller compared to the period after the change point. Nevertheless, for all return series the kurtosis values still surpass the critical normal distribution value of 3, indicating the series are peaked and affected by extreme values. The skewness values for all series indicate left-side biased asymmetric distributions. All in all, the return series before the change point show indications of non-normal leptokurtic distributions, with high peaks and fat-tails. This is also indicated by the J-B test which rejects the normal distribution hypothesis for all return series. The ADF statistic rejects the unit-root hypothesis indicating the series are stationary.
The period after the change point is characterised by larger minimum, maximum and standard deviation values indicating a larger dispersion in the returns. The kurtosis values are also well above the kurtosis values of the period before the change point, indicating a more peaked distribution. Similarly the skewness values show a higher magnitude, indicating more skewed distributions. The J-B statistic rejecting the normal hypothesis and the ADF statistic indicating the series are stationary.

**Figure 2.** *Logarithmic Return Series Divided into Two Intervals using the Change Point Test*




*Note.* The logarithmic difference (returns) time series for all indices in the sample. The x-axis shows the time in number of days from the start of the sample period, ranging from the 1st of January 2018 till the 31st of December 2022.

**Table 3.** *Sample Descriptive Statistics and Tests of the Pre- and Post COVID-19 period.*

**Panel A.** Pre COVID-19 Period

| | **min** | **max** | **mean** | **sd** | **Kurt** | **Skew** | **JB** | **ADF** | **N** |
|---|---|---|---|---|---|---|---|---|---|
| AEX | -0.03374 | 0.02681 | 0.00020 | 0.00790 | 4.84 | -0.64 | 110.63** | -22.35** | 525 |
| ATX | -0.03338 | 0.03092 | -0.00017 | 0.00943 | 3.95 | -0.27 | 26.62** | -22.07** | 535 |
| AXJO | -0.03253 | 0.01928 | 0.00030 | 0.00698 | 5.66 | -0.93 | 237.51** | -22.10** | 541 |
| BFX | -0.03481 | 0.02923 | 0.00001 | 0.00839 | 4.28 | -0.50 | 57.80** | -21.29** | 526 |
| BVLG | -0.02578 | 0.02487 | 0.00037 | 0.00717 | 3.67 | -0.21 | 14.02** | -22.46** | 546 |
| FCHI | -0.03635 | 0.02688 | 0.00024 | 0.00853 | 4.55 | -0.55 | 82.02** | -22.50** | 546 |
| FTMIB | -0.03787 | 0.03362 | 0.00029 | 0.01053 | 3.72 | -0.30 | 19.81** | -24.22** | 538 |
| FTSE | -0.03284 | 0.02325 | -0.00006 | 0.00772 | 4.46 | -0.39 | 61.71** | -23.22** | 542 |
| GDAXI | -0.03537 | 0.03314 | 0.00010 | 0.00936 | 3.93 | -0.40 | 33.59** | -23.88** | 538 |
| GSPTSE | -0.02491 | 0.02756 | 0.00017 | 0.00563 | 5.49 | -0.53 | 163.86** | -21.64** | 537 |
| HSI | -0.05252 | 0.04125 | -0.00028 | 0.01134 | 4.22 | -0.32 | 42.71** | -22.68** | 534 |
| IBEX | -0.02807 | 0.02485 | 0.00000 | 0.00823 | 3.64 | -0.32 | 18.40** | -22.41** | 544 |
| ISEQ | -0.03906 | 0.03666 | 0.00005 | 0.00923 | 4.11 | -0.14 | 29.79** | -23.62** | 544 |
| NZ50 | -0.03710 | 0.01937 | 0.00067 | 0.00634 | 5.63 | -0.63 | 189.92** | -21.91** | 536 |
| OMXC20 | -0.04586 | 0.02533 | 0.00030 | 0.00936 | 4.39 | -0.37 | 53.25** | -22.76** | 512 |
| OMXH25 | -0.02944 | 0.03157 | 0.00024 | 0.00925 | 3.33 | -0.04 | 2.62** | -22.76** | 535 |
| OMXSPI | -0.02854 | 0.02838 | 0.00045 | 0.00842 | 3.72 | -0.35 | 22.40** | -22.17** | 535 |
| OSEAX | -0.03691 | 0.02576 | 0.00023 | 0.00897 | 3.95 | -0.29 | 27.61** | -25.28** | 534 |
| SSMI | -0.03181 | 0.02811 | 0.00030 | 0.00793 | 4.42 | -0.32 | 53.89** | -23.65** | 533 |
| STI | -0.03043 | 0.02315 | -0.00018 | 0.00740 | 3.95 | -0.26 | 26.75** | -23.40** | 550 |
| TOPX | -0.05004 | 0.04785 | -0.00021 | 0.00979 | 6.47 | -0.46 | 277.11** | -22.45** | 518 |

**Panel B.** Post COVID-19 Period

| | **min** | **max** | **mean** | **sd** | **Kurt** | **Skew** | **JB** | **ADF** | **N** |
|---|---|---|---|---|---|---|---|---|---|
| AEX | -0.11376 | 0.08591 | 0.00017 | 0.01411 | 11.80 | -0.83 | 2527.52** | -27.80** | 756 |
| ATX | -0.14675 | 0.10206 | -0.00001 | 0.01803 | 14.71 | -1.16 | 4305.02** | -25.04** | 725 |
| AXJO | -0.10203 | 0.06766 | -0.00002 | 0.01331 | 13.54 | -1.17 | 3513.90** | -33.30** | 724 |
| BFX | -0.15328 | 0.07361 | -0.00010 | 0.01495 | 20.70 | -1.64 | 10192.10** | -26.84** | 755 |
| BVLG | -0.10935 | 0.08578 | 0.00025 | 0.01424 | 11.18 | -0.78 | 2124.88** | -26.42** | 735 |
| FCHI | -0.13098 | 0.08056 | 0.00010 | 0.01551 | 13.86 | -0.96 | 3724.65** | -27.56** | 735 |
| FTMIB | -0.18541 | 0.08549 | -0.00010 | 0.01708 | 26.23 | -2.24 | 17068.22** | -28.49** | 732 |
| FTSE | -0.11512 | 0.08667 | 0.00001 | 0.01337 | 15.34 | -1.10 | 4710.06** | -28.22** | 720 |
| GDAXI | -0.13055 | 0.10414 | 0.00003 | 0.01587 | 13.75 | -0.63 | 3559.74** | -27.75** | 729 |
| GSPTSE | -0.13176 | 0.11294 | 0.00012 | 0.01439 | 29.13 | -1.55 | 20681.01** | -32.34** | 717 |
| HSI | -0.06567 | 0.08693 | -0.00040 | 0.01652 | 5.95 | 0.31 | 263.37** | -26.52** | 698 |
| IBEX | -0.15151 | 0.08225 | -0.00028 | 0.01573 | 17.96 | -1.29 | 7055.29** | -28.20** | 735 |
| ISEQ | -0.10465 | 0.06710 | -0.00002 | 0.01623 | 8.22 | -0.68 | 886.80** | -26.40** | 733 |
| NZ50 | -0.07947 | 0.06937 | -0.00007 | 0.01012 | 13.07 | -0.52 | 3055.16** | -24.94** | 716 |
| OMXC20 | -0.07821 | 0.04098 | 0.00058 | 0.01353 | 5.01 | -0.47 | 151.75** | -26.97** | 736 |
| OMXH25 | -0.10679 | 0.06665 | 0.00011 | 0.01439 | 9.55 | -0.85 | 1374.69** | -25.75** | 721 |
| OMXSPI | -0.11805 | 0.07014 | 0.00010 | 0.01488 | 9.64 | -0.88 | 1418.11** | -27.04** | 722 |
| OSEAX | -0.09832 | 0.05842 | 0.00039 | 0.01394 | 10.50 | -1.22 | 1868.73** | -27.39** | 722 |
| SSMI | -0.10134 | 0.06780 | -0.00005 | 0.01151 | 14.88 | -1.02 | 4379.43** | -27.52** | 724 |
| STI | -0.07637 | 0.05895 | 0.00006 | 0.01058 | 13.01 | -0.68 | 3052.23** | -28.27** | 718 |
| TOPX | -0.05769 | 0.06640 | 0.00017 | 0.01210 | 5.62 | -0.04 | 200.35** | -25.55** | 699 |

*Note.* The abbreviations Skew, Kurt, JB and ADF in the header row refer to Skewness, Kurtosis, Jarque–Bera and Augmented Dickey-Fuller statistics, respectively. ** $p < 0.01$, indicating rejection of the null at the 1%.

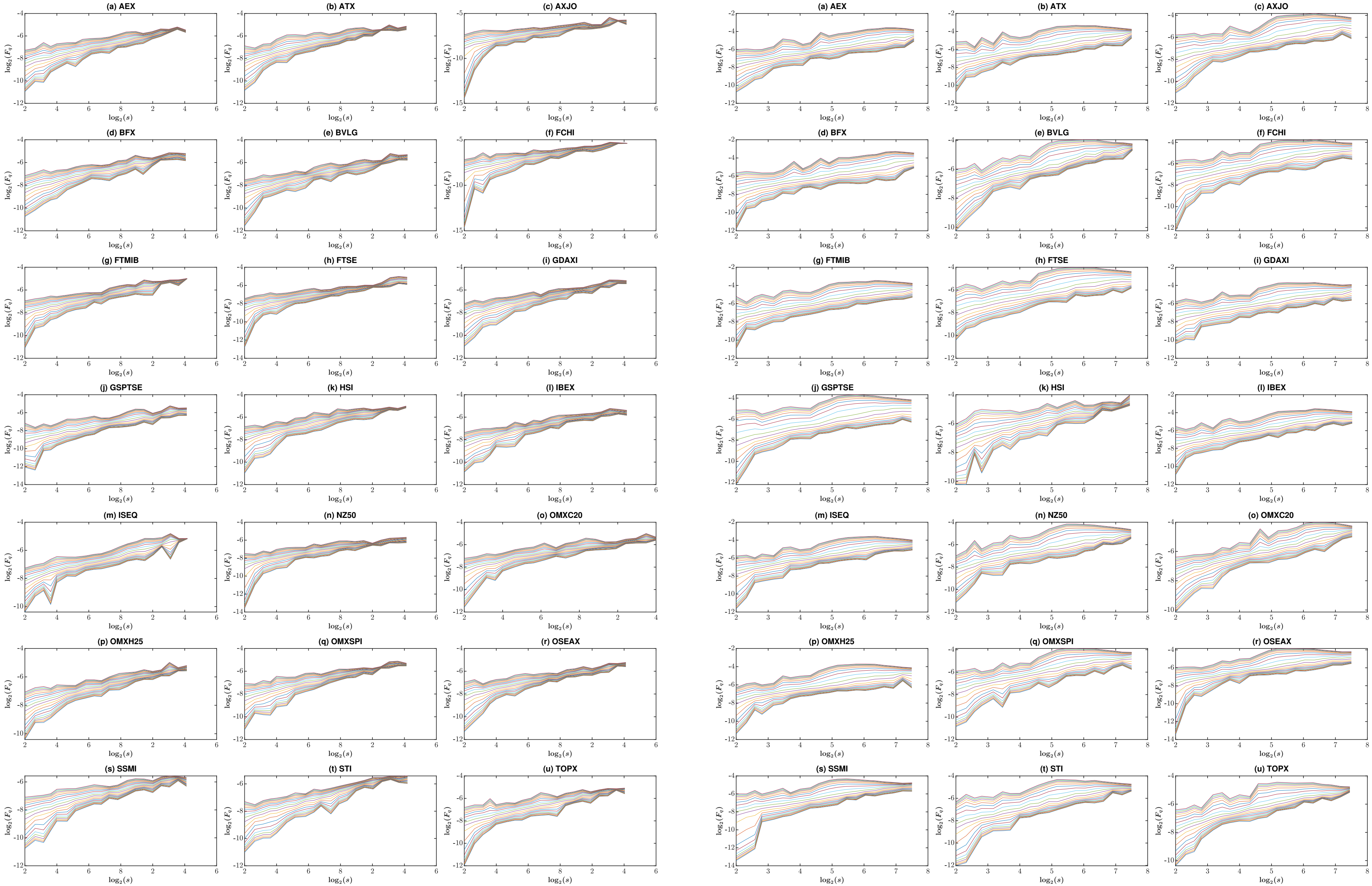
### 4.3 MF-DFA

In this section MF-DFA is applied to the logarithmic return series of both the pre- and post COVID-19 period to measure the market efficiency based on the generalized Hurst exponent, $H_q(2)$, the degree of multifractality, $\Delta h$ , and the width of the multifractal spectrum, $\Delta\alpha$. For a Hurst exponent of 0.5 for $q = 2$, $h(2)$, the series exhibits characteristics that reflect a Brownian motion and can be described by a random walk process. In this case the series reflect a non-correlated random-like behaviour and as a result the market is efficient. If $h(q) > 0.5$ the fluctuation related to $q$ is persistent whereas $h(q) < 0.5$ showing anti-persistent behaviour. A larger degree of multifractality or a wider multifractal spectrum implies less efficiency as the multifractal properties are negatively correlated with efficiency. For $q = 2$ the fractal structure of the time series is described by the generalized Hurts exponent.

Fig. 3 show the log-log plots of the q-th order fluctuation functions and the length scale for both the pre-COVID-19 period on the left side in (Fig. 3 (a)) and the post-COVID-19 period on the right side in (Fig. 3(b)). MF-DFA is performed with a first degree, $m = 1$, detrending polynomial. To capture both small and large fluctuations q ranges from -10 to 10 with a step size of 1. The length of the time scales, $s$, ranges from $s = 4$ to $s = \frac{N}{4}$. Note that in both figures the time scales are shown on a log-basis. In the $F(q) - s$ plots the bottom curve corresponds to $q = -10$ and the upper curve to $q = 10$. The fluctuation functions show that the return series exhibit multifractal properties as $h(q)$ depends on $q$, indicating different changes in fluctuation of the time series across different segments and q-values. The $q$-dependence is shown as all series show an upward sloping $F(q)$. The slopes of the regression lines of $F(q)$ for each $q$ are the Hurst exponents (Eqs. (9) and (10)). Hence, the upward sloping fluctuation functions show $h(q)$ is q-dependent as it varies with changes in $q$, thereby confirming the the presence of multifractal characteristics in the return series. In case the time series would exhibit monofractal properties $h(q)$ would not depend on $q$ which would result in $F(q)$ aligning at the same level, i.e. flat lines for the curves in the $F(q) - s$ figure.

The slopes of the q-order Hurst exponents, $h(q)$, is shown in Fig. 4 to further inspect the multifractality of the return series under different trends. The line connects the slopes of the of F(q) corresponding to each q of the fluctuation function shown in Fig. 3. Where the scaling behaviour of segments with large fluctuations is enhanced for $q > 0$ and the segments with small fluctuations for $q < 0$. The curves for all return series in both the pre- and post COVID-19 period are non-linear and decreasing, providing evidence of the multifractal properties of the return series, i.e. h(q) being q-dependent. The horizontal dotted line references the Hurts exponent taking on value 0.5. The curvature of the plots indicate the range of fractal dimensions where a more curved plot indicating more multifractality of the series. Comparing the plots for the same return series in the pre- and post-COVID-19 period it can be observed that their shape changes, indicating a change in the multifractal spectrum. Looking at the return series of the AEX for example the curvature is more pronounced in the post-COVID-19 period.

**Figure 3.** *Log-Log Plot of the Multifractal Fluctuation Function Fq(s) versus segment size scale (s)*

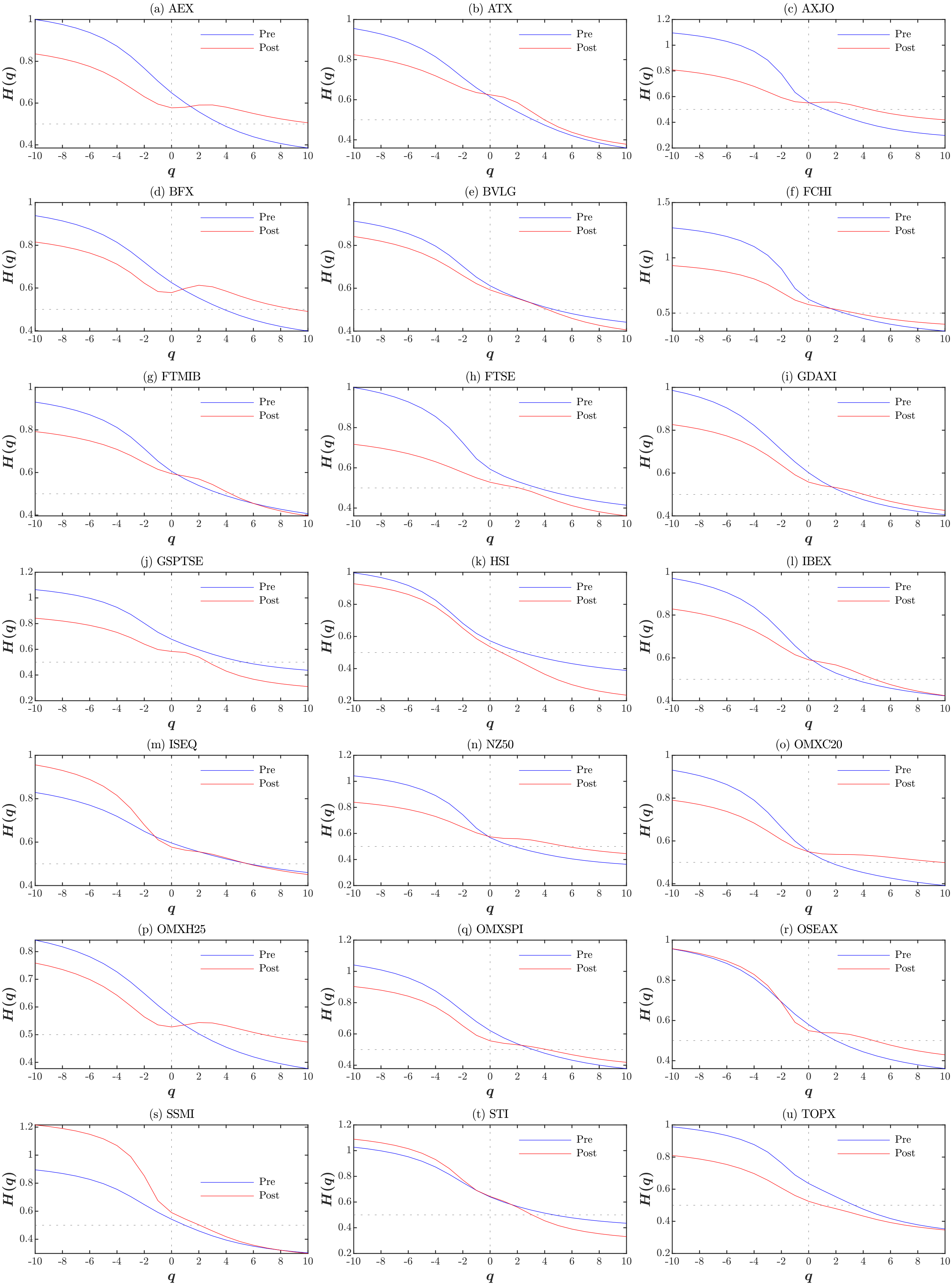



(a) Pre COVID-19 Period

(b) Post COVID-19 Period

*Note.* The time scale on the x-axis is the segment size on a logarithmic scale ranging from $s = 4$ to $s = \frac{N}{4}$ The bottom curve corresponds to $q = -10$ and the curves above increase $q$ with 1 until the upper curve $q = 10$. $m = 1$

**Figure 4.** *q-order Hurst Exponents H(q).*



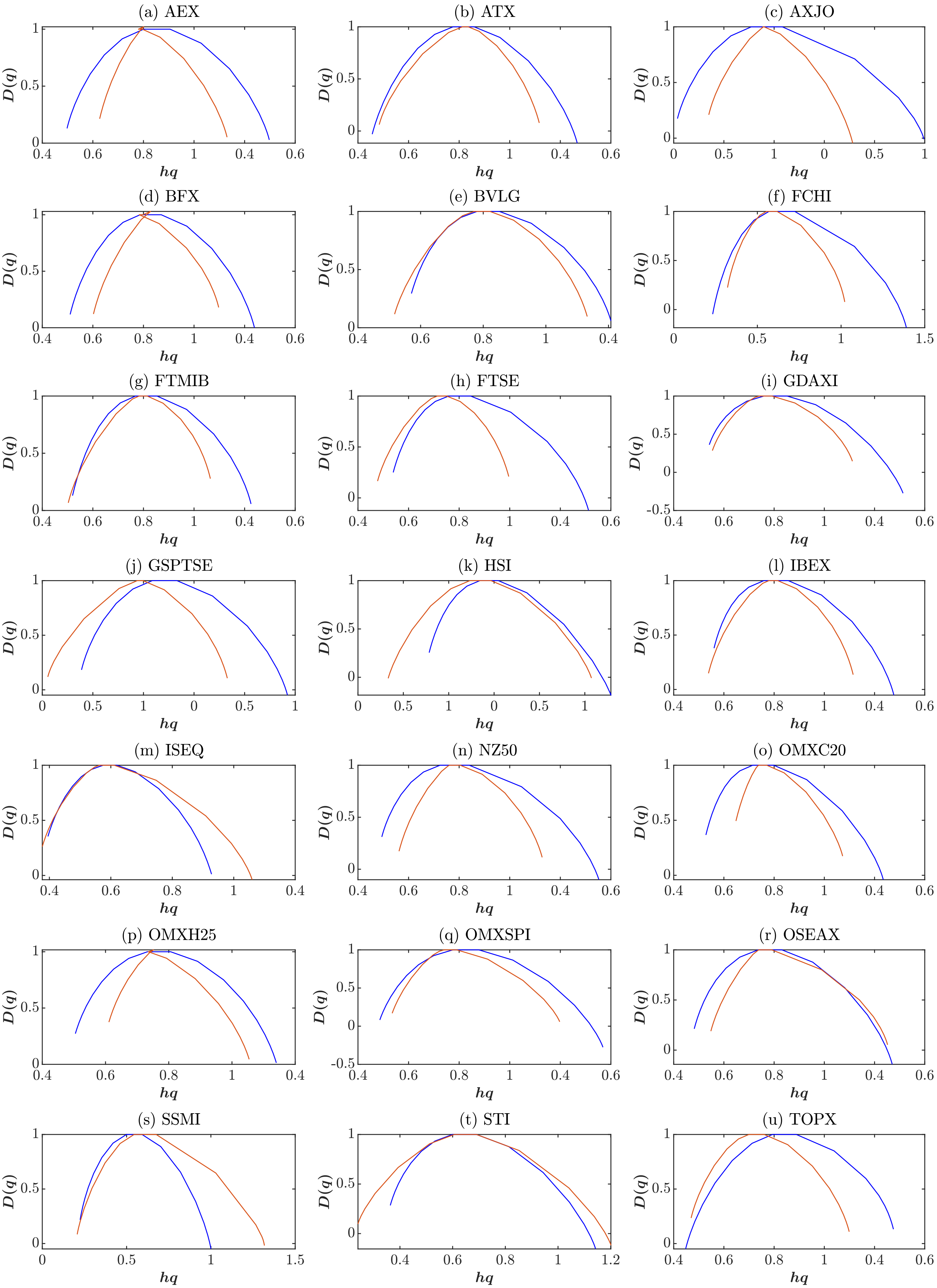

*Note.* The horizontal dotted line corresponds to a value of 0.5 for $H(q)$. The vertical dotted line at $q = 0$ separates the negative values for q enhancing small fluctuations and positive values for q enhancing large fluctuations.

To examine the market efficiency in more detail the values for the generalized Hurst exponent, that is $h(2)$, are investigated for each series in the pre- and post COVID-19 period. Values of $h < 0.5$ indicate the returns are anti-persistent and persistent for values of $H > 0.5$. For $h = 0.5$ the return series reflect a random walk without memory. The generalized Hurst exponents for $q = 2$ are shown in Table 4. Looking at the pre-COVID period the Hurst exponents vary between the different return series. The Hurst exponents for AXJO, NZ50, OMXC20, OSEAC and SSMI are lower than 0.5 during this period. Meaning that series are anti-persistent, mean-reverting, as there is negative autocorrelation in the series of returns. An increase (decrease) in the trend is more likely to be followed by a decrease (increase). With the lowest value being 0.4592 for SSMI. The Hurst exponent of OSEAX is very close to 0.5 with a value of 0.4996 indicating being close to efficiency. For the other series in the sample $h(2) > 0.5$ meaning the time series have positive autocorrelation, persistent behaviour, implying an increase (decrease) is more likely to be followed by an increase (decrease).
For the post-COVID period TOPX has a Hurst exponent below 0.5 with a value of 0.4786. All other time series hurts exponents are greater than 0.5. Looking at the changes in the values between the periods it is noteworthy that the Hurst exponent for the ISEQ series shows only a slight decrease from 0.5558 to 0.5555. For the other time series bigger changes are observed. AXJO, NZ50, OMXC20, OSEAX and SSMI change form being $h < 0.5$, anti-persistent, to $h > 0.5$ persistent. The Hurst exponent for OMXSPI, BVLG, STI and GSPTSE decreases slightly, and becomes closer to 0.5 implying it's efficiency increased. Similarly the Hurst exponent for FSTE, becomes closer to 0.5 with a value of 0.5022 for the post-COVID-19 period implying it's efficiency increased. The HSI and TOPX change from being persistent to anti-persistent. For all other series the Hurt exponent increases, further deviating from 0.5. As for all series the Hurt exponent does not equal 0.5 and consequently providing evidence they are not efficient in the weak form.

**Table 4.** *Calculated Hurst Exponents Using Monofractal DFA*

| | $h(2)$ Pre COVID-19 | $h(2)$ Post COVID-19 |
|---|---|---|
| AEX | 0.5584 | 0.5906 |
| ATX | 0.5398 | 0.5857 |
| AXJO | 0.4682 | 0.5567 |
| BFX | 0.5531 | 0.6130 |
| BVLG | 0.5544 | 0.5526 |
| FCHI | 0.5247 | 0.5342 |
| FTMIB | 0.5387 | 0.5696 |
| FTSE | 0.5323 | 0.5022 |
| GDAXI | 0.5253 | 0.5325 |
| GSPTSE | 0.5965 | 0.5395 |
| HSI | 0.5085 | 0.4514 |
| IBEX | 0.5287 | 0.5670 |
| ISEQ | 0.5558 | 0.5555 |
| NZ50 | 0.4917 | 0.5598 |
| OMXC20 | 0.4887 | 0.5371 |
| OMXH25 | 0.5029 | 0.5437 |
| OMXSPI | 0.5368 | 0.5306 |
| OSEAX | 0.4996 | 0.5381 |
| SSMI | 0.4592 | 0.5028 |
| STI | 0.5659 | 0.5596 |
| TOPX | 0.5528 | 0.4786 |

**Figure 5.** *Multifractal Spectrum.*




*Note* The blue line Shows the spectrum during the pre COVID-19 period and the red line the spectrum in the post-COVID-19 Period.

The multifractal spectrum for all return series both in the pre- and post- COVID-19 period is shown in Fig. 5. Where the hurst exponents in the Table 4 show the average Hurst exponent for q=2 the multifractal spectrum shows the deviation form its average for large and small fluctuation segments. Looking at the spectra it can be observed they have quite a large arch shape. This proves once again the multifractal properties of the series. The width of mono fractal time series is quite small compared to the monofractal series as the hurst exponent is not q-dependent. The most left and right point reflect the width of the spectrum. Looking at the differences between the pre- and post COVID-19 period, the blue arch shows the pre VODI-19 period and the red the post COVID-19 period, we see that for most indices the pre COVID-19 spectrum is surprisingly wider than the post-COVID-19 spectrum. The width shows the range of different types of fluctuations that are present. The pre and post COVID-19 spectra however take on different forms, indicating the type of fluctuations are different in both periods.
In the case of the SSMI the post COVID-19 spectrum is further located to the right contrary to the OMXSPI. Based on the width of the spectrum the degree of multifractality has not increased in the post-COVID-19 period compared to the pre-COVID-19 period. As the spectra are taking on different forms, the type of fluctuations however are indicated to be different.

# 5 Conclusion and Recommendations

This paper provides a look into the market efficiency in the period before and after the COVID-19 pandemic. More specifically examining the period ranging from 1-1-2018 until 31-12-2022. As the COVID-19 pandemic differs from earlier global health emergencies in a number of ways this type of event it causes widespread panic and resulting in fear of the unknown. The pandemic sent shock waves though out financial markets globally. During the corona pandemic governments, businesses and individuals had to react without having a choice or the information on how to best react. This uncertainty can go hand in had with large fluctuations in asset prices as investors might overreact to new information. The EMH relies on the notion that new information is received randomly and as such price changes should also reflect random behaviour. The EMH is a subtle concept, which is empirically hard to test. This paper by applying MF-DFA tries to investigate the market efficiency by investigating the price fluctuations and their persistent, anti-persistent or random behaviour.

By identifying a change point using the standard deviation in a change point test in order to split the time series returns into a pre- and post COVID-19 sub sample and subsequently performing MF-DFA on these sub periods. The results show that all time series in the sample are exhibit multifractal properties. This as the fluctuation function F(q) is q dependent for all return time series. F(q) shows an upward slope ans since the Hurst exponent are the slope of the fluctuation function it can be concluded that the Hurst exponents are q-dependent. Meaning the fluctuations are indicating different changes in fluctuation of the time series across different segments and q-value.

The market efficiency is investigated by the Hurst exponents estimated by the MF-DFA methodology. The values for the generalized Hurst ex- potent, that is h(2), are investigated for each series in the pre- and post COVID-19 period. Values of h $<$ 0.5 indicate the returns are anti-persistent and persistent for values of H $>$ 0.5. For h = 0.5 the return series reflect a random walk without memory. For all return series the Hurst exponent differs from 0.5 for both the pre- and post COVID-19 period. As such providing evidence contradicting the Efficient Market hypothesis.

For the pre-COVID-19 period the Hurst exponents for AXJO, NZ50,OMXC20, OSEAC and SSMI are lower than 0.5 during this period. Meaning that series are anti-persistent, mean-reverting, as there is negative autocorrelation in the series of returns. An increase (decrease) in the trend is more likely to be followed by a decrease (increase). The Hurst exponent of OSEAX is very close to 0.5 with a value of 0.4996 indicating being close to efficiency. For he other series in the sample h(2) $>$ 0.5 meaning the time series have positive autocorrelation, persistent behaviour, implying an increase (decrease) is more likely to be followed by an increase (decrease).

Looking at the differences between the pre- and post-COVID-19 period. The Hurst exponent for OMXSPI, BVLG, STI, FTSE and GSPTSE becomes closer to 0.5 implying their efficiency increased. For all other series the Hurt exponent increases, further deviating from 0.5.
All in all, for all series the Hurt exponent does not equal 0.5 and consequently providing evidence they are not efficient in the weak form.

The estimated multifractal spectra show all return series have multifractal properties. The multifractal spectrum shows the deviation form its average for large and small fluctuation segments. Looking at the differences the spectra show surprising results indicating that the spectrum is wider in the pre-COVID-19 period. The spectra show different shapes in the pre- and post COVID-19 periods indicating the type of fluctuations are different in both periods. Based on the depicted spectra it is hard to confirm the fluctuations differ significantly between the pre- and post COVID-19 period.

Further research could look into the dynamics of the fluctuations by taking a larger sample period. As in this study the examined period spans from the beginning of 2018 to the end of 2022 resulting in around 1300 observations for the full sample period. As such the scale size being relatively small. With examining a larger period the scale could be extended to 512 or 1024, providing a more in depth analysis of the long-range memory and dynamics. Furthermore the change point detection could be improved. Using more advanced methods such as wavelet estimated Hurst exponents could provide a more robust estimation of the change points. Also, the research can be broadened by examining multiple change point and performing MF-DFA on each of those. The asymmetry of the multifractal spectrum can also be taken in to account in determining the different periods.

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# Appendices

## A appendix A.

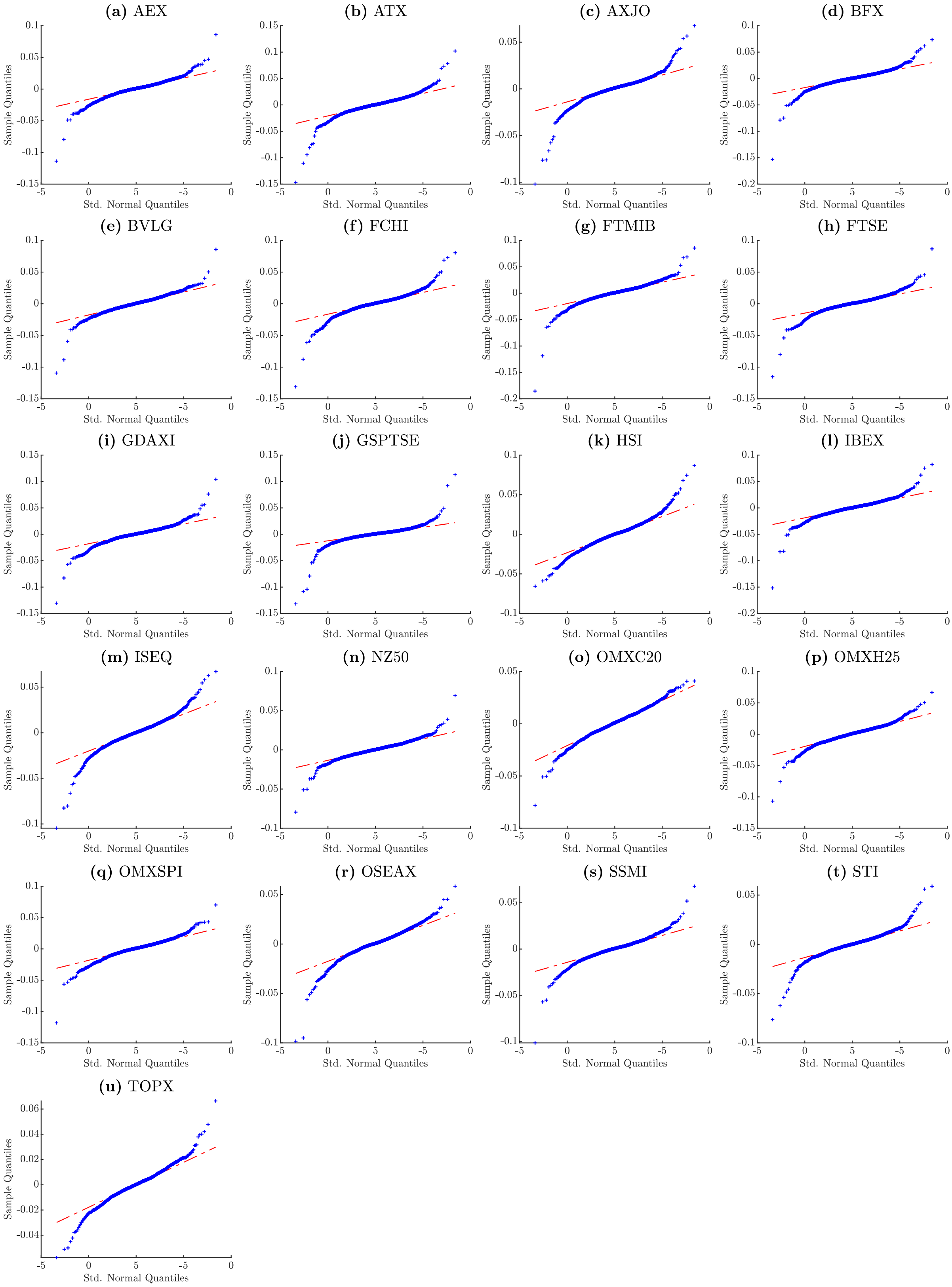


**Figure 6.** *Quantile-Quantile Plots of the Sample Data versus Standard Normal for the Full Sample. The linear red line extends the first and third quantiles of the data. Normally distributed data should appear in as linear points. For all return series data plotted this is not the case indicating the data does not follow a normal distribution.*