INSTITUTO
UNIVERSITÁRIO
DE LISBOA

ARE STOCK MARKETS ASYMPTOMATIC TO DAILY COVID-19 CASES OR DEATHS? AN EMPIRICAL STUDY BASED ON TWENTY-FOUR COUNTRIES

Raquel Sofia de Sousa Martins

Master in Finance

Supervisor:
PhD Pedro Manuel de Sousa Leite Inácio, Assistant Professor
Iscte-Iul

November, 2021

Department of Finance

ARE STOCK MARKETS ASYMPTOMATIC TO DAILY COVID-19 CASES OR DEATHS? AN EMPIRICAL STUDY BASED ON TWENTY-FOUR COUNTRIES

Raquel Sofia de Sousa Martins

Master in Finance

Supervisor:
PhD Pedro Manuel de Sousa Leite Inácio, Assistant Professor
Iscte-Iul

November, 2021

Acknowledgements

I would like to use this opportunity to voice my gratitude to everyone who supported and encouraged me throughout my Masters at ISCTE Business School and during my academic life until today. First and foremost, I have to thank my supervisor, Professor Pedro Leite Inácio, without his assistance, mentorship, constant availability and dedication, this research would not have been possible.

Second, to my family for their unconditional love, motivation, endless care, support and guidance. To my super mother, father and boyfriend, for the constant encouragement, help, patience, by believing in me even when I doubted the most, and for always motivating and inspiring me to pursue my dreams. More than anyone they witnessed first-hand all the anxiety, challenges and personal victories throughout the emotional rollercoaster than has been this process.

Lastly, I take this opportunity to thank all of the ISCTE's Finance Department faculty members for their help and support through this research and my work as an assistant in the department.

Resumo

Após a Síndrome Respiratória Aguda Grave em 2002 e a Síndrome Respiratória do Médio Oriente em 2012, o mundo assiste ao terceiro surto de coronavírus em menos de duas décadas. A doença, que de surto local evoluiu para pandemia mundial, originou um enorme leque de infeções e mortes, despoletou uma crise internacional única com devastadores consequências económicas e perturbou inquestionavelmente o mercado financeiro.

A presente dissertação pretende compreender o eventual impacto existente entre os casos diários de COVID-19 (e as respetivas mortes) no mercado das ações. Para isso, aplicamos o método de dados em painel, utilizando o crescimento diário de casos e mortes e as cotações dos principais índices de mercado de vinte e quatro países de cinco continentes. O modelo conta com variáveis dummy de efeitos fixos diários e variáveis de controlo por país, com observações desde 31 de dezembro de 2019 a 31 de dezembro de 2020.

Assim, verificámos que o mercado de ações reagiu negativamente ao aumento de casos entre 31 de dezembro de 2019 e 31 de maio de 2020. Contudo, para o restante tempo, não há evidência de tal impacto. Isto parece indicar que, embora a pandemia ainda assombre o mundo, o mercado de ações vai recuperando o equilíbrio à medida que a incerteza vai desaparecendo. Paradoxalmente, relativamente às mortes, o mercado não parece reagir. Esta conclusão pode revelar-se de grande interesse para os profissionais da banca de investimento, dos governos e investidores preocupados com as implicações da pandemia nos mercados financeiros.

Palavras chave: COVID-19, coronavírus, pandemia, análise do mercado de ações, dados em painel

JEL codes: G01, G15

Abstract

After battling the Severe Acute Respiratory Syndrome in 2002 and the Middle East Respiratory Syndrome in 2012, the world is witnessing its third severe coronavirus outbreak in less than two decades. The disease promptly progressed from a local outbreak to an international crisis event. COVID-19 pandemic is causing more human infections, deaths, and economic disruption while also negatively harming the stock market more than any other known disease.

This work aims to understand the relationship between the announcement of daily COVID-19 cases and its consequent deaths on stock market returns. With this in mind, the research uses daily coronavirus growth and daily stock market quotations data from twenty-four countries across five continents. To do so, we employ a panel data regression accounting for daily fixed-effects dummy variables and country-level control variables, with data from December 31, 2019, to December 31, 2020.

Results uncover that stock markets were sensitive to casualties between December 31, 2019, to May 31, 2020. However, for the remaining time, there is no evidence of such impact. This seems to indicate that, even though the pandemic still haunts the world, the stock market regained balance as uncertainty faded. On the other hand, stock markets do not react to COVID-19 fatalities. These findings can significantly interest policymakers, investment professionals, governments, and investors concerned with the pandemic implications on stock markets.

Keywords: COVID-19, coronavirus, pandemic, stock market analysis, panel data

JEL codes: G01, G15

Table of contents

Index of tables

Index of figures

List of abbreviations

BLUE: Best Linear Unbiased Estimator

CD: Cross-sectional dependence

COVID-19: Coronavirus disease 2019

EVD: Ebola Virus disease

GARCH: Generalized Autoregressive Conditional Heteroskedasticity

GDP: Gross Domestic Product

GMM: Generalized Method of Moments

GNP: Gross National Product

IMF: International Monetary Fund

IP: Industrial Production

IPS: Im, Pesaran and Shin

LM: Lagrange Multiplier

MERS: Middle East Respiratory Syndrome

MW: Maddala and Wu

NPI: Nonpharmaceutical interventions

OLS: Ordinary Least Squares

POLS: Pooled Ordinary Least Squares

RNA: Ribonucleic acid

SARS: Severe Acute Respiratory Syndrome

VIX: Volatility index

WEO: World Economic Outlook

WHO: World Health Organization

1. Introduction

The world's most recent pandemic is causing human suffering while triggering major economic and financial disruptions. If, on the one hand, the economic consequences are not yet precise and well-defined, financial markets have already witnessed substantial fluctuations on an unprecedented scale (Zhang et al., 2020).

The World Health Organization (henceforth WHO) acknowledged the disease on December 31, 2019, reporting a cluster of pneumonia cases in Wuhan (Topcu and Gulal, 2020). In February, the same organization revealed the official name for the disease – Coronavirus disease or COVID-19, where "CO" acts for "corona", "VI" stands for "virus", and "D" for "disease" ("Coronavirus Disease 2019 (COVID-19)", 2020). COVID-19 is an infectious respiratory disease with a particular and strong ability to spread from human to human. In February, the WHO declared COVID-19 a global emergency ("WHO Timeline - COVID-19", 2020). On March 11, due to the virus's rapid spread, the alarming levels of infections, and consequently, its threat to humans, the WHO officially characterized COVID-19 as a pandemic ("WHO Timeline - COVID-19", 2020). As of August 15, 2021, the disease has spread to 222 countries, areas, or territories, resulting in 207,948,984 cases with 4,374,328 deaths worldwide ("Coronavirus Update (Live)", 2021). Both numbers will continue to rise, but so will the number of recovered patients. Hence, Gates (2020) names it the "once-in-a-century pathogen".

This study aims to examine the relationship between the current pandemic and the stock market performance from December 31, 2019, to December 31, 2020, which covers the diseases' first wave fully and at least part of the second one. However, the sample is divided into two subperiods for each COVID-19 variable. The first subperiod begins with the first reported case on December 31, 2019, and ends on May 31, 2020. The second subperiod opens with the first stated coronavirus death on January 11, 2020, and finishes on May 31, 2020. The third subperiod is for the remaining time and is equal in both cases and deaths variables. Thus, this study covers the period from when the virus first appeared, peaked and a subsequent "flattening" of the infection curve followed by the emergence and peak of the second wave for some countries. It is important to note that, as it is challenging to clearly identify when waves begin and end, the studied period covers for some nations the second wave fully but for other nations only partially.

In detail, this work assesses the impact and repercussions of the daily announced COVID-19 cases and COVID-19 daily deaths (which countries have been revealing on a daily basis from the day of its first case) on stock market returns. With this in mind, daily COVID-19 data for twenty-four countries alongside their major stock market index are gathered. Hence, using Rstudio, a panel data analysis accounting for country characteristics and systematic risk due to international factors is employed. Additionally, to obtain robust and reliable estimators, further statistical tests are performed before presenting the main results. Therefore, estimations are adjusted for heteroskedasticity and autocorrelation using the method proposed by Newey and West (1987). This framework enables to effectively evaluate if growth in COVID-19 is meaningfully linked with index prices by employing daily growth in COVID-19 cases and deaths together with a variety of theoretical market factors as control variables.

Results provide evidence that stock markets are only negatively and significantly impacted by the growth in COVID-19 positive cases in the first subperiod (December 31, 2019, to May 31, 2020). Furthermore, response to the growth in deaths for any subperiod alongside growth in confirmed cases for the third subperiod is not statistically significant.

This dissertation derives its motivation from the current pandemic. It is not only expanding the literature on the stock market's reaction to different disasters (whether natural or unnatural) and crisis events, but it also contributes to the escalating literature on COVID-19's impact on financial markets. Second, by studying twenty-four countries across five continents, different from the majority of existent studies, this work offers a broader perspective of the current overall stock market performance/situation. Third, and to the best of the author's knowledge, this is the first study addressing the impact of new daily COVID-19 cases and deaths on the financial markets covering the first and second waves. Equally important, through this research, stockholders, authorities, scholars, policy makers, companies, administrations, and individuals will better interpret the current stock market condition. Therefore, this will help them plan and make superior investment decisions now and if a similar event occurs in the future. Finally, these findings also contribute to the contemporary limited but evolving literature on the economic and financial effects of COVID-19. As a last remark, this dissertation is more accurately connected to publications on COVID-19 and stock markets.

Lastly, it is essential to note that this pandemic is ongoing at the time of this writing. On the positive side, even though vaccines conventionally demand years to be fully approved, with COVID-19, scientists worldwide gathered towards a greater purpose. With this in mind, as of August 3, 2021, there are eight vaccines from different laboratories approved for full use (Zimmer et al., 2020). Furthermore, as of the same day, 28.6% of the global population has gotten no less than one inoculation of a COVID-19 vaccine, and 14.8% is already completely protected (Ritchie et al., 2021).

2. Literature Review

2.1 COVID-19

Over the last decades, global health professionals have been stressing that other devastating epidemic or pandemic with the magnitude of the 1918 influenza pandemic or worse was not a matter of not or if but of when (Gates, 2020). The fast dissemination of this virus raised uncertainty at the economic level and in financial markets (Akhtaruzzaman et al., 2021). In particular, David et al. (2021) stated that diseases produce distresses that disturb financial markets harshly. Hence, studying this outbreak and its consequences has become crucial (He et al., 2020). Simultaneously, unlike other known diseases or global health crises, the literature concerning COVID-19 and its impact on financial markets is still scarce and insufficient since the magnitude of the present pandemic has not been observed in over a century.

The current pandemic carried massive media attention and a higher amount of related news than previous public health outbreaks (Baig et al., 2021; Cepoi, 2020). News is a leading factor in understanding economic and stock market fluctuations (Salisu and Vo, 2020). The "bad news principle" identified by Svensson (2000), Cohen et al. (2018), and Akıncı and Chahrou (2018) proclaim that exclusively bad news affect investment alternatives. On the other hand, Narayan and Bannigidadmath (2015) and Narayan (2019) stated that both bad and good news influence investment decisions. Thereupon, this is of extreme importance since both daily announced COVID-19 positive cases, and deaths will be studied as health news.

The investment community broadly missed the threat the current pandemic poses (Albulescu, 2020a). When the number of confirmed cases started to rise, particularly outside China, global financial markets reacted, and volatility began to lift (Ali et al., 2020). By February 2020, stock markets already documented numerous shocks (Albulescu, 2020b). In fact, between January 21, when the US confirmed its earliest case, to March, America's S&P 500 plunged by 22% (Erdem, 2020). In like manner, both Australian, European, and Asian main indices plummeted. In the first quarter of 2020, UK's FTSE 100, Japan's Nikkei, and Germany's DAX dropped 24.80%, 29%, and 38%, respectively (Akhtaruzzaman et al., 2021; Cepoi, 2020). Moreover, Australia's S&P ASX dropped 25% between late January and March, and the Dow Jones Index faced its second-worst trading say in 124 years by falling over 12% on March 16 (Onali, 2020; Rahman et al., 2021). Even though the leading world stock market indices happen to be moderately recuperated by mid-April, uncertainty still predominates (Cepoi, 2020).

Topcu and Gulal (2020) study the effect of the disease only in emerging stock markets from March 10 to April 10, 2020, through a panel data approach. The authors advocate that each nation will sense the influence of COVID-19 in its stock market differently because of local features. As for emerging countries, the authors state that Asian markets are more affected by the disease, followed by South America and the Middle East. However, Central and Eastern Europe appear to be the lowest disturbed areas. Nevertheless, according to Shehzad et al. (2020), the European and the United States markets were more distressed than the Asian ones. Additionally, Topcu and Gulal (2020) uncover that between March 10 and March 20, a one-unit rise in COVID-19 infection rate leads to a 0.153% drop in stock returns. However, if the studied period is lengthened to April 10, 2020, the stock market of those countries is only impacted by 0.087%.

Ali et al. (2020) run bivariate regressions with a sample period from January 1 to March 20, 2020. The research aims to investigate the impact of the coronavirus disease on the stock market as the disease's epicentre changed from China to Europe, followed by the US, by dividing the sample into two parameters: first epidemic, second pandemic. Then the global spread: phase 1 where COVID-19's deaths were only occurring in China; the European spread is phase 2, and phase 3 corresponds to the disease spreading in North America. From the epidemic to the pandemic period, the authors find that the average volatility of the US, UK, Germany, and South Korea's stocks uplifted. Furthermore, even though phase 2 documented a higher lethality ratio, European indices suffered most during phase 3 (US period), whereas volatility in stock markets augmented in phase 3. In line with these conclusions are Antonakakis et al. (2013), Chen and Chiang (2020), and Tiwari et al. (2019) works. The most compelling evidence for the present research is that COVID-19 deaths negatively and significantly influence stock market returns.

The pandemic stage is acknowledged as the period with superior negative returns (Ali et al., 2020). While the European markets experienced the highest negative returns, China displayed a minor decrease in returns in the epidemic and pandemic days (Ali et al., 2020). Nevertheless, Corbet et al. (2020) document two stages of deterioration in China: first in mid-January, while casualties were escalating in China, and the second one in March following a phase of market progress, illustrative of the profound monetary consequences with the awareness of a second wave. Ali et al.'s (2020) work oppose to Li and Zhong (2020), stating that the main origin of China's financial markets volatility is uncertainty shockwaves coming from the country itself.

Instead, David et al. (2020) state that during the COVID-19 period, volatility is a reality for all financial indices, with Ibov-Brazil being the most damaged and struggling the most in recovering. To emphasize, Sharif et al. (2020), Zaremba et al. (2020), and Zhang et al. (2020)

conclude that COVID-19 boosts stock markets' volatility. Additionally, Khanthavit (2020a) found the pandemic severely and negatively affects national and world stock markets, which is also in line with Al-Awadhi et al.'s (2020) study.

Albulescu (2020b) studies the impact of official revelations of positive casualties and deaths on the financial markets volatility index (VIX) and establish that new infection cases announced only outside China positively influence financial volatility. In contrast, deaths reported out of China generate a more powerful impact on VIX than fatalities pronounced in mainland China. As a final observation, the author believes the higher the disease has spread, the higher the financial volatility.

Alber (2020) manage a research to explore the consequences of the disease's spread on stock markets by employing the GMM technique from March 1 to April 10, 2020. One main contribution is that stock market returns appear to be vulnerable to COVID-19 cumulative positive cases rather than to new cases, cumulative deaths, or new deaths. Besides, China, France, Germany, and Spain stock markets are more distressed by the pandemic.

Another worth mentioning study conducted by Ashraf (2020) observe the stock market's reaction to the current pandemic through panel data analysis covering the period from January 22 to April 17, 2020. The study notes that returns are negatively linked to new casualties, symbolizing that, on average, returns fall as the total COVID-19 cases upsurge. Moreover, while securities' returns are negatively linked to COVID-19 deaths, financial markets' volatility is positively related to the fatality ratio. Furthermore, this analysis states that markets react to the evolution of confirmed cases but not to coronavirus deaths, which also supports Alber's (2020) conclusions. Ashraf (2020) also affirms that the non-existent reaction to deaths is due to investors' expectations regarding the evolution of confirmed cases. In other words, COVID-19 mortality is, in principle, a result of a previously confirmed case and generally happens several days after receiving the infection certification. As a result, from the time growth in COVID-19 confirmed casualties begin to increase, wealthy investors price stocks in the anticipated adverse shock of COVID-19. Besides, the market reacted more negatively and firmly in the early phase of the outbreak.

Through Pooled OLS estimation, with a research period between April 9, 2019, until April 3, 2020, and covering sixteen countries, Khan et al. (2020) research aligns with Ashraf's (2020) inference. Indeed, pointing towards the negative and significant impact of weekly new coronavirus positive cases on stock markets returns.

Al-Awadhi et al. (2020) employ panel data methodology to study how the coronavirus disease affects stock market returns in two major stock indices in China – Hang Seng Index and Shanghai Stock Exchange Composite index – from January 10 to March 16, 2020. The study discloses that both COVID-19 daily growth in cases and deaths influence negatively and significantly stock returns.

Onali (2020) investigates the impact of COVID-19 cases and resultant fatalities for two stock indices in the United States – Dow Jones and S&P500 – from April 8, 2019, to April 9, 2020, using GARCH methodology. The primary conclusion from the study is that from the sample of six countries severely affected by the disease, only the cases reported in China affect US stock returns. Similarly, the Dow Jones index is disturbed by deaths reported in France and Italy.

According to Erdem (2020), who examined stock market indices of 75 countries from January 20 to April 30, 2020, COVID-19 does, in fact, negatively affect stock markets. Besides, the author mentions that both the growth in cases and deaths result in statistically significant negative returns on stock markets, but the first impacts it by almost three times more than the latter. The author believes investors perceive the number of cases as a red flag for the deaths that are likely to arise later. As a result, deaths caused by the disease are no new information and therefore are meaningless for investors, which is also in accordance with the research developed by Ashraf (2020). Equally important, the author emphasizes that the country's freedom level influences how investors analyse coronavirus information. As an example, when COVID-19 positive cases per million increase, in freer countries, stock returns decrease less than in less-free nations. Hence, the negative impact of the disease on stock markets is less austere in freer countries.

On the other hand, Bahrini and Filfilan (2020) uncover that Gulf Cooperation Council stock markets answer negatively and significantly to the daily new confirmed deaths and daily total confirmed deaths, both measures per million of population. At the same time, COVID-19 cases do not trigger any significant reaction in stock markets. On the contrary, O'Donnell et al. (2021), by investigating six international stock indices from December 31, 2019, to June 10, 2020, uncover that total cases acted as a significant negative influence on stock indices returns.

All things considered, according to Al-Awadhi et al. (2020), Alber (2020), Ashraf (2020), Erdem (2020), Khan et al. (2020), O'Donnell et al. (2021), and Topcu and Gulal (2020), COVID-19 positive cases negatively affect stock returns. At the same time, the impact of COVID-19 deaths produces mixed effect results. For Al-Awadhi et al. (2020), Ali et al. (2020), Bahrini and Filfilan (2020), and Erdem (2020), there is a significant negative impact of COVID-19 deaths on the stock market. On the other hand, Alber (2020) and Ashraf (2020) do not find evidence of such disturbance. Nonetheless, it is essential to emphasize that authors measure COVID-19 cases and deaths differently.

2.2 Behavioural Finance

There are four main theories explaining stock price movements – Efficient Market Hypothesis, Random Walk theory, Rational Expectations hypothesis, and Behavioural finance theory. The latter has been subject to considerable investigation in previous years and has emerged as the most recent approach in understanding stock market behaviour (Tvaronavičiene and Michailova, 2010).

Behavioural finance merges behavioural and cognitive psychology with economic theory (Shankar and Dhankar, 2015). Its appearance substitutes modern/standard finance, which is behaviourally undeveloped since it does not account for individual behaviour (Olsen, 1998). However, this author still considers that within particular boundaries, the standard financial theory is accurate.

This theory alleges that investors are occasionally limited in their rationality. By acknowledging this fact, it is understood to have a better performance in explaining behaviour in the financial marketplace (Reilly and Brown, 2012). The purpose of this theory is to understand how and why investors make decisions and to what extent those actions disturb the stock market with two particular emphases: detecting portfolio anomalies due to psychological attributes, for instance, wrong information management. Second, detection of situations where above-normal rates of returns are encountered (Reilly and Brown, 2012; Body, Kane and Marcus, 2009).

As an illustration, take any stock in high demand with its price escalating significantly over a short period and deprived of any modification in business's fundamentals, the behavioural finance supporters' credit this to mass psychology (Tvaronavičiene and Michailova, 2010). In the stock market, this latter phenomenon stands for investors drifting towards similar investments grounded only on the fact that other investors are buying the same securities (Shankar & Dhankar, 2015). For this reason, the followers of this theory credit fluctuations in stock prices to investor's psychology and not statistical information (Tvaronavičiene and Michailova, 2010). Additionally, Tvaronavičiene and Michailova (2010) determine that the transformations in investors' conduct trigger prices to decline or escalate abruptly.

2.3 Macroeconomic factors

Share prices are sensitive to numerous factors, and it has become decisive to understand how they behave under specific situations. Diverse studies find that macroeconomic variables are essential when accessing stock prices and the stock market (Tvaronavičiene & Michailova, 2006).

2.3.1 Supply and demand

The stock market is regarded as the economy's barometer, but also it is unquestionably one of the most significant components of it (Topcu and Gulal, 2020). Because, by incorporating both present and future profitability opportunities (namely dividends), share prices comprise vital information. In detail, when investors are confident that the dividends a company will pay to its shareholders will increase, investors are more prone to pay for a share of that business today. Thus, share prices increase. However, if the opposite occurs, investors are less likely to desire to hold shares of that company, and thus, prices fall (Body, Kane and Marcus, 2009). With this in mind, fluctuations in share prices provide extremely crucial information regarding the future and how a specific occurrence is perceived to impact on business prospects. Furthermore, stock market data is updated every second, with investors reacting almost immediately to news or events. Thus, making it beyond crucial information when aiming to understand how investors react to specific events.

In like manner, the notions of supply and demand are crucial both in economics and in financial markets. Demand refers to the amount of goods/services buyers are willing to acquire, while supply refers to how much the market can provide (Jain, 2014). Hence, price is a reflection of supply and demand (Jain, 2014). Although several factors influence the stock's demand or supply, this law helps explain a stock price at any specific period.

2.3.2 Fiscal and monetary policies

Chatziantoniou et al. (2013) conclude that both monetary and fiscal policies impact stock markets. Fundamentally, the authors believe policies are crucial to understand stock market changes.

"Monetary policy is the management of money supply and interest rates" (Mishkin, 2004, p.12). In the past, several studies attempted to classify the relationship between money supply and stock prices. For example, Rozeff (1974) states that increases in the money's growth rate raise stock returns. However, more up-to-date studies reveal a robust bond between money supply and stock prices, but variations in money's supply growth rate delayed stock returns in one to three months (Reilly and Brown, 2012). In contrast, the research conducted by Davidson and Froyen (1982) or Hafer (1986) uncover that stock prices adapt rapidly to unforeseen changes in money supply growth. However, Thorbecke (1997) reports that expansionary monetary policy boosts ex-post stock returns. Concerning interest rates, increases in the money supply cause interest rates to drop. Hence, firms can better finance new projects because borrowing happens to be more affordable. Low borrowing costs enable superior profits, therefore increasing the perceived value of a stock. Thus, we expect stock prices to rise (Tvaronavičiene and Michailova, 2006).

Fiscal policy involves decisions about government spending and taxation (Mishkin, 2004). According to Tvaronavičiene and Michailova (2006), an expansion of government spending stimulates the economy or its individual segments, such as share price, while any decrease in government spending produces the reverse result. Nevertheless, tax reductions boost the economy, profits, and share prices (Tvaronavičiene and Michailova, 2006).

2.3.3 Inflation

Inflation is the rate of modification of the price level and is associated with the deterioration of an individual's or companies' purchasing power (Antono et al., 2019). According to Antonakakis et al. (2017), it is widely acknowledged that inflation moves stock prices in the short run. However, it can either positively or negatively move stock prices depending on the theory employed.

On the other hand, Schwert (1981) stated that the US stock market answered negatively with the announcement of unanticipated inflation. Notwithstanding, the relationship between inflation, interest rates, and stock prices is neither as straightforward as the previous one. In most cases, there is a negative association between inflation, interest rates, and stock returns, but as mentioned by Jaffe and Mandelker (1976), and Fama (1981), this is not always true. However, even when the negative relationship is accurate for the market as a whole, it may not be accurate for specific industries, as confirmed by Reilly, Wright, and Johnson (2005) (Reilly and Brown, 2012).

2.3.4 Economic activity

Gross Domestic Product (GDP) quantifies aggregate economic output (Todaro and Smith, 2015). In addition, literature has long established a positive impact on indicators of real economic activity and stock prices. Among these indicators, recommended by Fama (1990) and Geske and Roll (1983), are GDP, Industrial production (IP), and Gross National Product (GNP).

2.4 World events influencing the stock market

Whether natural, political, related to health, financial, or economic, different world occasions affect the stock market. For instance, Kowalewski and Śpiewanowski (2020) observed how fifty-five catastrophes in potash mines distressed the stock market for thirty-three years and concluded that for human-made accidents, most of the time, stocks have a maximum fall of 5.06% within the two subsequent days of the disaster.

2.4.1 Previous epidemics and pandemics

Over the last years, the WHO exposed epidemics and pandemics that carried substantial human suffering and disrupted several economies worldwide. Learning from these past occasions can be a suitable method to better prepare for the future.

2.4.1.1 The great influenza pandemic (1918-1920)

The great influenza pandemic of 1918 to 1920, popularly known as the Spanish flu, was estimated to kill near 40 million citizens worldwide, with 675,000 beings on US soil (Garrett, 2008), equivalent to 2.1% of the earth's population at the time (Barro et al., 2020). In addition, World War I intensified the pandemic's spread (Garret, 2008). This pandemic appeared in three waves, the first in the spring of 1918, the second with the highest mortality rate from September 1918 to February of next year, and the last one for the rest of 1919 (Barro et al., 2020). Unlike other viruses, young males aged between 18 to 40 were the most affected. With the absence of the principal breadwinner, their families faced severe economic consequences. Subsequently, this loss of human resources also had terrific costs for firms (Garret, 2008).

Some parallels can be drawn between this outbreak and COVID-19. In the first place, both events are similar in nature, scale and comprise of respiratory disease that can evolve to pneumonia. Barro et al. (2020) believe the mortality and economic consequences witnessed during this pandemic serve as reasonable upper bounds for outcomes under COVID-19. The flu death rate observed during the 1918-1920 pandemic corresponds to around 150 million deaths worldwide when applied to the 2020's population. Consequently, this death rate resembles falls of 6% for GDP and 8% for private consumption for a standard nation. Furthermore, a study conducted on 43 countries by Barro et al. (2020) revealed that this pandemic instigated decreases in stock prices while also causing increases in volatility worldwide. Although the possibility of COVID-19 displaying a mortality rate similar to the great influenza pandemic appears isolated, due to advances in public-health knowledge, medical facilities, and the measures used to ease the virus dissemination, the economic consequences can be worse (Barro et al., 2020).

2.4.1.2 Severe Acute Respiratory Syndrome (SARS)

The SARS epidemic, produced by the SARS coronavirus (SARS-CoV), a viral respiratory illness with pneumonia-like symptoms, had its origin in November of 2002 in the province of Guangdong in China (Chen et al., 2007; Yang et al., 2020). As the whole genome of SARS-CoV-2 has 86% resemblance with SARS-CoV and its origin is the same as COVID-19 – China – it presents a unique opportunity to understand the economic impact of COVID-19 better (Wilder-Smith et al., 2020). Due to person-to-person transmission and international travel, SARS reached 32 countries/regions in five continents and caused 8,422 possible cases with 919 deaths, implying a fatality ratio of 11% within ten months (Yang et al., 2020).

Even though there was no vaccine and the virus spread globally, the clear understanding of transmission patterns, early identification of positive cases, and chain of transmission alongside the prompt adoption of containment measures slowed the virus' dissemination and avoided a public health catastrophe (Yang et al., 2020). On the other hand, even without a significant health crisis, which health experts worried about, the world economy was still considerably damaged (Smith, 2006). Several authors claim this epidemic's global cost to be between US$30–$100 billion (Smith, 2006). Tourism, retail sales, restaurants, air transportation, and hotel businesses were responsible for a large percentage of those losses, mainly in China (Smith, 2006; Wang et al., 2013). Simultaneously, in Taiwan, the stock market was disturbed, with the chemicals, buildings, department stores, food, hotels, fabrics, and vehicle industries having substantial negative cumulative abnormal returns (Wang et al., 2013).

Nevertheless, this outbreak acted as an example of what should be done if a similar one occurs. According to Yang et al. (2020), enormous quantities of medical supplies and personal protective equipment for front-line workers are needed while ensuring staff training on appropriately protecting themselves with the referred equipment. The author argues that these people and the materials were crucial in winning the battle of SARS. In addition, it was critical to have "fever clinics" established early on in the outbreak, to isolate infected individuals and patients suspected of being infected from others in hospitals. Individuals visiting those fever clinics had their body temperature measured. Reducing person-to-person transmission through quarantines and isolation of infected patients was also decisive. Lastly, it was imperative to timely and effectively inform the population on the status of the epidemic, individual measures, and recommendations to slow the virus' spread.

2.4.1.3 Middle East Respiratory Syndrome (MERS)

Middle East Respiratory Syndrome is a viral respiratory disease caused by a coronavirus (MERS-CoV) and was first detected in Saudi Arabia, a decade after the SARS outbreak, in 2012 (Yang et al., 2020). In total, there were 2,494 confirmed cases with 858 deaths, implying a fatality rate of 34.4% (Park et al., 2020). Although there were reported cases in 27 countries, nearly 80% of them were in Saudi Arabia. Other cases reported outside the Middle East are individuals infected during their stay in the Middle East that afterward traveled to other areas. ("Middle East respiratory syndrome coronavirus (MERS-CoV)", 2019). Nevertheless, there were few small outbreaks in other areas ("Middle East respiratory syndrome coronavirus (MERS-CoV)", 2019).

On the economic level, this outbreak triggered a real GDP per capita shrinkage of 32% in Kuwait, 25% in Qatar, 16% in Saudi Arabia, and 12% in the United Arab Emirates between 2012 and 2014 (Ceylan and Ozkan, 2020).

In the final analysis, while MERS did not display a considerable power of human transmission, it demonstrated a high mortality rate. On the other hand, SARS was effectively and successfully transmitted between individuals but with a low fatality level (Petrosillo et al., 2020).

2.4.1.4 Ebola outbreak, 2013-2016

Ebola Virus (EBOV) was formerly labeled Ebola Virus disease (EVD) when, in 1976, Zaire witnessed several outbreaks of hemorrhagic fever syndrome (Spengler et al., 2016). The largest and most severe Ebola outbreak started in Guinea in late 2013 (Coltart et al., 2017). Although the epidemic's most affected countries were Guinea, Liberia, and Sierra Leone, several African, European, and American countries reported cases. This outbreak had unique dissemination circumstances due to weak surveillance systems and inadequate health systems in West African countries (Kentikelenis et al., 2015). This event resulted in 28,646 total Ebola cases with 11,232 deaths, indicating a 40% mortality rate (Coltart et al., 2017).

There is a parallel between the intensity of the event occurrence, how investors respond to it, and the consequences of those reactions. For example, the 2014-2016 outbreak event had consequences in the financial markets. Ichev and Marinč (2018) find that the pandemic triggered negative returns in the financial market while increasing stock's implied volatility.

Additionally, the authors state that the media further emphasizes high-consequence and low probability occurrences, namely Ebola or other pandemics, consequently generating investor sentiment effects. With this in mind, securities that suffer from more media exposition face a higher event effect (Ichev and Marinč, 2018).

3. The ongoing pandemic and significant occurrences

On November 17, 2019, according to media reports on unpublished Chinese government data, the first patient suffering from a new virus causing respiratory illness was reported in Wuhan, Hubei Province, China. Although the origin of the new virus is not clear, experts believe the first cases were related to a large seafood and live animal market. Hence, the most accepted theory in the scientific community is that Chinese bats were the source of the virus before it spread to individuals through an intermediary host, according to genetic information established (Gale, 2021). The WHO first recognized the disease on December 31, 2019, reporting a cluster of cases of pneumonia in Wuhan (Park et al., 2020; Topcu and Gulal, 2020). A novel coronavirus with analogous characteristics to the Severe Acute Respiratory Syndrome (SARS) pandemic of 2002 was identified (Corbet et al., 2020).

COVID-19 is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), a beta coronavirus (Sauer, 2021). Coronaviruses are single-stranded-RNA virus impacting humans and animals. Animal coronavirus hardly contaminate the human species and then spreads between them, as this only occurred two times with the MERS and SARS (Sohrabi et al., 2020). Regarding humans, known coronaviruses cause respiratory infections, being MERS and SARS the most severe virus previous to this pandemic. However, unlike other known human coronaviruses species, COVID-19 has a different coronavirus-specific nucleic acid sequence (Lu et al., 2020).

Among the foremost common symptoms humans experience from this pathogen are fever, dry cough, fatigue, headache, sore throat, shortness of breath, or loss of taste/smell (Sauer, 2021). Approximately 0.6% of individuals affected by the disease have been in a severe or critical condition, with 99.4% of the patients experiencing mild symptoms or even being asymptomatic ("Coronavirus Update (Live)", 2021). Nevertheless, some groups, namely older people and individuals with particular underlying medical conditions, are more prone to face severe consequences with COVID-19 (Centers for Disease Control and Prevention, 2020b). However, this does not necessarily mean that younger individuals who have no other known significant medical condition cannot be in a critical situation.

On January 11, 2020, China announced the first death caused by the disease. Within days, several other countries, such as the United States of America, Taiwan, Japan, the Philippines, or South Korea, reported cases of people suffering from the virus (Taylor, 2021). The WHO issued the first report on the disease on January 21, 2020, with cases of infections and death figures in China and outside being detailed. One day after, the organization confirmed the virus was contagious, and person-to-person transmission of this pathogen was the primary cause of its dissemination (“WHO Timeline - COVID-19”, 2020). On January 25, the disease was confirmed to have spread to Oceania, with Australia verifying its very first case (“First confirmed case of novel coronavirus in Australia”, 2020). Less than one week later, the organization declared COVID-19 a global emergency. On February 11, the WHO revealed the official name for the disease that was causing the 2019 novel coronavirus outbreak – Coronavirus disease or COVID-19 in which “CO” denotes “corona”, “VI” stands for “virus”, and “D” for disease (“Basics of COVID-19”, 2021).

February 14 signs the first coronavirus death outside Asia, more accurately in Paris, when China already accounted for 1,500 deaths (Taylor, 2021). On the same day, the first COVID-19 cases in Africa were announced in Egypt (“COVID-19 cases top 10 000 in Africa”, 2020). Days later, Brazil confirms its first case, indicating the virus was already present in South America (Taylor, 2021). Under these circumstances, there were already COVID-19 confirmed cases in all five continents.

As a result, due to the virus’ rapid spread, the alarming levels of infections, and consequently, its threat to humans, March 11 marks the official announcement of the WHO in characterizing COVID-19 as a pandemic (“WHO Timeline - COVID-19”, 2020). On that same day, 11,646 new cases and 4,633 new deaths worldwide were reported (“Coronavirus Update (Live)”, 2020). On the negative side of a globalized world lies the fact that a contagious illness arising in one particular nation is more prone to disseminate to others in a short period of time. In addition, the development of dangerous illnesses can have disastrous implications for the worldwide economy (Chen et al., 2018). Up to this day, the outbreak continues to spread, and new cases of infection and resulting deaths are still growing. As a result, as of August 15, 2021, the world displayed a total of 207,948,984 confirmed cases with 4,374,328 fatalities (“Coronavirus Update (Live)”, 2021). Figures 1 and 2 demonstrate how total COVID-19 numbers distribute across the world as of August 15, 2021.

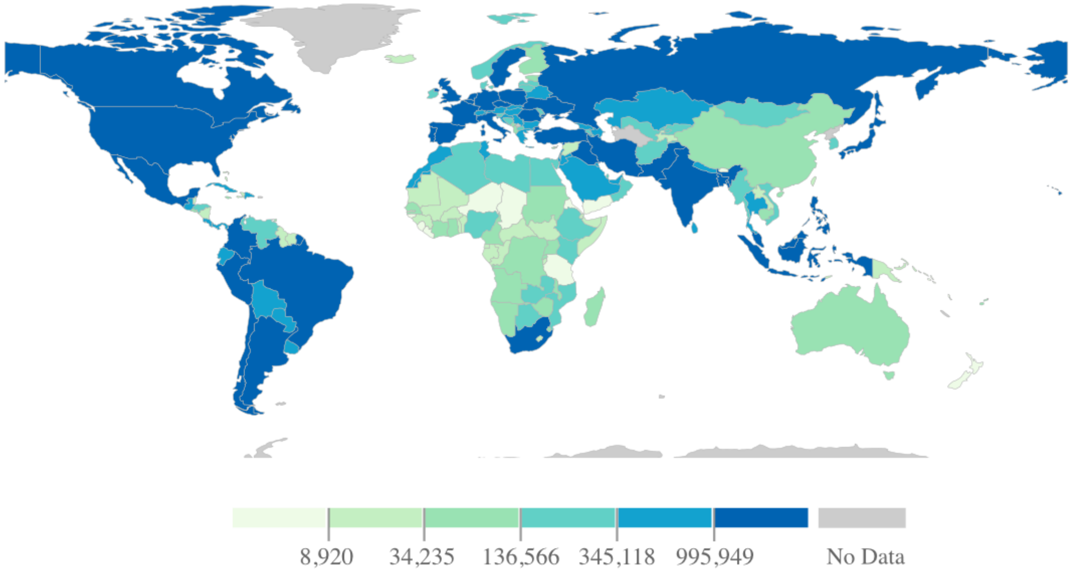


Figure 1 – Global reported cumulative COVID-19 cases (Source: "COVID-19 Data Tracker", 2021)

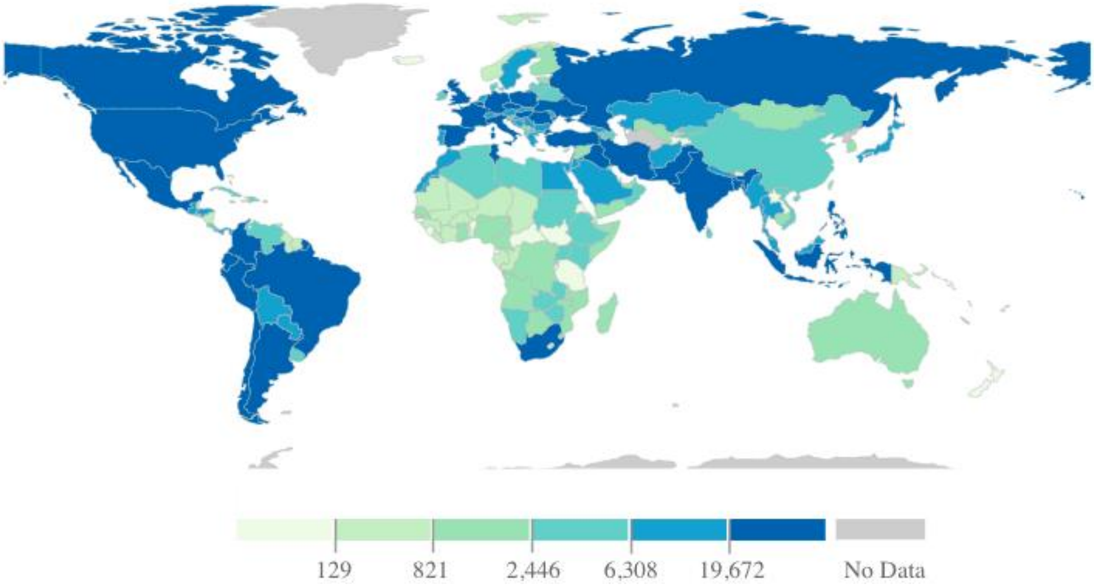


Figure 2 – Global reported cumulative COVID-19 deaths (Source: "COVID-19 Data Tracker", 2021)

Despite nations reacted differently to the most recent global pandemic, the majority employed some form of NPI (nonpharmaceutical interventions) to slow the transmission of the virus worldwide. When vaccines are not available, NPIs are known from past pandemics to be efficient and successful tools to decrease infections, save lives while also diminishing the burden on the health care system (Walker et al., 2020). With this in mind, most governments implemented unprecedented measures. Travel bans with international borders being closed thus, reducing air travel by 70% to 90% by the end of March, compared to figures of the previous year in major cities (Ashraf, 2020). Partial or complete lockdowns to limit the movement of citizens with schools and businesses being shut down. Additionally, major cultural, sports events, and other public events were canceled. Most countries also inflicted mandatory quarantines, social distancing, and mask-wearing (Cao et al., 2020).

Although these measures successfully reduce the virus' dissemination, it adversely affects the economy. Erdem (2020) claims the "economic consequences will likely surpass those of the 2007–09 global financial crisis", yet the real impact is still uncertain. The pandemic is disrupting the labor force, global supply networks with losses on consumer demand in most industries. Alongside the tourism sector and consumption behavior, with consumers' expenditure hypothetically deteriorating approximately one-third, which altogether incontestably disturbs the international economy ("Evaluating the initial impact of COVID-19 containment measures on economic activity", 2020; Topcu and Gulal, 2020). However, intending to diminish the adverse effects, stimulus packages worldwide for both businesses and workers that lost their jobs and income were created, funds to strengthen the healthcare system, tax measures to support households and enterprises alongside other measures (Narayan et al., 2021). Altogether, the International Monetary Fund (IMF) projected total government stimulus packages in the COVID-19 era that equaled $11 trillion with additional loans, equity injections, and guarantees totaling $5.4 trillion (IMF, 2020).

Furthermore, central banks have decreased policy interest rates and reserve requirements and also declared additional financing facilities. The Federal Reserve approved a zero-percent interest rate strategy and released a $700 billion Quantitative Easing parcel (Akhtaruzzaman et al., 2021). The European Central Bank also announced a temporary asset purchase programme (PEPP) totaling €1,850 billion (Bank, 2021). Nevertheless, despite all the efforts made by numerous institutions, the IMF, in its "World Economic Outlook" issued in July 2021, states a global growth rate of -3.2% in 2020, approximately two times lower than the lowest global growth rate recorded during the 2007-09 financial crisis. For the Euro area, the same report identifies a negative growth of 6.5%.

4. Data and variables description

This chapter describes the data employed in the research, the data sources, the definition of the variables, and the research period.

4.1 Sample description

This study comprises data from 24 countries, namely: Australia, Belgium, Brazil, Canada, China, France, Germany, India, Israel, Italy, Japan, Mexico, Netherlands, Portugal, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom and the United States of America. The reasoning for selecting the identified countries is fivefold: first, China, being the country where the virus first broke out, automatically justifies its integration in this study. Second, the US, UK, Japan, alongside China, have the largest stock markets globally and are seen as primary guides for international stock markets. Third, India, Brazil, France, Spain, Russia, Germany, Italy, and Mexico were some of the top nations with more confirmed cases on December 2, 2020. Fourth, while Portugal and Israel took effective and preventive measures in the first wave thus, being able to contain the virus and "flatten the curve" through quarantines, early isolations, and social distancing, the second wave was catastrophic (Financial Times, 2020; Financial Times, 2021).

On the other hand, Sweden did not apply sufficient measures to contain the virus' spread (for instance, no mandatory use of masks, lack of clustering restrictions, lack of testing, and contact tracing) (Claeson and Hanson, 2021). Fifth, Italy was the first European epicenter, followed by Spain, while the United Kingdom was the last. As importantly, the countries selected belong to five different continents to have a more generalized and world representative sample. Above all, these countries answered differently to the ongoing pandemic, thus encountering diverse stock market reactions and performances.

Additionally, this research only uses data from weekdays because even though COVID-19 data is available seven days a week (weekends and national holidays included), the stock market does not operate during those periods. Lastly, the study begins when nations announce COVID-19 cases and deaths. Table 1 detailly describes COVID-19 information for the present study – countries, stock market indices (the data used for a given nation), and the number of daily observations for each country. Furthermore, it specifies the date when the first COVID-19 case and death were verified in a nation. Thus, the data for each given nation in the sample begins on that date.

Table 1 – Sample information

This table describes the countries, the stock market indices selected for each studied country, the date when the first COVID-19 case and death were confirmed in a nation and the number of data observations for each studied subperiod from each country.

Country	Stock market index	The day the 1st case was confirmed	The day the 1st death was confirmed	Observations for confirmed cases		Observations for deaths	
				Dec/19 - May/20	Jun/20 to Dec/20	11 Jan/20 to May/20	Jun/20 to Dec/20
Australia	S&P/ASX 200	Jan 25, 2020	Mar 1, 2020	87	151	42	151
Belgium	BEL 20	Feb 4, 2020	Mar 10, 2020	80	153	36	153
Brazil	Ibovespa	Jan 26, 2020	Mar 18, 2020	64	146	30	146
Canada	S&P/TSX Composite	Jan 26, 2020	Mar 11, 2020	87	148	36	148
China	Shanghai Composite	Dec 31, 2019	Jan 11, 2020	98	146	72	146
France	CAC 40	Jan 24, 2020	Feb 14, 2020	88	152	52	152
Germany	DAX	Jan 28, 2020	Mar 10, 2020	86	150	36	150
India	BSE Sensex	Jan 30, 2020	Mar 13, 2020	80	149	31	149
Israel	TA 125	Feb 21, 2020	Mar 18, 2020	47	122	35	122
Italy	FTSE MIB	Jan 29, 2020	Feb 23, 2020	85	151	47	151
Japan	Nikkei 225	Jan 14, 2020	Feb 13, 2020	92	145	53	145
Mexico	S&P BMV IPC	Feb 28, 2020	Mar 20, 2020	62	150	28	150
Netherlands	AEX	Feb 28, 2020	Mar 7, 2020	64	153	37	153
Portugal	PSI 20	Mar 2, 2020	Mar 18, 2020	62	153	30	153
Russia	MOEX	Jan 31, 2020	Mar 26, 2020	82	148	26	148
Singapore	FTSE Straits Times Singapore	Jan 24, 2020	Mar 21, 2020	85	148	28	148
South Africa	TOP 40	Mar 5, 2020	Mar 28, 2020	58	149	21	149
South Korea	KOSPI	Jan 19, 2020	Feb 20, 2020	89	147	49	147
Spain	IBEX 35	Feb 2, 2020	Feb 13, 2020	82	152	54	152
Sweden	OMX Stockholm 30	Jan 31, 2020	Mar 12, 2020	81	149	34	149
Switzerland	SMI	Feb 24, 2020	Mar 5, 2020	65	150	39	150
United Arab Emirates	FTSE NASDAQ UAE	Jan 29, 2020	Mar 21, 2020	85	156	30	156
United Kingdom	FTSE 100	Feb 1, 2020	Mar 7, 2020	81	150	37	150
United States	S&P 500	Jan 21, 2020	Feb 29, 2020	91	149	43	149
Total				**1,881**	**3,567**	**1,373**	**3,567**

Source: Own production

This study uses daily data covering the period from December 31, 2019, to December 31, 2020. Hence, covering fully the first wave and no less than part of the second one of the current pandemic. However, as can be seen from Table 1, the sample is divided into three subperiods. The first subperiod for COVID-19 cases begins on December 31, 2019, and ends on May 31, 2020. On the other hand, the sample for COVID-19 deaths in the second subperiod ranges from January 11, 2020 (the first death in the sample is reported by China on this date) to May 31, 2020. As each countries' first death occurs in the second period of the sample, the third subperiod is equal to both cases and deaths – June 1, 2020, to December 31, 2020. It is crucial to emphasize that, even though there are media reports on unpublished Chinese government data from November 17, 2019, of the first patient suffering from COVID-19, the WHO only began officially reporting cases on December 31, 2019 (Corbet et al., 2020). Lastly, while most of the previously mentioned studies only cover shorter periods between January 2020 to April/May 2020, the purpose of this division is to analyze whether variables have a similar impact on both periods. The first period comprises several essential contexts: the disease surged, peaked, and eventually, its dissemination began to slow. For the second period, while the disease appeared to stabilize, rapidly the second wave emerged.

4.2 Variables

4.2.1 Dependent variable

Intending to understand whether there is an impact on the stock market due to the coronavirus disease, this study uses as the dependent variable of the model the stock market index daily returns. First, one major stock market index for each studied country is selected to have a consistent sample. Then, this return is computed daily for each studied country as follows:

$$Stock\ market\ return_{c,t} = \frac{Stock\ market\ quotation_{c,t} - Stock\ market\ quotation_{c,t-1}}{Stock\ market\ quotation_{c,t-1}} \tag{1}$$

where daily quotations were retrieved as adjusted closing prices from Yahoo Finance for each stock market index belonging to each country *c* except for the United Arab Emirates, which were collected from Investing.com.

4.2.2 Explanatory variables

The two main independent variables of this empirical study are daily growth COVID-19 confirmed patients and COVID-19 deaths. Once more, both variables are computed daily for each nation as demonstrated below:

$$Daily\ growth\ of\ COVID19\ cases_{c,t} = \frac{COVID19\ cases_{c,t} - COVID19\ cases_{c,t-1}}{COVID19\ cases_{c,t-1}} \tag{2}$$

$$Daily\ growth\ of\ COVID19\ deaths_{c,t} = \frac{COVID19\ deaths_{c,t} - COVID19\ deaths_{c,t-1}}{COVID19\ deaths_{c,t-1}} \tag{3}$$

where data for each country *c* is retrieved from the WHO website. It is essential to highlight that COVID-19 data is provided with a delay, meaning countries release infection and death information on the day after these are discovered. In other words, the data a country announces today belongs to yesterday. For instance, if today is friday, the COVID-19 data the government releases today is data corresponding to Thursday. Hence, although data is released today, it is relative to yesterday. Furthermore, it is important to note that both the dependent and the two independent variables described above will be applied in the same form as Ashraf (2020), Al-Awadhi et al. (2020), and Bahrini and Filfilan (2020) employed in their researches.

The sample of this study covers 24 countries; hence it is essential to control for differences across those countries with country-level control variables. With this in mind and following the study of Ashraf (2020) and Shear et al. (2021), four control variables are gathered: uncertainty avoidance, democratic accountability, investment freedom, and gross domestic product (GDP). These variables collectively account for the cross-country disparity in stock markets performances caused by institutional and macroeconomic disparities among different nations.

The investment freedom variable estimates the stock market liberalization. In other words, as most countries have constraints on investment, the goal of this index is to evaluate and classify those countries regarding freedom on investment. For instance, a country would receive a maximum score (that is, 100) on this matter if there were no restrictions on the movement of investment capital. This variable is taken from the Heritage Foundation of Economic Freedom for the 2020 year.

The uncertainty avoidance index is one of the six dimensions of national culture developed by Hofstede et al. (2010) for the 2020 year. This variable expresses how reluctant and frightened individuals across countries are to uncertain, ambiguous, or unclear occasions and have developed convictions and organizations that attempt to avoid these. Thus, a high index value stands for a country where individuals are, to some extent, narrow-minded and adhere to strict codes of belief and conduct. On the other hand, a low index value points to a country with a calmer and stress-free approach, where ideals are less important than behavior.

The democratic accountability variable characterizes the relationship between state/public institutions and citizens. It is not only about whether or not elections are free and unbiased, but it concerns the responsibility of governmental institutions or further authorities with public obligations to update, describe, clarify and explain their measures and conclusions. The less receptive and approachable a government or other public body is, while an administration may collapse calmly in a democratic state, it may happen with extreme brutality and aggressiveness in an undemocratic one. This data is collected from International Country Risk Guide (ICRG) database. However, the latest available data for this variable dates back to 2016.

The gross domestic product is measured in 2020 current US billion dollars. In the context of this study, this variable is employed in its natural logarithmic form. As a result, instead of seeing absolute increases, it is possible to see percentages increases. Therefore, it can be considered a proxy of economic growth. This data is gathered from the World Economic Outlook database, issued in April 2021.

5. Methodology

This chapter describes the model, frameworks, statistical tests, and theories behind the methodology applied in this study.

5.1 Panel data

The event study methodology is the most common statistical technique to analyze the impact of stocks price performance under a specific event (Binder, 1998). However, as the spread of COVID-19 and its resulting deaths are still occurring, there is no complete estimation window, and thus, this cannot be yet considered an "event". Likewise, Khanthavit (2020b) states that a pandemic is a sequence of occurrences rather than a particular one. With this in mind, the methodology that suits the present study better is panel data. Besides, some previous research recommended employing panel data methodology instead of the event study method because of the dynamic and changing nature of the COVID-19 spread throughout time (Al-Awadhi et al., 2020; Ashraf, 2020).

Panel data, also identified as longitudinal data, is a statistical procedure that merges cross-section and time-series data to track the same persons, businesses, nations, or others throughout time (Wooldridge, 2017). The literature suggests some particular benefits from employing this technique instead of cross-sectional or time-series data alone. First, according to Hsiao (2014), with only time-series data, the likelihood of producing precise and correct predictions for individual outcomes is remarkably smaller than with panel data. In particular, this method specifies evidence on the proper level of aggregation, facilitates cross-sections or time-series data inferential methods, and decreases estimation bias and data multicollinearity, which is supported by both Baltagi (2008) and Hsiao (2014). Additionally, Al-Awadhi et al. (2020) also find the times-varying link among dependent and independent variables.

Hence, this study applies panel data models that include both cross-sectional and time-series aspects for each nation. As the number of days outnumbers the number of countries, this sample may be considered a macro-panel.

As mentioned, the goal of this study is to test the eventual impact of COVID-19 casualties and fatalities on the stock market throughout the different time periods. Hence, we formulate the subsequent hypothesis:

H_1: *There is a negative and statistical significant effect of coronavirus cases on stock market returns in the first subperiod (from December 31, 2019 to May 31, 2020).*

H₂: *There is a negative and statistical significant effect of coronavirus cases on stock market returns in the third subperiod (from June 1, 2020 to December 31, 2020).*

H₃: *There is a negative and statistical significant effect of coronavirus deaths on stock market returns in the second subperiod (from January 11, 2020 to May 31, 2020).*

H₄: *There is a negative and statistical significant effect of coronavirus deaths on stock market returns in the third subperiod (from June 1, 2020 to December 31, 2020).*

The model employed by Ashraf (2020) will also be applied in this study to test these hypotheses. In the same line, Al-Awadhi et al. (2020), Bahrini and Filfilan (2020), and Shear et al. (2020) work's employ a similar model choice. However, due to the time lag of at least two weeks, in the studied countries, between the first COVID-19 infected person and the first death of an infected individual, the number of observations and its statistics are different. Thus, the study consists of two separate equations with different periods as follows:

$$SMR_{i,t} = \alpha + \beta_1 CASES_{i,t-1} + \sum_{k=1}^{k} \beta_k X_i^k + \sum_{t=1}^{T-1} \epsilon_t D_t + \varepsilon_{i,t} \tag{4}$$

$$SMR_{i,t} = \alpha + \beta_1 DEATHS_{i,t-1} + \sum_{k=1}^{k} \beta_k X_i^k + \sum_{t=1}^{T-1} \epsilon_t D_t + \varepsilon_{i,t} \tag{5}$$

Where variables *c* and *t* denote country and day, correspondingly, while α is a constant parameter and each β_k stands for the weight of each explanatory variable X_i^k. $SMR_{i,t}$, the dependent variable represents the return of the stock market index for country *i* on day *t*. Regarding variable CASES, it denotes the daily growth in COVID-19 positive cases for each country *i*. On the other hand, the variable DEATHS represents the growth in fatalities caused by COVID-19 for each country *i*. The vector X_i^k stands for the country-level control variables that are time constant but differ across countries. The term D_t corresponds to a group of fixed-effects dummy variables that manage worldwide occasions. This term aims to capture the global shocks, that is, controls for factors changing frequently shared by all nations. On a final note, the last term of the equation denotes the error term. Henceforth, equation 4 will be stated as cases' regression and equation 5 as deaths' regression.

Any panel data set can be balanced or unbalanced based on the number of observations in the time series and cross-sectional dimensions. A balanced panel is one in which the number of observations in the time series is constant for each cross-sectional unit. On the other hand, it is unbalanced if the number of observations in the two dimensions does not match. In the frame of this study, as previously exposed, countries reported first cases and deaths on various dates. Therefore, this analysis only begins on the day a country first announces positive COVID-19 cases or deaths. Furthermore, due to that and the fact that nations have particular public holidays, not all countries will have the same number of observations. Therefore, this study comprises unbalanced panel data since the number of time periods t is not equal for every country c.

5.2 Statistical tests

5.2.1 Panel unit root tests

The first step in this estimation is to analyze whether the dataset includes or not unit roots, that is, if it is non-stationary or stationary. Stationarity implies that the distribution of the mentioned variable does not depend upon time. However, in the case of the distribution being time-dependent, non-stationarity arises, being the principal source of unit roots. One of the most significant repercussions of non-stationarity in both dependent and independents variables is the possibility of obtaining a spurious regression, which can lead to erroneous interpretation of the estimated findings.

It is critical to test the model's variables for stationarity to determine the basis on which they will be employed in the study. In the case of non-stationarity, linear modifications will be performed to the corresponding variable. Otherwise, the study can continue without modifications. The literature identifies numerous possible unit root tests to analyze this matter. In the frame of this research, since the panel in this study is unbalanced, Im, Pesaran and Shin (2003) test and Maddala and Wu (1999) will be performed.

The Im-Pesaran-Shin (IPS) test takes the Augmented Dickey-Fuller statistics and averages them over n panel units. The decision to perform this specific test is due to evidence stating it is more robust than other test types (Fisher type tests) under the assumption of no cross-sectional correlation in errors (Im, Pesaran, & Shin, 2003). Hypothesis for the IPS test are the following:

H_0: All panels/individuals are not stationary/contain unit roots

H_A: Some (but not all) panels/individuals are stationary/do not contain unit roots

Hence, if the null hypothesis is rejected, in effect, the probability associated with the test is lower than the significance level, which implies that there is no evidence of all panels in the data set not being stationary. Therefore, several panels are stationary.

The Maddala and Wu panel unit root test, referred to as the MW test, is inspired by a Fisher-type test that combines p-values from unit root tests for each cross-section i. This test conducts unit root tests for each time series individually and then combine the p-values of those tests to produce an overall test result. Hypothesis for this test are the following:

H_0: All panels/individuals are not stationary/contain unit roots

H_A: All panels/individuals are stationary/do not contain unit roots

As a result, if the null hypothesis is rejected, it denotes that there is no evidence of panels in the data containing unit roots, that is, not being stationarity.

Considering the nature of the variables in the present study, one does not expect that control variables are non-stationary as they do not change over time for each individual. Regarding the growth in confirmed cases and deaths, its variation is most likely also not directly related to time. Concerning the stock market variable, as it is employed in a return basis rather than in its price form, it is expected to be stationary.

5.2.2 Model specifications

Three distinct models can be applied when analyzing panel data: Pooled OLS (POLS), Fixed Effects, or Random Effects. There are three statistical tests to select which one to employ: the F test, the Hausman test (1978), and the Breusch Pagan Lagrange Multiplier test. However, in order to be able to perform the tests, first, it is mandatory to run the regressions with the three different models in Rstudio.

While this study's goal is not to discuss the primary aspects of every model, it is crucial to identify which one best fits the dataset when examining panel data. Baltagi (2005) states that Fixed Effects is an appropriate model when the focus lies on a specific set of individuals and not on the whole group. In other words, it is not possible to make conclusions on the sample population/group as a whole. On the other hand, Hsiao (2014) expresses that Random Effects is a suitable model when one randomly extracts a sample of N individuals from a large population to make inferences on the population based on the retrieved sample. As for the Ordinary Least Squares (OLS) model, it is also named a homogeneous model, since both constant and slope coefficients remain unchanged across individuals. As a result, it pools all individuals together, implying no evidence of significant differences across individuals.

As the purpose of this study is to make inferences on how COVID-19 cases and deaths affect stock returns on a more general level, and the models include time-invariant variables, one does not expect to apply fixed effects. Hence, the most likely model choice will be between POLS and Random effects.

The analysis begins by applying the F-test. For this test, the null hypothesis stands for the pooled regression, while the alternative one is that the preferred model is the Fixed Effects.

Thus, rejecting the null in this test indicates that the Fixed Effects model suits the data better. The second test to be applied is the Hausman specification test (1978), which suggests a test grounded on the difference between Random Effects and Fixed Effects estimates with the null pointing for Random Effects and the alternative hypothesis for Fixed Effects. Hence, rejecting the null hypothesis means that Random effects estimators are not consistent. Lastly, the Breusch Pagan Lagrange Multiplier is employed to uncover confirmation of the presence or rejection of the Random Effects model. The test has a null of pooled regression and an alternative hypothesis of Random effects. Consequently, rejecting the null hypothesis suggests the use of the Random effects regression.

5.2.3 Estimator's efficiency (POLS)

To estimate equations 4 and 5, it is crucial to ensure that the estimators for regression parameters are unbiased and efficient (Wooldridge, 2011). As a disclaimer, the Pooled OLS technique is the one that suits the data better. With this in mind, this section aims to enumerate the assumptions that must hold for the purpose of effectively testing them. Those assumptions, as stated by Wooldridge (2011), are the following:

1. Zero Conditional Mean, which means that for each *t*, the expected value of the error term is zero for all the independent variables and the unobserved effect;
2. There is no perfect collinearity among the explanatory variables;
3. There is no autocorrelation between errors of different observations (the idiosyncratic errors are serially uncorrelated);
4. Homoskedasticity, which implies that the error term has the same variance for any values of the independent variables in all time periods;

Under the Gauss-Markov Theorem, if assumptions 1 to 4 are verified, it is feasible to affirm that each estimated coefficient is BLUE (Best Linear Unbiased Estimator). This indicates that not only the estimator is unbiased but also that it has the minimum variance when paralleled with every linear and unbiased estimator. However, if any of the assumptions are violated, the estimators' efficiency is compromised. On the other hand, under assumptions 1 and 2, estimators are already unbiased. That is, estimators anticipated and population values are equivalent (Wooldridge, 2011). Other authors also add the Normality assumption, which affirms that sample means distribution (throughout independent samples) is normal.

While assumption 1 is considered valid, in order to verify assumption 2, a Pearson correlation matrix is further computed and analyzed. The following section provides a short explanation of what statistical tests are performed in order not only to assess if assumptions are verified but also to ensure a robust statistical inference and what the consequences are if any of these do not hold.

5.2.4 Cross-sectional dependence

When analyzing panel data, it is critical to examine and test for cross-sectional dependence since it is frequently found within panel data. If ignored, the benefits from pooling data can vanish (Henningsen and Henningsen, 2019; Philips and Sul, 2003). In addition, cross-sectional dependence arises when individuals (in this case, countries) in the dataset do not present independently drawn observations. Hence, mutually impacting others' results (Henningsen and Henningsen, 2019).

As this research includes twenty-four countries, the likelihood of having COVID-19 cases or deaths impacting other country's stock returns may occur. For this reason, testing for the presence of cross-sectional dependence is of extreme importance. To validate if residuals from the selected countries are correlated, i.e., exhibit cross-sectional dependence, as both are valid even with unbalanced panels, the Pesaran (2004) cross-sectional dependence test and the Breusch-Pagan LM (1980) are employed. The hypothesis for both tests are the same as follows (Baltagi, 2005):

H_0: Residuals across entities are not correlated

H_A: Cross-sectional dependence

Rejecting the null implies that residuals across entities are correlated, and the sample displays cross-sectional dependence.

5.2.5 Serial correlation in the idiosyncratic error term

Another essential assumption that must be evaluated is whether sample errors suffer from serial correlation/autocorrelation, that is, if errors are correlated across time (Woolridge, 2012). In other words, as stated by Woolridge (2010) if errors of a panel dataset include a time-constant omitted factor in every time period. As a result, the Breusch-Godfrey test for panel models is used, which is a serial correlation test for the idiosyncratic component of panel model errors, with the following hypotheses:

H_0: No serial correlation/autocorrelation in idiosyncratic errors

H_A: Serial correlation/autocorrelation in idiosyncratic errors

OLS estimators' unbiasedness and consistency are not affected by serial correlation, but their efficiency is. Because standard errors are underestimated, the significance tests emerge as statistically more significant than their real value. Likewise, the value of R-squared is amplified, pointing for a superior fit than should be the case. As a result, estimated parameter values arise more exact than they are.

5.2.6 Normality of the error term

To assess whether the population error is independent of the explanatory variables, i.e., if the data is normally distributed, the Jarque-Bera test is performed. For this test hypothesis are the following:

H_0: Population is normally distributed

H_A: Population is not normally distributed

In this case, rejecting the null hypothesis implies that conclusions retrieved from the coefficient estimates are perhaps misinterpreted. However, depending on the sample size, those inferences can be correct. In such circumstances, non-normality can arise in the present study as it contains some notably large negative and positive residuals for both growth in COVID-19 positive cases and deaths.

5.2.7 Homoskedasticity in the error term

To verify if the homoskedasticity assumption holds, an homoskedasticity test must be performed. The Breusch-Pagan test proposed by Breusch and Pagan (1979) has the corresponding hypotheses:

H_0: There is homoskedasticity in the error term

H_A: There is heteroskedasticity in the error term

Not rejecting the null indicates that there is no evidence of heteroskedasticity in the data. In such case, residuals are believed to exhibit constant variance; that is, residual’s variance is not affected by the values of the independent variables. Nevertheless, when the variance is not constant, heteroskedasticity arises. Thus, even though POLS estimators remain unbiased and consistent, they are no more the most effective ones as it is possible to attain estimators with lower variance. Besides, because estimators for the variances and covariances are biased and inconsistent, the t and F tests deliver incorrect outcomes. Therefore, some corrective action should be taken to make accurate inferences from the regressions (Woolridge, 2012).

6. Empirical analysis

In this chapter, data and regression models are analyzed. Furthermore, the dataset has been formatted in Excel before running regressions and tests on the panel dataset. Afterward, all the regressions and statistical tests were estimated on Rstudio. As a final note, statistical tests' and equations' outputs presented in this section are accessible in the Appendix section.

6.1 Descriptive statistics analysis

As mentioned in the previous section, after selecting the variables, specifying the model, collecting and clearing the data, the empirical analysis can begin. The dataset used in this study includes information on twenty-four countries from December 2019 to December 2020. The descriptive statistics for the dataset are presented next in Table 2.

Table 2 – Summary statistics

This table reports the summary statistics (mean, median, standard deviation, minimum and maximum) for each variable. Panel A represents equation 4 (cases) in the first subperiod, while panel B accounts for equation 5 (deaths) in the second subperiod. Panel C represents both regressions in the third subperiod. Stock market return represents the daily returns of stock market indices. Growth in cases and deaths represents the daily growth of casualties and fatalities due to the coronavirus disease. Investment freedom, uncertainty avoidance, and democratic accountability are indices used as proxies for free capital markets, for nationwide culture, and for the type of administration, correspondingly. Log (GDP) is used as a proxy for economic development.

Variable	Mean	Median	Std. Deviation	Minimum	Maximum	Observations
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)						
Stock market return	-0.0016142	0.0005225	0.0293	-0.169279	0.130908	1,881
Growth in cases	0.1642	0.0000	1.1137	-8.0000	20.5802	1,881
Investment freedom	69.24	80.00	19.9505	20.00	90.00	1,881
Democratic Accountability	5.436	6.000	1.7938	1.500	10.00	1,881
Uncertainty avoidance	63.49	65.00	25.0298	8.00	99.00	1,881
Log (GDP)	28.27	28.12	1.7938	26.17	31.58	1,881
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)						
Stock market return	0.001019	0.001978	0.0806	-0.162979	0.119571	1,373
Growth in deaths	0.1478	0.0000	0.8646	-1.0000	7.3333	1,373
Investment freedom	69.55	80.00	20.0359	20.00	90.00	1,373
Democratic Accountability	5.424	6.000	1.7256	1.500	10.00	1,373
Uncertainty avoidance	64.23	65.00	24.4051	8.00	99.00	1,373
Log (GDP)	28.29	28.12	1.2923	26.17	31.58	1,373
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)						
Stock market return	0.001243	0.000842	0.0053	-0.05951	0.08573	3,567
Growth in cases	0.114284	0.009434	0.6169	-4.346614	10.0000	3,567
Growth in deaths	0.1688	0.000	1.1286	-2.6667	24.000	3,567
Investment freedom	69.62	80.00	19.3343	20.00	90.00	3,567
Democratic Accountability	5.499	6.000	1.7333	1.500	10.00	3,567
Uncertainty avoidance	64.27	65.00	24.5686	8.00	99.00	3,567
Log (GDP)	28.15	28.02	1.2966	26.17	31.58	3,567

Source: Own production

As mentioned earlier in this study, the number of observations for the daily growth in deaths is lower than the growth in cases variable in the first period, as there is a time interval between the first case reported by a nation and the ultimate first passing of an infected patient.

Starting in Panel A (cases' equation in subperiod 1), it shows a mean value of stock index returns of -0.16142%. Similarly, the average daily growth in COVID-19 patients is 16.42%, with a wide standard deviation - a measure of volatility - of 1.1137. This indicates that, most of the observations (about 2/3 if the variable follows a normal distribution) lie 1.1137 away from the mean of -0.16142%. Moreover, this variable fluctuates between -800% and positive 2058%, indicating the sample contains a wide variety of scenarios.

Panel B displays a mean value of stock market returns (dependent variable) of 0.001019, showing that, on average, countries experienced a positive 0.1019% return in stock markets. This is, on average, a return significantly higher when compared to the time period that accounts for the first COVID-19 case. Thus, indicating that the negative stock returns happened mainly on the period between December 31, 2019 to January 11, 2020, which is the period that differentiates these two subperiods. Minimum and maximum values of -0.169279 and 0.119571, correspondingly, indicating that stock returns suffered significant fluctuations between approximately -16.93% and positive 11.96%. Besides, the average daily growth in COVID-19 deaths is 14.78%, with a broad standard deviation of around 0.8646. Moreover, this variable has a considerable amplitude since minimum, and maximum values are -100% (the lower boundary) and positive 733.33%, respectively. This indicates that the panel contains a wide variety of situations, from negative growth of confirmed deaths (that is, considerably fewer losses today than yesterday) to the exponential daily growth of deaths (enormous increases in fatalities daily).

Panel C covers a longer time period and contains both the cases and deaths equation's statistics. In terms of stock market return, the variable fluctuates between -5.951% and positive 8.573%. Compared to previous periods, this variable exhibits a noticeably lower value range, with minimum and maximum values remarkably closer than before. Moreover, on average, countries experienced a positive 0.1243% return in stock markets with the lowest observed standard deviation of 0.0053. Thus, representing a higher return on this period than on the other subperiods. Hence, as time goes by and as the pandemic unfolds, it appears that stock markets regain balance, and observations are now closer to the mean value. The daily growth in COVID-19 cases has a mean value of 11.4284%, with a standard deviation of 0.6169. Following a similar trend, daily deaths grew on average 16.88%, with a standard deviation of around 1.13. The growth in deaths is, in this subperiod, superior to what was observed when countries began announcing deaths, but that is not the situation for cases. Henceforth, proving again that the stock market does not react as much to the increase in cases and deaths as it did initially.

In what concerns control variables, as these are time constant, minimum and maximum values uphold the same throughout the different periods with only minimal differences on mean, median, and standard deviations. Investment freedom displays a minimum of 20.00 and a maximum of 90.00 belonging to China and the Netherlands, respectively. Furthermore, it presents averages between 69.24 (panel A) and 69.62 (panel C). Democratic accountability displays a mean value of approximately 5.4 in all panels, with minimum and maximums of 1.50 and 10.00, corresponding to China and the United Arab Emirates, respectively. Uncertainty avoidance exhibits averages between 63.49 (panel A) and 64.27 (panel C) with minimum and maximum values of 8.00 and 99.00 for Singapore and Portugal, respectively. Lastly, log (GDP) displays the closer minimum and maximum values of 26.17 for Portugal and 31.58 for Sweden, respectively. This variable presents an average across the panels of around 28.

Furthermore, it is possible to take conclusions from the individual graphics for stock returns, daily growth of confirmed cases, and deaths presented in Appendix A, B, C, D, E, and F. In particular, for all countries, except Singapore, COVID-19 cases and deaths are particularly volatile. These variables fluctuate between negative and positive growth rates heavily in every period. Additionally, between March 11 (the day WHO categorized the outbreak as a pandemic) and March 16, stock returns reached expressive negative returns of around -13%, as represented in Appendix E. This is not the case for China, as it dealt with high cases and deaths figures for a far longer time.

6.2 Pearson correlation matrix

The second step in this empirical analysis is to compute the Pearson correlation matrix to analyze if variables have a strong or fragile relationship and whether such relationship is in the same or reverse direction. Woolridge (2012) refers to multicollinearity as when variables are highly (but not perfectly) correlated. Also, to establish if multicollinearity is a problem, it is considered that a correlation coefficient above 0.7 between two or more explanatory variables indicates multicollinearity problems. Table 3 reports the Pearson linear correlation coefficients and statistical significance for all variables and subperiods. Despite the primary interest being on the relationship between explanatory variables, the statistical significance of the correlation coefficients amongst stock index returns and COVID-19 variables might provide valuable information on inferences that will be further reached.

Table 3 – Pearson correlation matrix

This table reports the pairwise Pearson correlations between all variables, in every subperiod, for both equations alongside their statistical significance. Panel A represents the cases' equation in the first subperiod. In contrast, panel B accounts for the deaths' equation in the second subperiod and Panel C for both equations in the third subperiod. Stock market return represents the daily returns of stock market indices. Growth in cases and deaths represents the daily growth of casualties and fatalities due to the coronavirus disease. Investment freedom, uncertainty avoidance, and democratic accountability are indices used as proxies for free capital markets, for nationwide culture, and for the type of administration, correspondingly. Log (GDP) is used as a proxy for economic development. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Growth in cases	Growth in deaths	Stock market return	Investment freedom	Uncertainty avoidance	GDP	Democratic accountability
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)							
Growth in cases	1	-					
Stock market return	-0.04391*	-	1				
Investment freedom	-0.052772 **	-	-0.000983	1			
Uncertainty avoidance	-0.004325	-	-0.004307	-0.020838	1		
GDP	0.059384 ***	-	0.014702	-0.066040***	-0.327825 ***	1	
Democratic accountability	-0.068279 ***	-	-0.006564	0.319295***	0.283087 ***	-0.146338 ***	1
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)							
Growth in deaths	-	1					
Stock market return	-	-0.029283	1				
Investment freedom	-	-0.014866	-0.008032	1			
Uncertainty avoidance	-	0.034637	-0.01384	0.086184 ***	1		
GDP	-	0.036517	-0.023974 *	-0.146350 ***	-0.379209 ***	1	
Democratic accountability	-	0.001763	0.012813	0.431868 ***	0.310488 ***	-0.233090 ***	1
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)							
Growth in cases	1						
Growth in deaths	0.090505 ***	1					
Stock market return	-0.028129 *	-0.011138	1				
Investment freedom	0.034288 **	0.033459 **	-0.023161	1			
Uncertainty avoidance	-0.045943 ***	0.026383	0.003335	-0.037326 **	1		
GDP	0.013133	0.000891	0.003334	-0.028445 *	-0.335781 ***	1	
Democratic accountability	-0.028855 *	0.035632 **	-0.002493	0.287953 ***	0.260213 ***	-0.137334 ***	1

Source: Own production

In the first place, matrixes reveal that correlations among variables are all below 0.7 in absolute value – the critical point for multicollinearity. With this in mind, there is no evidence of multicollinearity in the data sample.

For the country-level control variables in the first subperiod, apart from the GDP variable, all others are negatively correlated with growth in COVID-19 deaths. Additionally, from the four control variables, only Uncertainty avoidance is not statistically significant. For the third subperiod, apart from GDP, all other control variables display statistically significant correlations with growth in positive cases. For instance, for Uncertainty avoidance and COVID-19 cases, the negative and significant correlation coefficient indicates that countries that experience higher growth in cases are more prone to have a lower Uncertainty avoidance value. On the other hand, correlations are all positive between growth in fatalities and control variables. Furthermore, for this variable, correlations are only significant for Investment freedom and Democratic accountability.

From all of the explanatory variables, the correlations between Democratic accountability with Investment freedom, Uncertainty avoidance with GDP, and Uncertainty avoidance with Democratic accountability exhibit the highest correlations for every subperiod and regression and are all statistically significant at a 1% significance level.

The correlation between the stock index returns and growth in COVID-19 confirmed cases, although weak, is negative and significant at a 10% significance level for the two respective subperiods, as expected. In other words, there is an inverse relationship between the two variables; when COVID-19 cases increase, stock index returns decrease. On the other hand, the correlation between stock returns and the growth in COVID-19 deaths is negative but not significant for the corresponding two subperiods. That is, variables tend to move in the opposite direction; when COVID-19 deaths increase, stock index returns decrease. However, in the first subperiod, when the disease is still a recent concern, the correlation between the two is more negative than in more recent times, for both cases and deaths. Lastly, the correlation between the two COVID-19 variables in the third subperiod is, as predicted, positive and significant at a 0.1% significance level. This is reasonable since as cases increase, deaths are more likely to increase too.

6.3 Panel statistical analysis

In the present section, a group of statistical tests are implemented to test POLS assumptions, unit roots, cross-sectional dependence and understand what model fits the data better, which altogether allows to determine if the statistical inference is correct.

6.3.1 Panel unit root tests

Following the methodology described in the previous chapter, the first step is to assess if panels contain unit roots. With this in mind, the first test to be performed is the Im, Pesaran, and Shin (2003) test.

As seen in Table 4, the p-values for the dependent and independent variables in every equation and for every time period are below the significance level of 1%. Hence, the null hypothesis is rejected for all periods and variables. This is representative of stationarity and the absence of unit roots, as shown in the table below.

Table 4 – Probabilities associated to the Im, Pesaran, and Shin (2003) unit root test.

This table reports the p-values associated to the Im, Pesaran, and Shin (2003) test for each variable in each equation and for every subperiod. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod and Panel C for both equations in the third subperiod. Stock market return represents daily returns of stock market indices. Growth in cases and deaths represents the daily growth of casualties and fatalities due to the coronavirus disease. Investment freedom, uncertainty avoidance and democratic accountability are indices used as proxies for free capital markets, for nationwide culture and for type of administration, correspondingly. Log (GDP) is used as a proxy for economic development. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)		
Daily stock market return	-15.911	$< 2.2e^{-16}$***
Growth in cases	-18.498	$< 2.2e^{-16}$***
Investment freedom	-7.2368	$2.296e^{-13}$***
Democratic Accountability	-6.6876	$1.135e^{-11}$***
Uncertainty avoidance	-6.7852	$5.794e^{-12}$***
Log (GDP)	-6.8629	$3.373e\text{-}^{12}$***
Panel B – subperiod 1 (January 11, 2020 to May 31, 2020)		
Daily stock market return	-15.214	$< 2.2e^{-16}$***
Growth in deaths	-14.996	$< 2.2e^{-16}$***
Investment freedom	-6.8816	$2.96e^{-12}$ ***
Democratic Accountability	-6.5245	$3.41e^{-11}$***
Uncertainty avoidance	-6.6923	$1.098e^{-11}$***
Log (GDP)	-6.6392	$1.577e^{-11}$***
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)		
Daily stock market return	-21.777	$< 2.2e^{-16}$ ***
Growth in cases	-15.432	$< 2.2e^{-16}$ ***
Growth in deaths	-13.928	$< 2.2e^{-16}$ ***
Investment freedom	-7.5002	$3.186e^{-14}$ ***
Democratic Accountability	-6.9468	$1.868e^{-12}$ ***
Uncertainty avoidance	-7.0108	$1.185e^{-12}$ ***
Log (GDP)	-7.0624	$8.182e^{-13}$ ***

Source: Own production

The Maddala and Wu (1999) test, which comprises the identical null hypothesis and the alternative of stationarity, is also used to corroborate this outcome. The test's outputs (available in Appendix E) show that all p-values are also below the 1% significance level. Hence, again, the null hypothesis is rejected for all periods and variables. Therefore, this indicates that the sample is stationary and does not include any unit roots, which is in accordance with the findings from the Im, Pesaran, and Shin (2003) test. All things considered, after conducting both tests, the findings from the two tests point to stationarity and the inexistence of unit roots in the sample.

6.3.2 Model specifications

To test the hypothesis described in the previous section, first, it is compulsory to understand which model (Pooled OLS, Fixed effects, or Random effects model) fits the data better to estimate the regressions more adequately. Hence, the F-test, the Breusch Pagan LM test and, if necessary, the Hausman specification test (1978) are implemented. The values in Table 5 represent the probabilities associated with each mentioned test, which are achieved by firstly running in Rstudio the Pooled OLS, Fixed, and Random effects regressions. The significance level considered by default is 1%.

Table 5 – Probabilities associated with the F-test, and Breusch-Pagan LM test

This table reports the p-values associated with the F-test, and Breusch-Pagan Lagrange Multiplier test for both equations in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)		
F test	0.35547	0.998
BP test	3.7568	0.05367
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)		
F test	0.81842	0.7105
BP test	1.9922	0.1581
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)		
F test	0.33143	0.9989
BP test	5.7891	0.01613
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)		
F test	0.33696	0.9987
BP test	5.6855	0.01711

Source: Own production

From the results presented above, beginning with the cases' equation for the first subperiod (Panel A), the p-value associated with the F-test test is greater than the 1% significance level (p-value = 0.998), which points towards the non-rejection of the null hypothesis. Thus, based on the sample, the favored model is the Pooled OLS. Additionally, the Breusch Pagan LM test has a p-value above the significance level of 1% (p-value = 0.05367). Hence one fails to reject the null and conclude that Random effects is not appropriate. Altogether, there is not the need of performing the Hausman specification test as the most suitable model for this subperiod is the Pooled OLS.

In what concerns the same equation but for the third subperiod (Panel C), the F-test displays a p-value associated with the test above the 1% significance level (p-value = 0.9989), acknowledging to not reject the null. As a result, based on this sample, Pooled OLS is the favored model. The Breusch Pagan LM test reveals an associated p-value above the 1% significance (p-value = 0.01613), the null is not rejected, and Random effects is not, in fact, an appropriate model. Henceforth, the model that fits the data better is Pooled OLS.

Regarding the deaths' regression in the second subperiod (Panel B), the null is not rejected for the F test (p-value = 0.7105) since it presents a p-value above the 1% significance level. Hence, based on this test and sample, the indicated model is the Pooled OLS. Finally, for the Breusch Pagan LM test, its p-value is above the significance level of 1% (p-value = 0.1581), and therefore the null hypothesis cannot be rejected. Thereupon, grounded on the outcomes described above, the selected model for this regression and subperiod is the Pooled OLS model.

Last but foremost, concerning deaths regression but for the third subperiod (Panel D), the F-test displays a p-value above the 1% significance level (p-value = 0.9987), which evidences the non-rejection of the null hypothesis. Therefore, considering this sample and test, the proper model to employ is Pooled OLS. Additionally, when computing the Breusch-Pagan LM test, it is observable that the p-value is above the 1% significance level (p-value = 0.01711) and, therefore, fails to reject the null and conclude that random effects is not appropriate.

Considering all of the above, the model that better suits the data in all subperiods and equations is the Pooled OLS. Thus, there is no evidence of significant differences across countries. This is in line with both Ashraf (2020), Erdem (2020), Al-Awadhi et al (2020), and Shear et al. (2021), which find no difference across the studied countries and thus employ the pooled OLS regression technique.

6.3.3 Cross-sectional dependence

As seen in Table 6, the p-values are all greater than the 1% significance level for all the equations and periods. With this in mind, H_0 is not rejected; thus, residuals are not cross-sectional dependent.

Table 6 – Probabilities associated with Pesaran (2004) CD test

This table reports the p-values associated with Pesaran (2004) cross-sectional dependence test for both equations in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)	0.67717	0.4983
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)	0.08563	0.9318
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)	-0.98074	0.3267
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)	-0.99237	0.321

Source: Own production

A second test, the Breusch-Pagan LM test with the same null hypothesis as the previous test, is used to validate this result. As observable in Table 7, the p-values associated with Breusch–Pagan's LM test (1980) are higher than the 1% significance level for all regressions and time periods. Hence, one does not reject the null hypothesis. As a result, both tests indicate that residuals across entities are not correlated.

Table 7 – Probabilities associated with the Breusch-Pagan LM test (1980)

This table reports the p-values associated with the Breusch-Pagan Lagrange Multiplier test to access cross-sectional dependence for both equations in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)	331.7	0.01205
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)	294.35	0.2141
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)- REG1	318.02	0.04153
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)- REG2	318.48	0.03998

Source: Own production

6.3.4 Serial correlation in the idiosyncratic error term

From Table 8, as p-values for all subperiods and panels are lower than the 1% significance level, the null hypothesis is rejected. The outcome of this test indicates that there is serial correlation in the idiosyncratic component of the errors in panel models.

Table 8 – Probabilities associated with the Breusch-Godfrey/Wooldridge test

This table reports the p-values associated with the Breusch-Godfrey/Wooldridge test to access autocorrelation for both equations in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)	196.04	$< 2.2e^{-16}$***
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)	145.51	$1.995e^{-15}$ ***
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)	232.78	$6.224e^{-09}$ ***
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)	232.51	$6.654e^{-09}$ ***

Source: Own production

Albeit the assumption of no autocorrelation is not verified, OLS estimators are still unbiased and consistent. Notwithstanding, several statistical measures cannot be further relied on, and while standard errors are undervalued, the value of R-squared is overestimated. For the first matter, the outcome is that p-values directly associated with the estimators display lower (more significant) values. Likewise, for the second concern, it suggests a superior model fit than it truly is. For this reason, parameter estimates appear more accurate than they genuinely are. Thus, they no longer generate the most efficient estimators.

6.3.5 Normality of the errors

By applying the Jarque-Bera test, it is possible to see that all p-values are below the 1% significance level, as seen in Table 9, and the null is rejected. Thus, even though the errors' normality is violated, this study comprises large samples (N= 1,881, N= 1,373, and N= 3,567 for the three different subperiods). Consequently, under the Central Limit Theorem, the assumption that the estimators are asymptotically normally distributed can be made.

Table 9 – Probabilities associated with the Jarque-Bera test

This table reports the p-values associated with the Jarque-Bera test to access the normality assumption in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)	2286	$< 2.2e^{-16}$***
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)	963.14	$< 2.2e^{-16}$***
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)	423.25	$< 2.2e^{-16}$***
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)	419.69	$< 2.2e^{-16}$***

Source: Own production

6.3.6 Homoskedasticity in the error term

The last statistical test to be applied to the data set is a homoskedasticity test. Based on the results displayed in Table 10, it is noticeable that p-values associated with the Breusch-Pagan test are inferior to the 1% significance level for all regressions and periods. Consequently, the null hypothesis is rejected for all sub-periods. Accordingly, the variance is not constant; hence there is heteroscedasticity in the residuals of the data set. This result was expected since both regressions include financial data and time-invariant variables – country-level control variables.

Table 10 – Probabilities associated with the Breusch-Pagan test

This table reports the p-values associated with the Breusch-Pagan test to access the normality assumption in the three subperiods. Panel A represents the cases' equation in the first subperiod, while panel B accounts for the deaths' equation in the second subperiod. Panel C represents the cases' equation in the third subperiod, while Panel D stands for the deaths' equation for the same subperiod. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)	438.44	$< 2.2e^{-16}$***
Panel B – subperiod 2 (January 11, 2020 to May 31, 2020)	324.86	$< 2.2e^{-16}$***
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)	531.82	$< 2.2e^{-16}$ ***
Panel D – subperiod 3 (June 1, 2020 to December 31, 2020)	532.85	$< 2.2e^{-16}$***

Source: Own production

Notwithstanding, violation of this hypothesis does not imply that the estimated parameters are inconsistent or biased. However, not only are standard errors incorrect, and there is a bias in the variance-covariance matrix. But also, the standard model testing procedures, the t and F statistics, and p-values fail to be further relied upon. Consequently, there is the risk of reaching the wrong conclusions.

All things considered, the data set suffers from heteroskedasticity and autocorrelation problems. In order to mitigate these problems found through statistical tests and achieve reliable and accurate estimates on the impact of the coronavirus on the stock market, there is the need to use heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimation. In light of this, following Mobarek et al.'s (2014) work, who suggest the use of the Newey-West (1987) estimator to achieve heteroskedastic and autocorrelation consistent variances for all OLS regressions. Thus, the present research also employs the Newey-West (1987) estimator to attain heteroskedastic and autocorrelation coherent variances for both equations.

6.4 Empirical results and discussion

In this section, the emphasis is on analyzing the equations' results with the aim of reaching conclusions regarding the impact of COVID-19 on stock market returns. Based on the results of all the statistical tests described in the previous section, both equations are estimated using Pooled OLS and Pooled OLS robust – which accounts for heteroskedasticity and autocorrelation as mentioned previously (the Newey-West (1978) technique) – for the three distinct time periods. Although the POLS robust estimators are of more importance, both methods are presented. The debate concludes with a decision on the validation or rejection of the four previously defined research hypotheses. Table 11 presents the model results for the cases' regression.

Table 11 – Impact of daily growth of COVID-19 cases on the stock market.

This table reports the results of the panel POLS technique concerning the impact of COVID-19 cases on stock market returns, with the latter being the dependent variable in the model. These market quotations are retrieved from Yahoo Finance and from Investing.com for each stock market index belonging to each country *c*. Growth in cases is measured as the daily growth of casualties per country due to COVID-19 and is collected from the WHO website. Investment freedom, Uncertainty avoidance, and Democratic accountability are indices used as proxies for free capital markets, for nationwide culture, and the type of political institutions, correspondingly. These variables are taken from the Heritage Foundation of Economic Freedom, Hofstede et al. (2010), and International Country Risk Guide archive, respectively. Finally, log (GDP) is used as a proxy for economic development retrieved from WEO database. Standard errors in each model are presented in parenthesis under the coefficients. Heteroskedasticity and autocorrelation robust standard errors through the Newey West (1987) method are used in models 4 and 8. *,** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	Stock market return							
	December 31, 2019 to May 31, 2020				June 1, 2020 to December 31, 2020			
	(1)	(2)	(3)	POLS robust (4)	(5)	(6)	(7)	POLS robust (8)
Growth in cases	$-1.1154e^{-03}$** ($6.0543e^{-04}$)	$-1.1946e^{-03}$** ($6.0870e^{-04}$)	$-6.9006e^{-04}$* ($3.8617e^{-04}$)	$-6.9006e^{-04}$* ($3.6056e^{-04}$)	$-5.6197e^{-04}$ * ($3.3447e^{-04}$)	$-5.4369e^{-04}$ ($3.3525e^{-04}$)	$-1.9973e^{-04}$ ($2.5623e^{-04}$)	$-1.9973e^{-04}$ ($2.6085e^{-04}$)
Investment freedom		$7.0985e^{-07}$ ($3.6047e^{-05}$)	$-2.6575e^{-06}$ ($2.2690e^{-05}$)	$-2.6575e^{-06}$ ($1.2789e^{-05}$)		$-1.4694e^{-05}$ ($1.1244e^{-05}$)	$-1.5818e^{-05}$* ($8.3824e^{-06}$)	$-1.5818e^{-05}$* ($8.9771e^{-06}$)
Democratic accountability		-1.3511^{-04} ($4.1783e^{-04}$)	$7.2933e^{-05}$ ($2.6655e^{-04}$)	$7.2933e^{-05}$ ($1.4877e^{-04}$)		$2.4752e^{-05}$ ($1.2983e^{-04}$)	$3.6142e^{-05}$ ($9.8391e^{-05}$)	$3.6142e^{-05}$ ($9.6341e^{-05}$)
Uncertainty avoidance		$4.1511e^{-06}$ ($2.9772e^{-05}$)	$-1.2094e^{-05}$ ($1.8033e^{-05}$)	$-1.2094e^{-05}$ ($9.0632e^{-06}$)		$8.4705e^{-07}$ ($9.2396e^{-06}$)	$-2.1495e^{-07}$ ($6.7194e^{-06}$)	$-2.1495e^{-07}$ ($5.7869e^{-06}$)
Log (GDP)		$3.9008e^{-04}$ ($5.5064e^{-04}$)	$3.9772e^{-04}$ ($3.3755e^{-04}$)	$3.9772e^{-04}$*** ($1.4892e^{-04}$)		$3.8791e^{-05}$ ($1.6932e^{-04}$)	$2.7599e^{-05}$ ($1.2323e^{-04}$)	$2.7599e^{-05}$ ($1.0776e^{-04}$)
Daily fixed-effects dummy variables			Yes	Yes			Yes	Yes
Constant	$-1.4248e^{-03}$** ($6.8138e^{-04}$)	$-1.2025e^{-02}$ ($1.6663e^{-02}$)	$-1.1752e^{-02}$ ($2.0477e^{-02}$)	$-1.1752e^{-02}$ ($1.7718e^{-02}$)	$1.3075e^{-03}$*** ($2.0982e^{-04}$)	$1.0458e^{-03}$ ($5.1070e^{-03}$)	$1.2266e^{-04}$ ($4.1723e^{-03}$)	$1.2266e^{-04}$ ($3.1132e^{-03}$)
Observations	1,881	1,881	1,881	1,881	3,567	3,567	3,567	3,567
R-squared	0.0019	0.0023	0.6359	0.6359	0.0005	0.0013	0.5003	0.5003
F (Global significance)	3.6310	0.8612	20.4408	20.4408	2.823	0.9341	18.1937	18.1937
Prob > F	0.0569	0.5065	$< 2.22e^{-16}$	$< 2.22e^{-16}$	0.093	0.4575	$< 2.22e^{-16}$	$< 2.22e^{-16}$

Source: Own production

The primary conclusion one can infer from the results presented in Table 11, as expected, is that coefficients are precisely equal in both POLS and POLS robust. However, the distinction among these two models is in the standard errors shown in parenthesis in the mentioned table. Consequently, this affects t-values associated with each coefficient since it results from the ratio between the estimated coefficient and its standard errors, culminating in the amendment of p-values. Thereupon, both R-squared, F test, and the probability associated with it remain unchanged from Pooled OLS (model 3 and 7) to robust Poled OLS (model 4 and 8).

Beginning with the first subperiod (December 31, 2019, to May 31, 2020), based on the sample of 24 countries across the world comprehending 1,881 observations, the growth in COVID-19 positive cases impacts the stock market negatively in all models, implying that stock markets in the sample answer negatively to the growth in confirmed cases. However, this value loses expression, mainly when daily fixed-effects dummy variables are introduced in model 3. Nonetheless, grounded on the t-test, this variable remains statistically significant throughout all models (with p-values constantly below the 10% significance level), denoting that the null hypothesis is rejected. Hence, growth in confirmed cases has, in fact, an impact on the stock market, and the robust model forecasts that per unit variation of the infection rate, stock returns are expected to decrease by $6.9006e^{-04}$, *ceteris paribus*. This indicates that confirmed cases infuse a negative sentiment in investors. As they were psychologically negatively affected by the pandemic and uncertainty prevailed, investors preferred to cease their financial investments, triggering decreases in stock returns. Hence, one can conclude that the stock market reacted negatively to COVID-19 confirmed patients from when each country announced its first positive case until May 31, 2020.

Regarding the slope-intercept coefficient, model 1 presents a p-value associated with the t-test below the 5% significance level (p-value= 0.0367). As a result, the null hypothesis is rejected, and the coefficient is said to be statistically different from zero. Therefore, when there is no growth in cases, stock returns are expected to decrease by approximately $1.4248e^{-03}$. On the contrary, for model 4, the slope coefficient displays a p-value above the 10% significance level and therefore is considered not statistically significant. Henceforth, COVID-19 cases can be more important than the overall market behavior.

Moreover, R-squared measures the overall goodness-of-fit of the model. For the first model, R-squared is 0.19%, expressing that from the total variation the dependent variable – stock market returns – experienced, only 0.19% is attributed to the main independent variable in the models – virus' confirmed cases. Similar to this number is the R-squared for model 2, which incorporates country-level control variables. In this case, around 0.23% of the stock market return's variation is attributed to both COVID-19 cases and country-level control variables. By comparing both R-squared values, as the difference between values is minor, it is possible to conclude that most stock market returns fluctuations' can be attributed to growth in COVID-19 positive cases. Likewise, in model 4 with the introduction of daily fixed-effects dummy variables, R-squared moves upwards to 63.59%, indicating that from the total variation the dependent variable – stock market returns – experienced, 63.59% is attributed to the five independent variables in the model plus daily fixed effects.

Another critical point in the analysis is the p-value associated with the F- test, which allows to access the overall significance of R-squared. The null hypothesis is that all slope coefficients are equal to zero; thus, the coefficient of determination of the population is also equal to zero. For model 1, where the only independent variable is COVID-19 cases, the test outcome is lower than the significance level of 10% (p-value = 0.0569). As a result, the null hypothesis is rejected and, based on the sample, there is at least one estimated coefficient that is statistically significant/different from zero. In other words, there is at least one explanatory variable whose variation contributes to explain the variation on the dependent variable. Therefore, the model is statistically significant. The same occurs in model 4, where the null hypothesis is rejected with a significance level of 1% (p-value $< 2.2e^{-16}$), and the model is statistically significant. On the contrary, in model 2, the model loses significance when country-level control variables are added.

Concerning the third subperiod (June 1, 2020, to December 31, 2020), the growth in COVID-19 cases' coefficient is still negative, indicating the virus still disrupts stock market returns. However, unlike the initial subperiod, this value is now considerably smaller, and as before, it decreases even further as daily fixed-effects dummy variables are introduced in model 7. Alongside, according to the t-test statistics, the main independent variable in all four models for this period is not statistically significant as it displays a probability above the 10% significance level, indicating that as time passes, this impact becomes less harmful. With this in mind and based on the sample of 24 countries worldwide comprehending 3,567 observations, the null hypothesis is not rejected. This leads to the conclusion that there is no significant effect of COVID-19 cases on stock market returns. Hence, the second hypothesis defined in this study is not verified.

Altogether it is possible to conclude about hypothesis 1 and 2 proposed in this research. Regarding the first subperiod, as has been noted, hypothesis 1 does hold, having COVID-19 confirmed cases destructively impacted the stock market. This finding is consistent with researches conducted by Al-Awadhi et al. (2020), Alber (2020), Asraf (2020), Erdem (2020), Khan et al. (2020), and Topcu and Gulal (2020), which all point towards the existence of a negative and significant effect on stock market returns due to COVID-19 confirmed infections.

On the contrary, there is no statistical evidence from the sample in the third subperiod to conclude that stock markets are adversely affected by COVID-19 cases, and hypothesis 2 is rejected. Thus, on the one hand, if investors "overreacted" in the begging, as research and progress are made on the disease and as more information becomes available, investors become more aware, and the market corrects itself. Besides, the first subperiod contains the first significant lockdown for all countries. However, between May and June, most countries slowly began to reopen schools, businesses, and other services from the first lockdown. Hence, as the economy is on the path to recovery, investors process this information also as a sign that better days may be within reach. On the other hand, from June to November, not only did European leaders agree on a €750 billion recovery fund to tackle the effects of the disease, and debt and contract reliefs increased enormously around the world. Also, governments remained implementing economic and financial packages to generate jobs and support the economy. But stay-at-home requirements and lockdowns ease in this period until the beginning of November, and countries began to lift restrictions on international travel controls. That is, borders were no longer closed, and most countries only applied the need for quarantine when traveling from a "high risk" country. Additionally, the first promising news regarding coronavirus vaccines started in November with Pfizer/BioNTech, Sputnik V, Moderna, and AstraZeneca, declaring efficacy rates above or equal to 90%. A month later, many countries had some of these vaccines approved and promoted mass inoculation campaigns. Hence, all of the reasons stated above, but most importantly the stimulus packages provided by governments and the hope of a successful vaccine shortly, have a prominent role in offsetting the effects of the pandemic.

Consequently, as uncertainty began to fade, investors regained their confidence in the market. This is in agreement with Ashraf's (2020) conclusion that markets answered more powerfully and harmfully at the beginning of the outbreak. Furthermore, it is also sustained by the average positive stock market returns faced on this period, contrary to the negative value in the previous period. However, on the negative side, this conclusion cannot be further compared to the literature since, to the best of our knowledge, no study with a research period as long as the current one exists.

In what concerns death's analysis, Table 12 presents the model results. Again, both regression techniques are exhibited.

Table 12 – Impact of daily growth of COVID-19 deaths on the stock market.

This table details the results of panel POLS method considering the effect of COVID-19 deaths on stock market returns, with the latter being the dependent variable in the model. This market quotations are retrieved from Yahoo Finance and Investing.com for each stock market index belonging to each country *c*. Growth in deaths is measured as the daily growth in fatalities per country due to the coronavirus disease and is collected from the WHO website. Investment freedom, Uncertainty avoidance and Democratic accountability are indices used as proxies for free capital markets, for nationwide culture and for type of political institutions, correspondingly. These variables are taken from the Heritage Foundation of Economic Freedom, Hofstede et al. (2010) and International Country Risk Guide archive, respectively. Log (GDP) is used as a proxy for economic development as is retrieved from WEO database. Heteroskedasticity and autocorrelation robust standard errors through the Newey West (1987) method are used in models 12 and 16. Standard errors in each model are presented in parenthesis under the coefficients. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variables	Stock market return							
	January 11, 2020 to May 31, 2020				June 1, 2020 to December 31, 2020			
	(9)	(10)	(11)	POLS robust (12)	(13)	(14)	(15)	POLS robust (16)
Growth in deaths	$-9.7042e^{-04}$	$-9.0802e^{-04}$	$-2.6637e^{-04}$	$-2.6637e^{-04}$	$-1.2162e^{-04}$	$-1.1558e^{-04}$	$-6.4974e^{-05}$	$-6.4974e^{-05}$
	$(8.9461e^{-04})$	$(8.9708e^{-04})$	$(6.0611e^{-04})$	$(6.2182e^{-04})$	$(1.8288e^{-04})$	$(1.8315e^{-04})$	$(1.3744e^{-04})$	$(1.1903e^{-04})$
Investment freedom		$-2.9759e^{-05}$	$6.6308e^{-06}$	$6.6308e^{-06}$		$-1.5230e^{-05}$	$-1.5960e^{-05}$*	$-1.5960e^{-05}$*
		$(4.3019e^{-05})$	$(2.8668e^{-05})$	$(2.8677e^{-05})$		$(1.1242e^{-05})$	$(8.3798e^{-06})$	$(8.9628e^{-06})$
Democratic accountability		$3.9677e^{-04}$	$-3.5533e^{-05}$	$-3.5533e^{-05}$		$3.2574e^{-05}$	$3.9199e^{-05}$	$3.9199e^{-05}$
		$(5.24e^{-04})$	$(3.5104e^{-04})$	$(3.1416e^{-04})$		$(1.2984e^{-04})$	$(9.8389e^{-05})$	$(9.6085e^{-05})$
Uncertainty avoidance		$-3.6023e^{-05}$	$-1.9357e^{-05}$	$-1.9357e^{-05}$		$1.4903e^{-06}$	$4.7443e^{-08}$	$4.7443e^{-08}$
		$(3.5519e^{-05})$	$(2.279e^{-05})$	$(1.8827e^{-05})$		$(9.2399e^{-06})$	$(6.7178e^{-06})$	$(5.8045e^{-06})$
Log (GDP)		$-7.1136e^{-04}$	$2.9534e^{-04}$	$2.9534e^{-04}$		$4.0784e^{-05}$	$2.8651e^{-05}$	$2.8651e^{-05}$
		$(6.5563e^{-03})$	$(4.2226e^{-04})$	$(3.2717e^{-04})$		$(1.6938e^{-04})$	$(1.2325e^{-04})$	$(1.0782e^{-04})$
Daily fixed-effects dummy variables			Yes	Yes			Yes	Yes
Constant	$1.1623e^{-03}$	$2.3508e^{-02}$	$-8.4534e^{-03}$	$-8.4534e^{-03}$	$1.2638e^{-03}$***	$9.0008e^{-04}$	$6.9183e^{-05}$	$6.9183e^{-05}$
	$(7.7835e^{-04})$	$(2.0080e^{-02})$	$(2.2288e^{-02})$	$(1.0114e^{-02})$	$(2.0867e^{-04})$	$(5.1089e^{-03})$	$(4.1734e^{-03})$	$(3.1754e^{-03})$
Observations	1,373	1,373	1,373	1,373	3,567	3,567	3,567	3,567
R-squared	$8.5753e^{-04}$	$2.4696e^{-03}$	0.6359	0.6359	0.00012	0.00068	0.50024	0.50024
F (Global significance)	0.0876	0.6769	20.4408	20.4408	0.4423	0.4875	18.1896	18.1896
Prob > F	0.27822	0.6410	$< 2.22e^{-16}$	$< 2.22e^{-16}$	0.5061	0.7858	$< 2.22e^{-16}$	$< 2.22e^{-16}$

Source: Own production

Again, as seen above, coefficients display the same values in both Pooled OLS and Pooled OLS robust for the two subperiods. Nonetheless, the dissimilarities between the models lie in the standard errors provided in parentheses alongside the p-values associated with each coefficient in the preceding table.

Regarding both subperiods, fatalities caused by COVID-19 variable enters small but negative for all models, meaning that stock markets answer adversely to deaths caused by the disease. However, based on the associated p-value, which is always above the 10% significance level, the variable is not statistically different from zero for any subperiod. With this in mind and based on the sample composed of 1,373 and 3,567 observations from 24 countries, it is possible to conclude that COVID-19 deaths are not a factor in stock market returns fluctuation. Furthermore, no robust model displays an associated p-value below the 10% significance level in what concerns the slope-intercept. Hence, the null hypothesis is not rejected, and the coefficients are said to be not statistically different from zero.

The p-value associated with the F-test for models 12 and 16 is lower than $2.2e^{-16}$, which points to the null hypothesis' rejection. Thus, the model is statistically significant. Unlike in models 10 and 14, when country-level variables are added, where models are not statistically significant. Notwithstanding, R-squared for models 12 and 16 is 63.59% and 50.024% respectively. This indicates that, for instance, in model 12, 63.59% of total stock returns' variation is explained by the five independent variables plus daily dummy variables.

All things considered, based on the considered sample, it is possible to conclude that both hypothesis 3 and 4 defined previously are not verified since the variable growth in COVID-19 deaths, although negative, is not statistically significant for any subperiod. When comparing to the literature, this is not in agreement with Al-Awadhi et al. (2020), Ali et al. (2020), Bahrini and Filfilan (2020), and Erdem (2020) that all found significant negative disturbances on stock returns due to coronavirus' deaths. On the other hand, it is in accordance with Ashraf (2020) and Alber (2020) as they also uncover that stock markets do not exhibit any significant reaction to COVID-19 fatalities. If this information is analyzed through behavioral finance, the realization of deaths is an occurrence that does not originate any negative feelings or emotions in investors' minds, and so they are not disturbed by those numbers. Therefore, investors do not react to that evolution. In contrast, another theory suggests that as cases escalate, deaths are also more likely to increase, and investors use this as a proxy for the future. That is, when pricing stocks, investors already incorporate this information beforehand. As a result, COVID-19 cases impact stock returns but deaths do not.

7. Robustness tests

In this section, to add credence to the present study, additional tests are performed to validate the robustness of the main findings of this study. First, to ensure that the previously obtained results are not influenced by omitted factors in a cross-country scenario, equations 4 and 5 are recalculated with country fixed-effects dummy variables rather than country-level control variables accounting for heteroskedasticity and autocorrelation.

According to Table 13 and Table 14, growth in COVID-19 confirmed casualties is negative and significant in the first subperiod. In contrast, cases' growth is insignificant for the second subperiod, and deaths are insignificant in any subperiod.

Table 13 – Impact of daily growth of COVID-19 cases on the stock market.

This table details the results of the panel robust POLS method considering the effect of COVID-19 cases on stock market returns, with the latter being the dependent variable in the model. These market quotations are retrieved from Yahoo Finance for each stock market index, except for the United Arab Emirates that were collected from Investing.com. Growth in cases is measured as the daily growth of casualties per country due to the coronavirus disease and is collected from WHO website. Investment freedom, Uncertainty avoidance, and Democratic accountability are indices used as proxies for free capital markets, nationwide culture, and the type of political institutions. These variables are taken from the Heritage Foundation of Economic Freedom, Hofstede et al. (2010), and the International Country Risk Guide archive, respectively. Finally, log (GDP) is used as a proxy for economic development as is retrieved from World Development. Standard errors in each model are presented in parenthesis under the coefficients. Heteroskedasticity and autocorrelation robust standard errors through the Newey West (1987) method are used. *,** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	Stock market return	
	December 31, 2019 to May 31, 2020	June 1, 2020 to December 31, 2020
	(1)	(2)
Growth in cases	$-6.9536e^{-04}$ *	$-3.1078e^{-04}$
	($3.6132e^{-04}$)	($6.2660e^{-04}$)
County fixed-effects dummy variables	Yes	Yes
Daily fixed-effects dummy variables	Yes	Yes
Constant	$-1.5320e^{-03}$	$-2.6106e^{-03}$
	($1.7242e^{-02}$)	($2.9866e^{-03}$)
Observations	1,881	3,567
R-squared	0.50165	0.5017
F (Global significance)	16.504	16.5068
Prob > F	$< 2.22e^{-16}$	$< 2.22e^{-16}$

Source: Own production

Table 14 – Impact of daily growth of COVID-19 deaths on the stock market

This table details the results of the panel robust POLS method concerning the effect of COVID-19 deaths on stock market returns, with the latter being the dependent variable in the model. These market quotations are retrieved from Yahoo Finance for each stock market index belonging to each country *c* except for the United Arab Emirates that was collected from Investing.com. In this models, country fixed-effects dummy variables are included instead of country control variables. Growth in deaths is measured as the daily growth of fatalities per country from the coronavirus disease and is collected from WHO. Results are computed with pooled OLS estimator accounting for heteroskedasticity and autocorrelation through the Newey West (1987) method. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variables	Stock market return	
	January 11, 2020 to May 31, 2020	June 1, 2020 to December 31, 2020
	(3)	(4)
Growth in deaths	$-3.1078e^{-04}$	$-5.5294e^{-05}$
	($6.2660e^{-04}$)	($1.2204e^{-04}$)
County fixed-effects dummy variables	Yes	Yes
Daily fixed-effects dummy variables	Yes	Yes
Constant	$-2.6106e^{-03}$	$-3.2805e^{-04}$
	($2.9866e^{-03}$)	($6.0834e^{-04}$)
Observations	1,373	3,567
R-squared	0.1884	0.6633
F (Global significance)	2.2753	23.056
Prob > F	$1.2041e^{-12}$	$< 2.22e^{-16}$

Source: Own production

Second, equations 4 and 5 are re-estimated with a panel Random effects model. From Tables 15 and 16, one can observe that results are identical to what was obtained with POLS. Regarding the cases' regression, stock returns are only impacted by it in the first subperiod. In what concerns deaths', there is no evidence of its impact on the stock market in any subperiod. The results from these two different robustness tests confirm the findings revealed in the previous section while also ensuring that results are not driven by omitted factors.

Table 15 – Impact of daily growth of COVID-19 cases on the stock market.

This table details the results of the Random effects model considering the effect of COVID-19 cases on stock market returns, with the latter being the dependent variable in the model. These market quotations are retrieved from Yahoo Finance for each stock market index, except for the United Arab Emirates that were collected from Investing.com. Growth in cases is measured as the daily growth in cases per country and is collected from WHO website. Investment freedom, Uncertainty avoidance, and Democratic accountability are indices used as proxies for free capital markets, nationwide culture, and the type of political institutions. These variables are taken from the Heritage Foundation of Economic Freedom, Hofstede et al. (2010), and the International Country Risk Guide archive, respectively. Finally, log (GDP) is used as a proxy for economic development as is retrieved from World Development. Standard errors in each model are presented in parenthesis under the coefficients. *,** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	Stock market return	
	December 31, 2019 to May 31, 2020	June 1, 2020 to December 31, 2020
	(5)	(6)
Growth in cases	$-6.8972e^{-04}$ *	$-1.8953e^{-04}$
	($3.8635e^{-04}$)	($2.5668e^{-04}$)
Investment freedom	$-1.2008e^{-06}$	$-1.545e^{-05}$
	($3.8635e^{-04}$)	($1.0168e^{-05}$)
Democratic accountability	$8.7612e^{-05}$	$2.9387e^{-05}$
	($2.8663e^{-05}$)	($1.2021e^{-04}$)
Uncertainty avoidance	$-1.3897e^{-05}$	$-3.7981e^{-07}$
	($1.8983e^{-05}$)	($8.1776e^{-06}$)
Log (GDP)	$3.7435e^{-04}$	$1.5141e^{-05}$
	($3.6259e^{-04}$)	($1.4947e^{-04}$)
Daily fixed-effects dummy variables	Yes	Yes
Constant	$-1.1103e^{-02}$	$5.1143e^{-04}$
	($2.0839e^{-02}$)	($4.8757e^{-03}$)
Observations	1,881	3,567
R-squared	0.6625	0.5003
Chisq	3436.88	3384.51
Prob > F	$< 2.22e^{-16}$	$< 2.22e^{-16}$

Source: Own production

Table 16 – Impact of daily growth of COVID-19 deaths on the stock market.

This table details the results of the panel robust POLS method concerning the effect of COVID-19 deaths on stock market returns, with the latter being the dependent variable in the model. These market quotations are retrieved from Yahoo Finance for each stock market index belonging to each country *c* except for the United Arab Emirates that was collected from Investing.com. In this models, country fixed-effects dummy variables are included instead of country control variables. Growth in cases and deaths is measured as the daily growth of casualties and fatalities per country from the coronavirus disease and is collected from WHO. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variables	Stock market return	
	January 12, 2020 to May 31, 2020	June 1, 2020 to December 31, 2020
	(7)	(8)
Growth in deaths	$-3.2769e^{-04}$	$-6.3686e^{-05}$
	$(6.0883e^{-04})$	$(1.3796e^{-04})$
Investment freedom	$1.7746e^{-05}$	$-1.5634e^{-05}$
	$(3.7204e^{-05})$	$(1.0176e^{-05})$
Democratic accountability	$-2.346e^{-04}$	$3.1609e^{-05}$
	$(4.6347e^{-04})$	$(1.2037e^{-04})$
Uncertainty avoidance	$-3.0551e^{-05}$	$-1.2717e^{-07}$
	$(3.0374e^{-05})$	$(8.185e^{-06})$
Log (GDP)	$-7.5214e^{-05}$	$1.6156e^{-05}$
	$(5.5652e^{-04})$	$(1.4965e^{-04})$
Daily fixed-effects dummy variables	Yes	Yes
Constant	$1.4408e^{-03}$	$4.6673e^{-04}$
	$(2.4854e^{-02})$	$(4.8809e^{-03})$
Observations	1,881	3,567
R-squared	0.6356	0.5003
Chisq	2204.88	3383.84
Prob > F	$< 2.22e^{-16}$	$< 2.22e^{-16}$

Source: Own production

8. Conclusions

This research studies the impact of both COVID-19 cases and deaths on stock market returns in a panel of twenty-four countries across the five continents. This analysis covers the period from December 31, 2019, to December 31, 2020, of which, within this period, the world witnessed COVID-19's first and second wave. Although for some countries, this period may not cover the second wave fully, for others, it is entirely covered.

As for positive cases, the results indicate that stock returns were negatively and significantly affected between December 31, 2019, to May 31, 2020. This conclusion is consistent with Al-Awadhi et al. (2020), Alber (2020), Asraf (2020), Erdem (2020), Khan et al. (2020), and Topcu and Gulal (2020). Conversely, for the subperiod between June 1 to December 31, 2020, there is no evidence of stock markets being distressed by COVID-19 cases. Several occasions may be the reason for no such disturbance. First, from May to June, schools, businesses and other services began operating again in most countries. Second, between June and November, the European Union established a recovery package of €750 billion to mitigate the pandemic's consequences while governments introduced money into the economy. At the same time, debt/contract reliefs increased immensely on a global scale. In addition, most international barriers were canceled, and some nations adopted quarantines only when traveling from "high risk" countries. Moreover, the scientific community released new hopeful information regarding vaccine developments. Altogether, these occurrences, with stimulus packages and the likelihood of having a vaccine in a short period having a particular weight, mitigate the pandemic's impact and boost investors' confidence.

Regarding COVID-19 deaths, there is no evidence of their impact on stock returns for neither subperiod. As a matter of fact, this is in line with Ashraf's (2020) and Alber's (2020) studies, but it contradicts Al-Awadhi et al. (2020), Ali et al. (2020), Bahrini and Filfilan (2020), and Erdem (2020) research. Furthermore, all results are achieved by accounting for country-specific and time-specific factors. However, similar conclusions are reached when using both Random effects model and a robust method with country fixed effects dummy variables rather than country-level control variables.

Although the primary goal of this research is to reach a more global conclusion on how stock markets across the world answer to COVID-19 confirmed cases and deaths, by only analyzing twenty-four countries, it is not possible to extrapolate this conclusion to every nation in the world. Thus, even though the sample in this research includes a diversity of nations, in essence, at least one country from each continent, from developed nations to developing ones, with different regimes and cultures, analyzing only a percentage of worldwide countries can be insufficient.

On a higher note, there are numerous factors affecting the stock market every day. On the Literature review of this work, some were mentioned. Regarding Monetary and Fiscal policies as well as Inflation, even though they were not directly applied in the model, indirectly its impact is still present on other used variables. This also presents itself as a limitation of the present work since important variables were not taken directly into account.

A highly contagious SARS-CoV-2 virus strain – Delta variant – first appeared in India in late December. By June 2021, 96 countries report growing cases and deaths of this variant. As a result, investors faced fears of resurgence, and consequently, markets suffered losses. With this in mind, future research worth conducting can be related to how stock returns reacted to this specific event. Additionally, researchers may be interested in studying the effect of vaccine inoculations and their developments on the stock market.

9. Bibliography

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID–19 crisis. Finance *Research Letters*, 38, 101604. https://doi.org/10.1016/j.frl.2020.101604

Akıncı, Ö., & Chahrour, R. (2018). Good news is bad news: Leverage cycles and sudden stops. *Journal of International Economics*, *114*, 362–375. https://doi.org/10.1016/j.jinteco.2018.07.006

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

Alber, N. (2020). The Effect of Coronavirus Spread on Stock Markets: The Case of the Worst 6 Countries. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3578080

Albulescu, C. (2020a). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, 101699. https://doi.org/10.1016/j.frl.2020.101699

Albulescu, C. (2020b). Coronavirus and Financial Volatility: 40 Days of Fasting and Fear. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3550630

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

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, *120*(1), 87–92. https://doi.org/10.1016/j.econlet.2013.04.004

Antonakakis, N., Gupta, R., & Tiwari, A. K. (2017). Has the correlation of inflation and stock prices changed in the United States over the last two centuries? *Research in International Business and Finance*, *42,* 1–8. https://doi.org/10.1016/j.ribaf.2017.04.005

Antono, Z. M., Jaharadak, A. A., & Khatibi, A. A. (2019). Analysis of factors affecting stock prices in mining sector: Evidence from Indonesia Stock Exchange. *Management Science Letters*, 1701–1710. https://doi.org/10.5267/j.msl.2019.5.018

Archived: WHO Timeline - COVID-19. (2020, April 28). World Health Organization. https://www.who.int/news/item/27-04-2020-who-timeline---covid-19

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

First confirmed case of novel coronavirus in Australia. (2020, January 25). Australian Government Department of Health. https://www.health.gov.au/ministers/the-hon-greg-hunt-mp/media/first-confirmed-case-of-novel-coronavirus-in-australia

Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2021). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters*, 38, 101701. https://doi.org/10.1016/j.frl.2020.101701

Baltagi, B. H. (2008). *Econometric Analysis of Panel Data* (4th edition). Wiley

Bahrini, R. and Filfilan, A. (2020). Impact of the novel coronavirus on stock market returns: evidence from GCC countries. *Quantitative Finance and Economics*, 4(4), 640-652. https://doi.org/10.3934/QFE.2020029

Barro, R. J., J. F. Ursúa, and J. Weng (2020). The coronavirus and the great influenza pandemic: Lessons from the "Spanish flu" for the coronavirus's potential effects on mortality and economic activity. *Working Paper 26866*, National Bureau of Economic Research

Binder, J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting*, *11(2)*, 111–137. https://doi.org/10.1023/a:1008295500105

Bodie, Z., Kane, A., & Marcus, A. J. (2009). Investments (8th ed.). McGraw-Hill/Irwin

Breusch, T. S., and A. R. Pagan (1979). A Simple Test for Heteroskedasticity and Random Coefficient Variation. *Econometrica* 47, 987–1007.

Cao, K. H., Li, Q., Liu, Y., & Woo, C.-K. (2020). Covid-19's adverse effects on a stock market index. *Applied Economics Letters*, 1–5. https://doi.org/10.1080/13504851.2020.1803481

Cepoi, C. (2020). Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Finance Research Letters*, *36*, 101658. https://doi.org/10.1016/j.frl.2020.101658

Ceylan, R. F., & Ozkan, B. (2020). The Economic Effects of Epidemics: From SARS and MERS to COVID-19. *Research Journal in Advanced Humanities*, 1(2), 21-29. https://royalliteglobal.com/advanced-humanities/article/view/132

Chatziantoniou, I., Duffy, D., & Filis, G. (2013). Stock market response to monetary and fiscal policy shocks: Multi-country evidence. *Economic Modelling*, *30*, 754–769. https://doi.org/10.1016/j.econmod.2012.10.005

Chen, M.-H., Jang, S. C. S., & Kim, W. G. (2007). The impact of the SARS outbreak on Taiwanese hotel stock performance: An event-study approach. *International Journal of Hospitality Management*, 26(1), 200–212. https://doi.org/10.1016/j.ijhm.2005.11.004

Chen, M., Lee, C., Lin, Y., & Chen, W. (2018). Did the S.A.R.S. epidemic weaken the integration of Asian stock markets? Evidence from smooth time-varying cointegration analysis. *Economic Research-Ekonomska Istraživanja*, *31*(1), 908-926. http://doi.org/10.1080/1331677x.2018.1456354

Chen, X., & Chiang, T. (2020). Empirical investigation of changes in policy uncertainty on stock returns—Evidence from China's market. *Research In International Business And Finance*, *53*, 101183. https://doi.org/10.1016/j.ribaf.2020.101183

Claeson, M., & Hanson, S. (2021). COVID-19 and the Swedish enigma. *The Lancet*, *397*(10271), 259-261. http://doi.org/10.1016/s0140-6736(20)32750-1

Cohen, L. J., Marcus, A. J., Rezaee, Z., & Tehranian, H. (2018). Waiting for guidance: Disclosure noise, verification delay, and the value-relevance of good-news versus bad-news management earnings forecasts. *Global Finance Journal*, 37, 79–99. https://doi.org/10.1016/j.gfj.2018.03.001

Coltart, C. E. M., Lindsey, B., Ghinai, I., Johnson, A. M., & Heymann, D. L. (2017). The Ebola outbreak, 2013–2016: old lessons for new epidemics. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 372(1721), 20160297. https://doi.org/10.1098/rstb.2016.0297

Corbet, S., Hou, G., Hu, Y., & Oxley, L. (2020). The Influence of the COVID-19 Pandemic on Asset-Price Discovery: Testing the Case of Chinese Informational Asymmetry. *International Review of Financial Analysis*, 72, 101560. https://doi.org/10.2139/ssrn.3623252

Corbet, S., Hou, Y. G., Hu, Y., Oxley, L., & Xu, D. (2021). Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics & Finance*, 71, 55–81. https://doi.org/10.1016/j.iref.2020.06.022

Basics of COVID-19. (2020, February 11). Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/cdcresponse/about-COVID-19.html

Breusch, T. and Pagan, A. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1), p.239.

Coronavirus Update (Live): 207,948,984 Cases and 4,374,328 Deaths from COVID-19 Virus Pandemic - Worldometer. (2021, August 15). COVID-19 Coronavirus Pandemic. https://www.worldometers.info/coronavirus/

COVID Data Tracker. (2021). Centers for Disease Prevention and Control. https://covid.cdc.gov/covid-data-tracker/#global-counts-rates

COVID-19 cases top 10 000 in Africa. (2020, April 7). World Health Organization Regional Office For Africa. https://www.afro.who.int/news/covid-19-cases-top-10-000-africa

David, S. A., Inácio Jr., C. M. C., & Tenreiro Machado, J. A. (2021). The recovery of global stock markets indices after impacts due to pandemics. *Research in International Business and Finance, 55*, 101335. https://doi.org/10.1016/j.ribaf.2020.101335

Davidson, L. S., & Froyen, R. T. (1982). Monetary Policy and Stock Returns: Are Stock Markets Efficient? *Review*, *64*. https://doi.org/10.20955/r.64.3-12.cfc

Erdem, O. (2020). Freedom and stock market performance during Covid-19 outbreak. *Finance Research Letters*, *36*, 101671. https://doi.org/10.1016/j.frl.2020.101671

Evaluating the initial impact of COVID-19 containment measures on economic activity. (2020, June 10). Organisation for Economic Co-operation and Development. https://www.oecd.org/coronavirus/policy-responses/evaluating-the-initial-impact-of-COVID-19-containment-measures-on-economic-activity-b1f6b68b/#p-d1e60

Fama, E. (1981). Stock Returns, Real Activity, Inflation, and Money. The American Economic Review, 71(4), 545-565. Retrieved August 28, 2021, from http://www.jstor.org/stable/1806180

Fama, E. (1990). Stock Returns, Expected Returns, and Real Activity. *The Journal of Finance*, 45(4), 1089-1108. https://org/10.2307/2328716

Garrett, T. A. (2008). Pandemic Economics: The 1918 Influenza and Its Modern-Day Implications. *Federal Reserve Bank of St. Louis*. *Review*, *90*(2). https://doi.org/10.20955/r.90.74-94

Gale, J. (2021, March 4). Where Are We in Hunting for the Coronavirus's Origin?. Bloomberg. https://www.bloomberg.com/news/articles/2021-03-04/where-are-we-in-hunting-for-the-coronavirus-s-origin-quicktake

Gates, B. (2020). Responding to Covid-19 — A Once-in-a-Century Pandemic? *New England Journal of Medicine*, *382*(18), 1677–1679. https://doi.org/10.1056/nejmp2003762

Geske, R., & Roll, R. (1983). The Fiscal and Monetary Linkage Between Stock Returns and Inflation. *The Journal of Finance*, 38(1), 1-33. https://doi.org/10.2307/2327635

Hafer, R. W. (1986). The Response of Stock Prices to Changes in Weekly Money and the Discount Rate. *The Federal Reserve Bank of St. Louis. Review*, *68*. https://doi.org/10.20955/r.68.5-14.hzb

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, 46(6), 1251. https://doi.org/10.2307/1913827

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's Impact on Stock Prices Across Different Sectors—An Event Study Based on the Chinese Stock Market. *Emerging Markets Finance and Trade*, *56*(10), 2198–2212. https://doi.org/10.1080/1540496x.2020.1785865

Henningsen, A., & Henningsen, G. (2019). Analysis of Panel Data Using R. *Panel Data Econometrics*, 345-396. http://doi.org/10.1016/b978-0-12-814367-4.00012-5

Hong, H., Bian, Z., & Lee, C. (2021). COVID-19 and instability of stock market performance: evidence from the U.S. *Financial Innovation*, 7(1). http://doi.org/10.1186/s40854-021-00229-1

Hopman, C. (2007). Do supply and demand drive stock prices? *Quantitative Finance*, *7(1)*, 37–53. https://doi.org/10.1080/14697680600987216

Hsiao, C. (2014). Analysis of Panel Data (Econometric Society Monographs). (3rd ed.). Cambridge University Press.

Ichev, R., & Marinč, M. (2018). Stock prices and geographic proximity of information: Evidence from the Ebola outbreak. International *Review of Financial Analysis*, *56*, 153–166. https://doi.org/10.1016/j.irfa.2017.12.004

Im, K., Pesaran, M., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74. http://doi.org/10.1016/s0304-4076(03)00092-7

International Monetary Fund (IMF). (2020, June). *World Economic Outlook Update*. Washington, D.C: International Monetary Fund.

Jaffe, J., & Mandelker, G. (1976). The "Fisher Effect" for Risky Assets: An Empirical Investigation. *The Journal of Finance*, 31(2), 447-458. https:///doi.org/10.2307/2326616

Jain, E. (2014). Impact of Law of Demand & Supply on Stock Market: A Study of Most Active BSE Indices with the Help of RSI. *IOSR Journal of Economics and Finance*, *5(6)*, 06–15. https://doi.org/10.9790/5933-05620615

Kentikelenis, A., King, L., McKee, M., & Stuckler, D. (2015). The International Monetary Fund and the Ebola outbreak. *The Lancet Global Health*, *3*(2), e69–e70. https://doi.org/10.1016/s2214-109x(14)70377-8

Khan, K., Zhao, H., Zhang, H., Yang, H., Shah, M. H., & Jahanger, A. (2020). The impact of Covid-19 pandemic on stock markets: An empirical analysis of world major stock indices. *The Journal of Asian Finance, Economics and Business*, *7*(7), 463–474. https://doi.org/10.13106/jafeb.2020.vol7.no7.463

Khanthavit, A. (2020a). World and national stock market reactions to COVID-19. *Working Paper, Thammasat University*. https://doi.org/10.13140/RG.2.2.22792.57606

Khanthavit, A. (2020b). An Event Study Analysis of Thailand's 2019 General Election: A Long Window of Multiple Sub-events. *International Journal of Financial Research*, *11*(4), 502. https://doi.org/10.5430/ijfr.v11n4p502

Kowalewski, O., & Śpiewanowski, P. (2020). Stock market response to potash mine disasters. *Journal of Commodity Markets*, *20*, 100124. https://doi.org/10.1016/j.jcomm.2020.100124

Li, Z. and Zhong, J. (2020). Impact of economic policy uncertainty shocks on China's financial conditions. *Finance Research Letters*, 35, 101303. https://doi.org/10.1016/j.frl.2019.101303

Lu, H., Stratton, C., & Tang, Y. (2020). Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. *Journal Of Medical Virology*, *92*(4), 401-402. https://doi.org/10.1002/jmv.25678

Maddala, G., & Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics And Statistics*, *61*(S1), 631-652. http://doi.org/10.1111/1468-0084.0610s1631

Middle East respiratory syndrome coronavirus (MERS-CoV). (2019, December 20). World Health Organization. https://www.who.int/news-room/q-a-detail/middle-east-respiratory-syndrome-coronavirus-(mers-cov)

Mishkin, F. S. (2004). Economics of Money, Banking, and Financial Markets (7th ed.). Pearson College

Mobarek, A., Mollah, S., Keasey, K. (2014). A Cross-Country Analysis of Herd Behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, 32, 107-127. https://doi.org/10.1016/j.intfin.2014.05.008

Narayan, P., Phan, D., & Liu, G. (2021). COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. *Finance Research Letters*, 38, 101732. https://doi.org/10.1016/j.frl.2020.101732

Narayan, P. K. (2019). Can stale oil price news predict stock returns? *Energy Economics*, 83, 430–444. https://doi.org/10.1016/j.eneco.2019.07.022

Narayan, P. K., & Bannigidadmath, D. (2015). Are Indian stock returns predictable? *Journal of Banking & Finance*, 58, 506–531. https://doi.org/10.1016/j.jbankfin.2015.05.001

Newey, W.K., West, K.D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 703–708. https://doi.org/10.2307/1913610

Olsen, R. A. (1998). Behavioral Finance and Its Implications for Stock-Price Volatility. *Financial Analysts Journal*, *54*(2), 10–18. https://doi.org/10.2469/faj.v54.n2.2161

Onali, E. (2020). COVID-19 and Stock Market Volatility. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3571453

O'Donnell, N., Shannon, D. & Sheehan, B. (2021). Immune or at-risk? Stock markets and the significance of the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance*, 30, 100477. https://doi.org/10.1016/j.jbef.2021.100477

Park, M., Thwaites, R.S. and Openshaw, P.J.M. (2020). COVID-19: Lessons from SARS and MERS. *European Journal of Immunology*, 50(3), 308-311. https://doi.org/10.1002/eji.202070035

Pesaran, M. (2004). General diagnostic tests for cross section dependence in panels. University of Cambridge, Faculty of Economics, Cambridge Working Papers in Economics No. 0435

Petrosillo, N., Viceconte, G., Ergonul, O., Ippolito, G., & Petersen, E. (2020). COVID-19, SARS and MERS: are they closely related?. *Clinical microbiology and infection: the official publication of the European Society of Clinical Microbiology and Infectious Diseases*, *26*(6), 729–734. https://doi.org/10.1016/j.cmi.2020.03.026

Philips, P. C. B. & Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. Econometrics Journal, 6(1), 217-259. http://doi.org/10.1111/1368-423X.00108

Rahman, M. L., Amin, A., & Al Mamun, M. A. (2021). The COVID-19 outbreak and stock market reactions: Evidence from Australia. *Finance Research Letters*, 38, 101832. https://doi.org/10.1016/j.frl.2020.101832

Reilly, F. K., & Brown, K. C. (2012). Investment Analysis and Portfolio Management (10th ed.). Cengage Learning

Ritchie, H., Ortiz-Ospina, E., Beltekian, D., Mathieu, E., Hasell, J., & Macdonald, B. et al. (2021, August 3). Coronavirus (COVID-19) Vaccinations. Our World in Data. https://ourworldindata.org/covid-vaccinations

Rozeff, M. S. (1974). Money and stock prices: market efficiency and the lag in effect of monetary policy. *Journal of Financial Economics*, *1*(3), 245–302. https://doi.org/10.1016/0304-405x(74)90020-8

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis*, *71*, 101546. https://doi.org/10.1016/j.irfa.2020.101546

Sauer, L. (2021, May 19). What Is Coronavirus?. Johns Hopkins Medicine. https://www.hopkinsmedicine.org/health/conditions-and-diseases/coronavirus

Schwert, G. W. (1981). The Adjustment of Stock Prices to Information About Inflation. *The Journal of Finance*, *36*(1), 15–29. https://doi.org/10.1111/j.1540-6261.1981.tb03531.x

Shankar, D., & Dhankar, R. S. (2015). Understanding the Behavior of Stock Market Functionality: Need and Role of Behavioral Finance. *Review of Management*, *5*(3/4), 5–11

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Shear, F., Ashraf, B., & Sadaqat, M. (2021). Are Investors' Attention and Uncertainty Aversion the Risk Factors for Stock Markets? International Evidence from the COVID-19 Crisis. *Risks*, 9(1), 2. https://doi.org/10.3390/risks9010002

Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19's disasters are perilous than Global Financial Crisis: A rumor or fact?. *Finance Research Letters*, *36*, 101669. https://doi.org/10.1016/j.frl.2020.101669

Smith, R. D. (2006). Responding to global infectious disease outbreaks: Lessons from SARS on the role of risk perception, communication and management. *Social Science & Medicine*, *63*(12), 3113–3123. https://doi.org/10.1016/j.socscimed.2006.08.004

Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., Iosifidis, C., & Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). International journal of surgery (London, England), 76, 71–76. https://doi.org/10.1016/j.ijsu.2020.02.034

Spengler, J. R., Ervin, E. D., Towner, J. S., Rollin, P. E., & Nichol, S. T. (2016). Perspectives on West Africa Ebola Virus Disease Outbreak, 2013–2016. *Emerging Infectious Diseases*, *22*(6), 956–963. https://doi.org/10.3201/eid2206.160021

Srivastava, M. (2020, September 13). Israel to enter lockdown again as second wave of Covid-19 surges. Financial Times. https://www.ft.com/content/79f8323b-6cf8-48ca-9118-bdc764756fef

Svensson, J. (2000). Is the bad news principle for real? *Economics Letters*, *66*(3), 327–331. https://doi.org/10.1016/s0165-1765(99)00205-0

Taylor, D. (2021, March 17). A Timeline of the Coronavirus Pandemic. The New York Times. https://www.nytimes.com/article/coronavirus-timeline.html

Thorbecke, W. (1997). On Stock Market Returns and Monetary Policy. *The Journal of Finance, 52*(2), 635–654. https://doi.org/10.1111/j.1540-6261.1997.tb04816.x

Tiwari, A.K., Jana, R.K., Roubaud, D. (2019). The policy uncertainty and market volatility puzzle: Evidence from wavelet analysis. *Finance Research Letters*, 31, 278–284. https://doi.org/10.1016/j.frl.2018.11.016

Todaro, M. P., & Smith, S. C. (2015). Economic Development (12th ed.). Pearson

Topcu, M., & Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets. *Finance Research Letters, 36*, 101691. https://doi.org/10.1016/j.frl.2020.101691

Tvaronavičiene, M., & Michailova, J. (2006). Factors affecting securities prices: theoretical versus practical approach. *Journal of Business Economics and Management*, *7*(4), 201–211. https://doi.org/10.3846/16111699.2006.9636142

Walker, P., Whittaker, C., Watson, O., et al. (2020). The impact of COVID-19 and strategies for mitigation and suppression in low- and middle-income countries. *Science*. http://doi.org/10.1126/science.abc0035

Wang, Y.-H., Yang, F.-J., & Chen, L.-J. (2013). An investor's perspective on infectious diseases and their influence on market behavior. *Journal of Business Economics and Management*, *14*(Supplement_1), S112–S127. https://doi.org/10.3846/16111699.2012.711360

Wilder-Smith, A., Chiew, C. J., & Lee, V. J. (2020). Can we contain the COVID-19 outbreak with the same measures as for SARS? *The Lancet Infectious Diseases*, *20(5)*, e102–e107. https://doi.org/10.1016/s1473-3099(20)30129-8

Wise, P. (2021, January 20). Portugal suffers surging Covid-19 deaths after mastering first wave. Financial Times. https://www.ft.com/content/fbeb622e-0a69-4f5c-a6fe-6653a72d2377

Wooldridge, J. (2011). *Econometric analysis of cross section and panel data*. Cambridge, Massachusetts: MIT Press

Wooldridge, J. (2012). *Introductory economics: A modern approach* (5th ed.). South-Western, Cengage Learning

Yang, Y., Peng, F., Wang, R., Guan, K., Jiang, T., Xu, G., Sun, J., & Chang, C. (2020). The deadly coronaviruses: The 2003 SARS pandemic and the 2020 novel coronavirus epidemic in China. *Journal of Autoimmunity, 109*, 102434. https://doi.org/10.1016/j.jaut.2020.102434

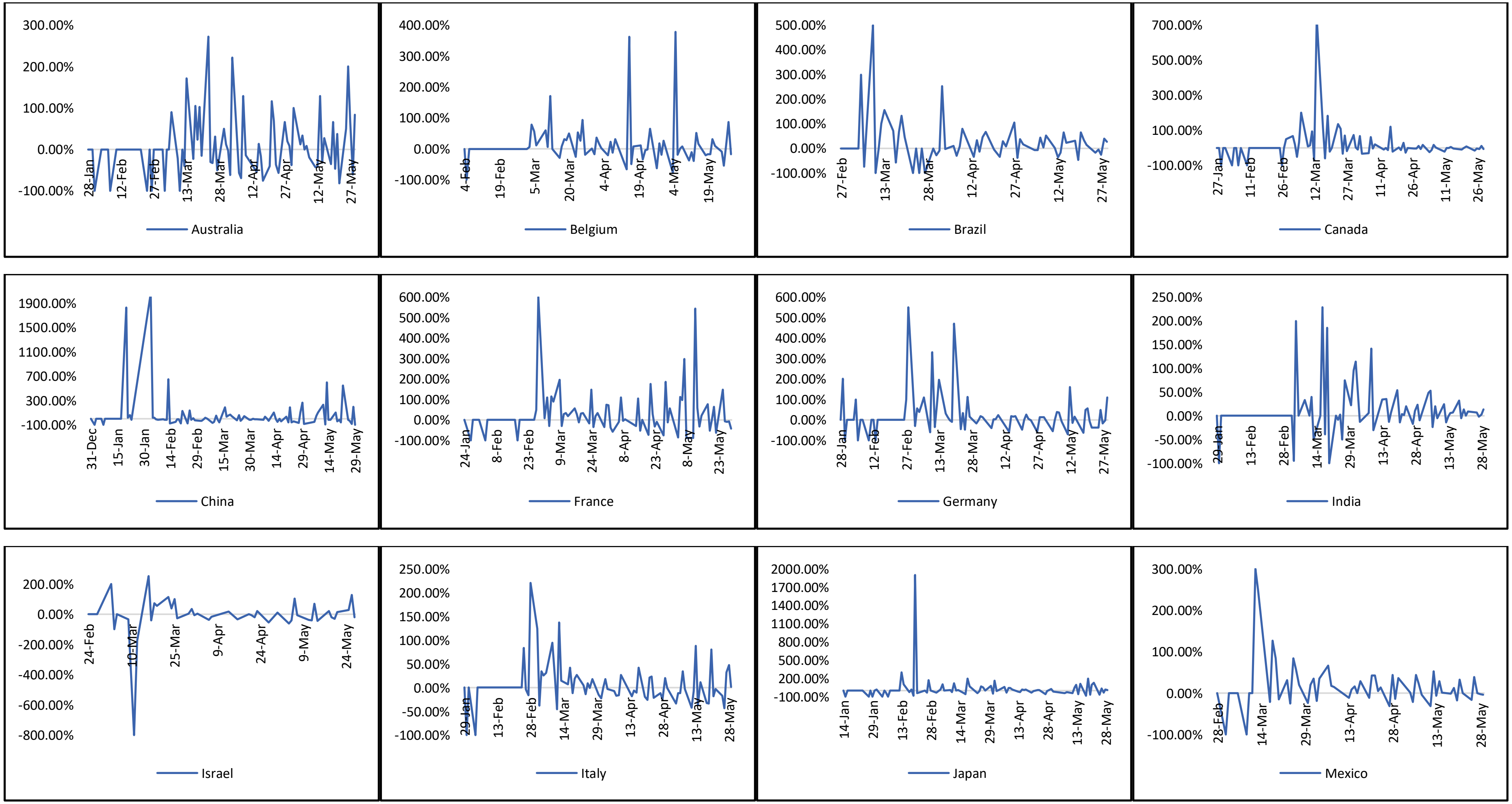
Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters*, *35*, 101597. https://doi.org/10.1016/j.frl.2020.101597

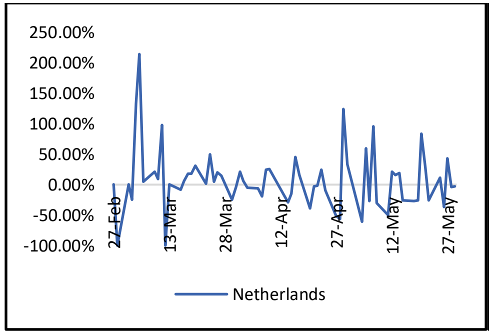
Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

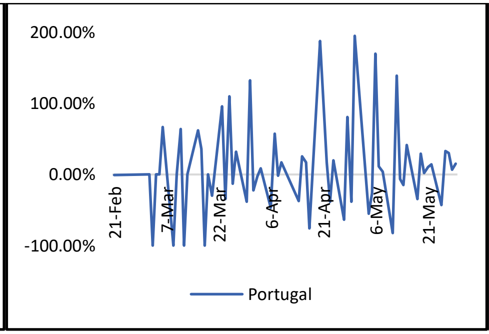
Zimmer, C., Corum, J., & Wee, S. (2020, December 13). *Covid-19 Vaccine Tracker: Latest Updates*. The New York Times. https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html

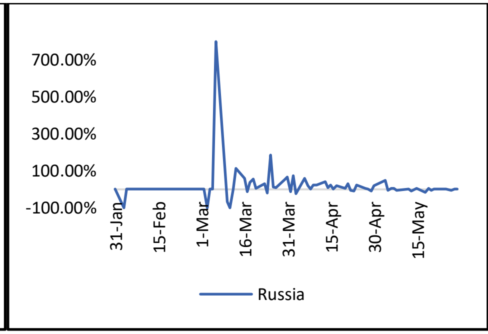
10. Appendix

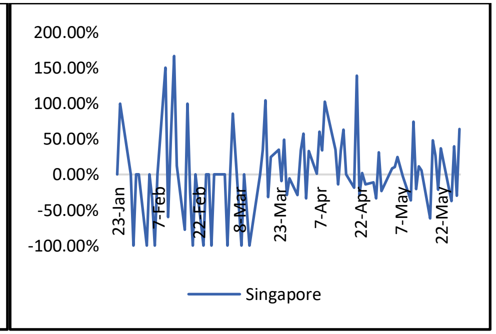
Appendix A – Growth in COVID-19 cases per country for the first subperiod (December 31, 2019 to May 31, 2020)

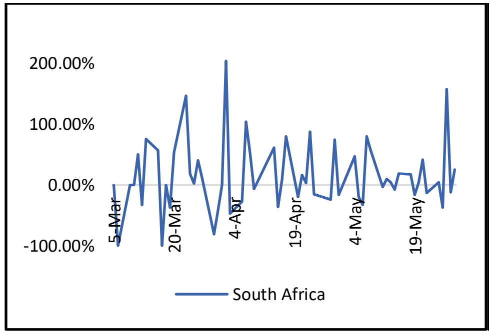


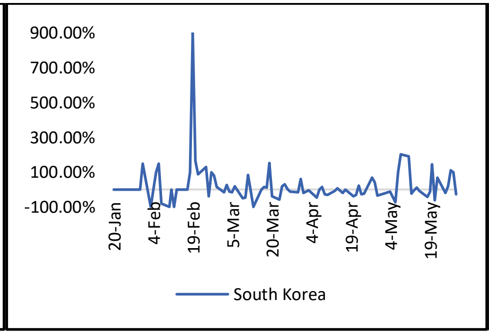

250.00%
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
27-Feb
13-Mar
28-Mar
12-Apr
27-Apr
12-May
27-May
Netherlands

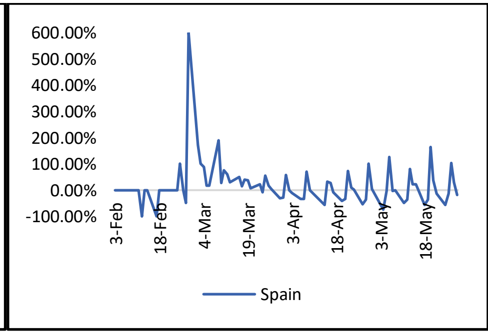

200.00%
100.00%
0.00%
-100.00%
21-Feb
7-Mar
22-Mar
6-Apr
21-Apr
6-May
21-May
Portugal

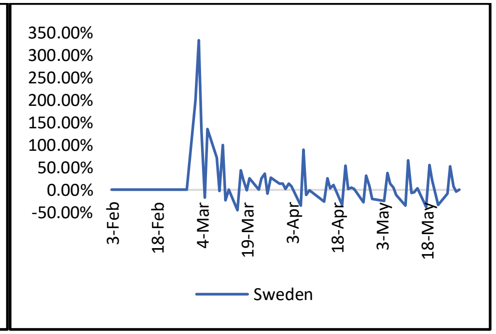

700.00%
500.00%
300.00%
100.00%
-100.00%
31-Jan
15-Feb
1-Mar
16-Mar
31-Mar
15-Apr
30-Apr
15-May
Russia

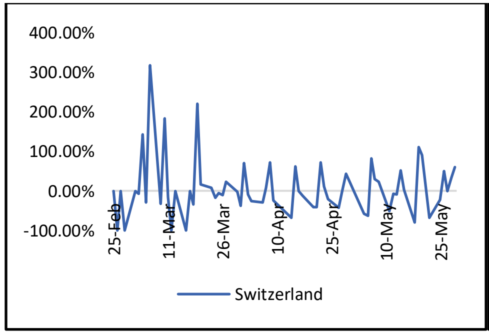

200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
23-Jan
7-Feb
22-Feb
8-Mar
23-Mar
7-Apr
22-Apr
7-May
22-May
Singapore

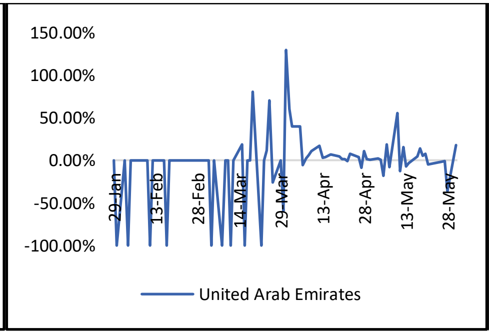

200.00%
100.00%
0.00%
-100.00%
5-Mar
20-Mar
4-Apr
19-Apr
4-May
19-May
South Africa

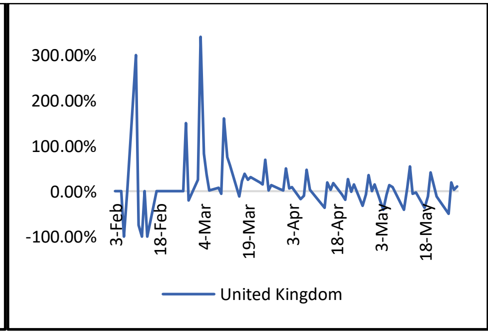

900.00%
700.00%
500.00%
300.00%
100.00%
-100.00%
20-Jan
4-Feb
19-Feb
5-Mar
20-Mar
4-Apr
19-Apr
4-May
19-May
South Korea

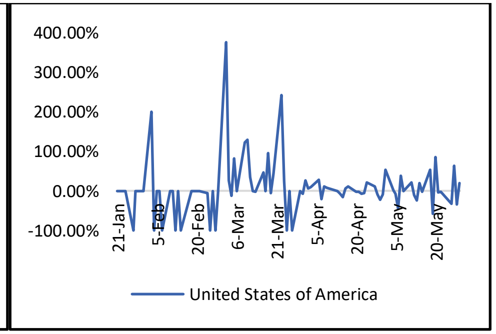

600.00%
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
Spain


350.00%
300.00%
250.00%
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
Sweden

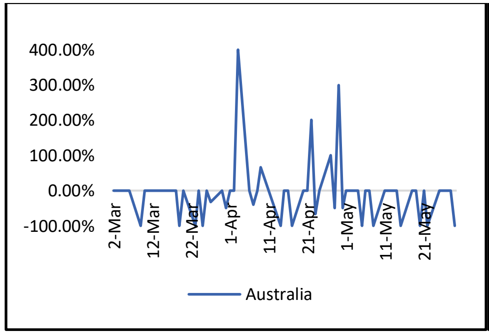

400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
25-Feb
11-Mar
26-Mar
10-Apr
25-Apr
10-May
25-May
Switzerland

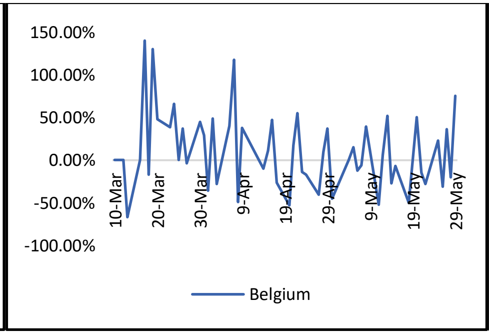

150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
29-Jan
13-Feb
28-Feb
14-Mar
29-Mar
13-Apr
28-Apr
13-May
28-May
United Arab Emirates

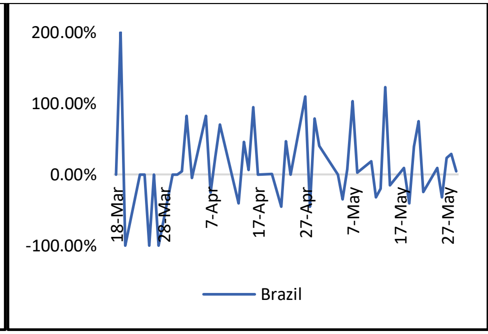

300.00%
200.00%
100.00%
0.00%
-100.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
United Kingdom

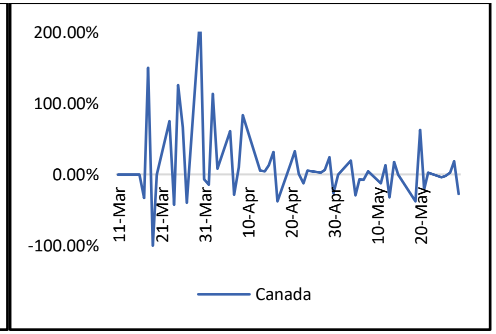

400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
21-Jan
5-Feb
20-Feb
6-Mar
21-Mar
5-Apr
20-Apr
5-May
20-May
United States of America

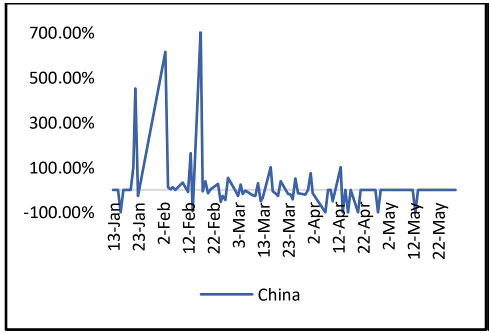
Appendix B – Growth in COVID-19 fatalities per country for the second subperiod (January 11, 2020 to May 31, 2020)

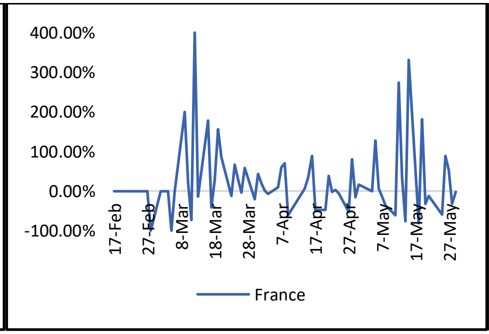


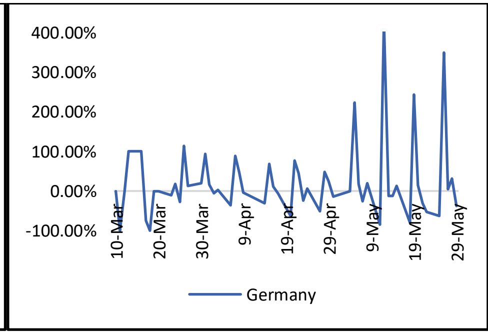


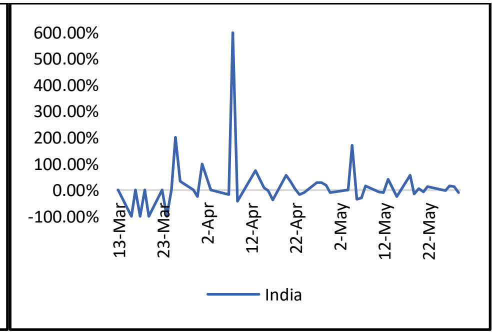


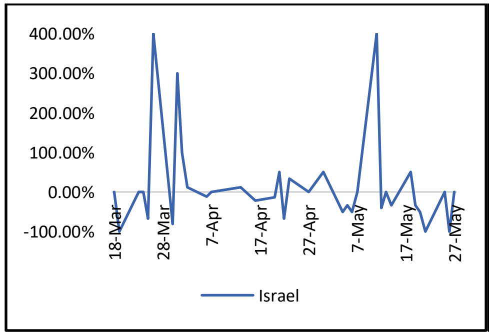


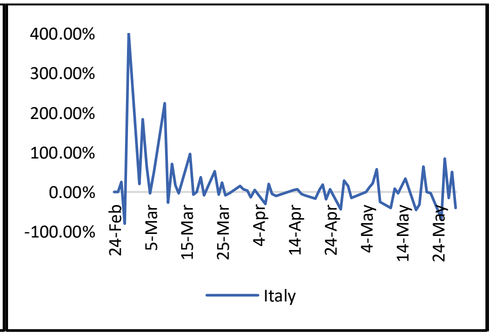


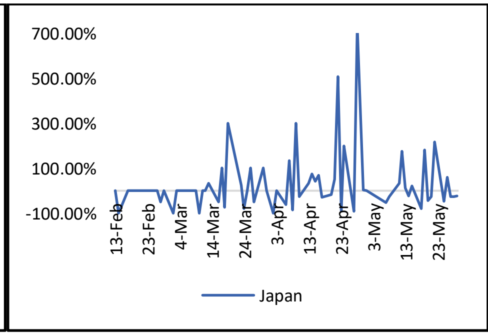


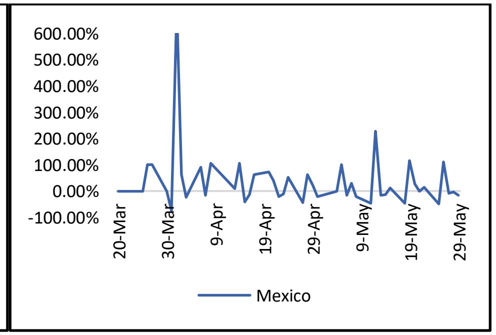


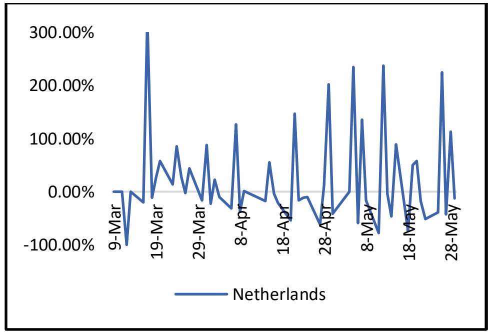


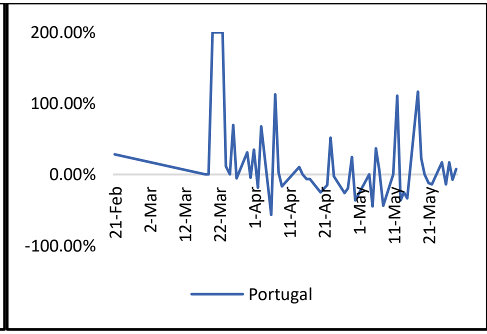


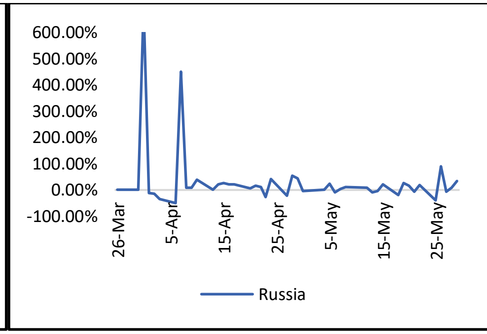


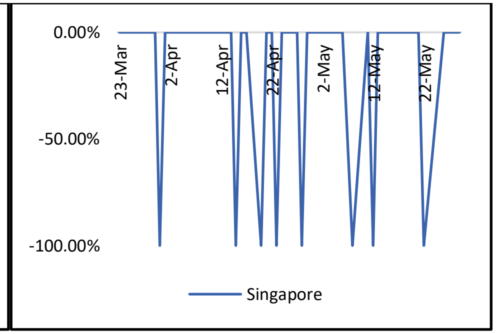


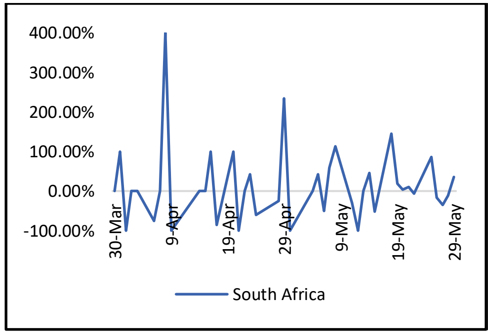


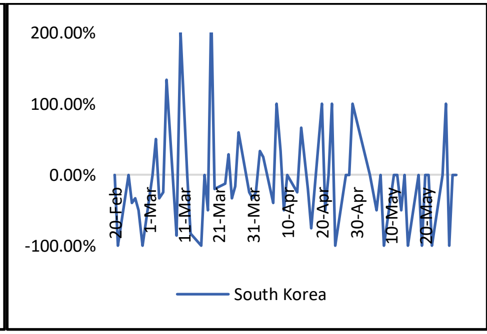

300.00%
200.00%
100.00%
0.00%
-100.00%
9-Mar
19-Mar
29-Mar
8-Apr
18-Apr
28-Apr
8-May
18-May
28-May
Netherlands

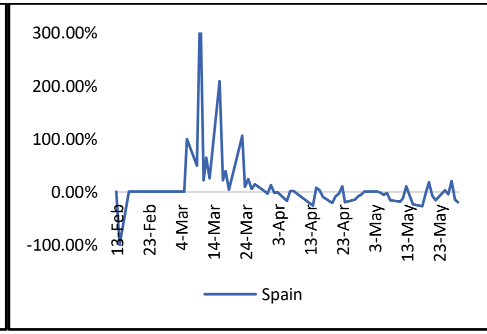

200.00%
100.00%
0.00%
-100.00%
21-Feb
2-Mar
12-Mar
22-Mar
1-Apr
11-Apr
21-Apr
1-May
11-May
21-May
Portugal

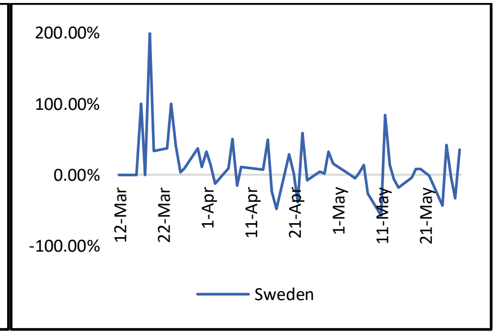

600.00%
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
26-Mar
5-Apr
15-Apr
25-Apr
5-May
15-May
25-May
Russia

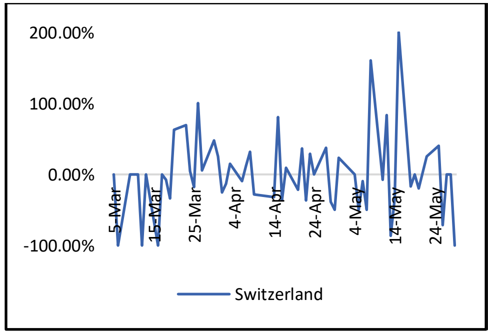

0.00%
-50.00%
-100.00%
23-Mar
2-Apr
12-Apr
22-Apr
2-May
12-May
22-May
Singapore

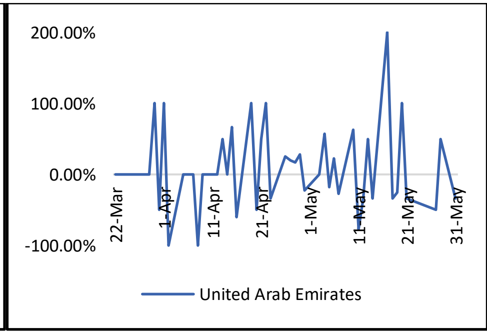

400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
30-Mar
9-Apr
19-Apr
29-Apr
9-May
19-May
29-May
South Africa

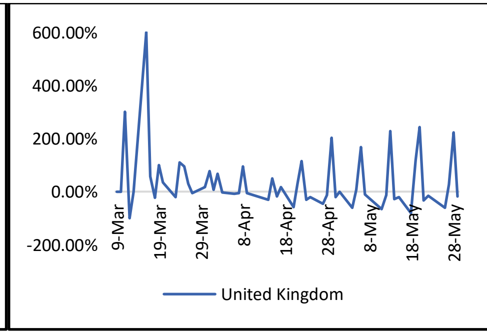

200.00%
100.00%
0.00%
-100.00%
20-Feb
1-Mar
11-Mar
21-Mar
31-Mar
10-Apr
20-Apr
30-Apr
10-May
20-May
South Korea

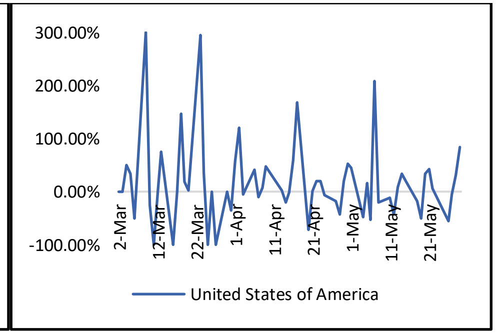

300.00%
200.00%
100.00%
0.00%
-100.00%
13-Feb
23-Feb
4-Mar
14-Mar
24-Mar
3-Apr
13-Apr
23-Apr
3-May
13-May
23-May
Spain


200.00%
100.00%
0.00%
-100.00%
12-Mar
22-Mar
1-Apr
11-Apr
21-Apr
1-May
11-May
21-May
Sweden

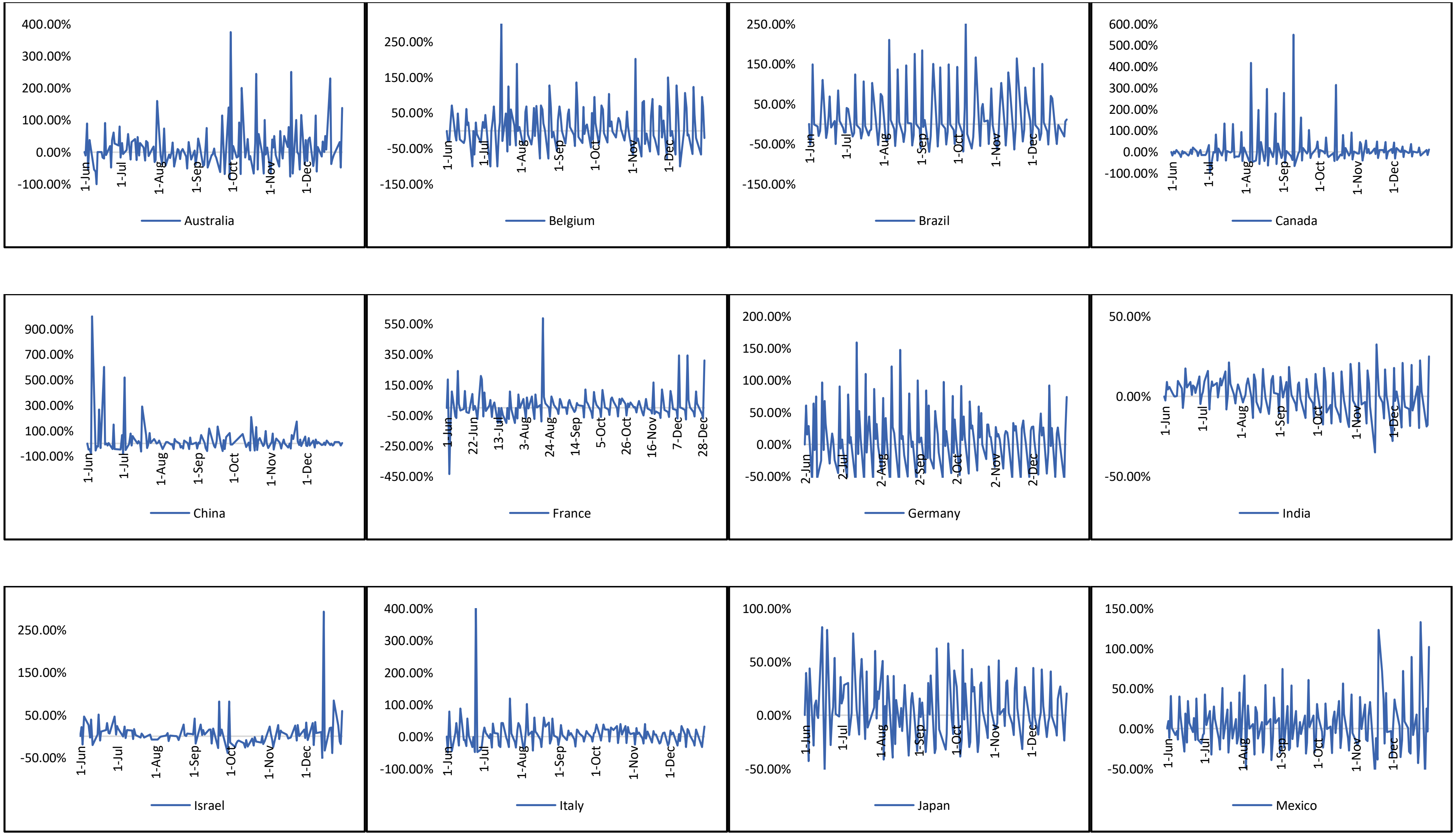

200.00%
100.00%
0.00%
-100.00%
5-Mar
15-Mar
25-Mar
4-Apr
14-Apr
24-Apr
4-May
14-May
24-May
Switzerland

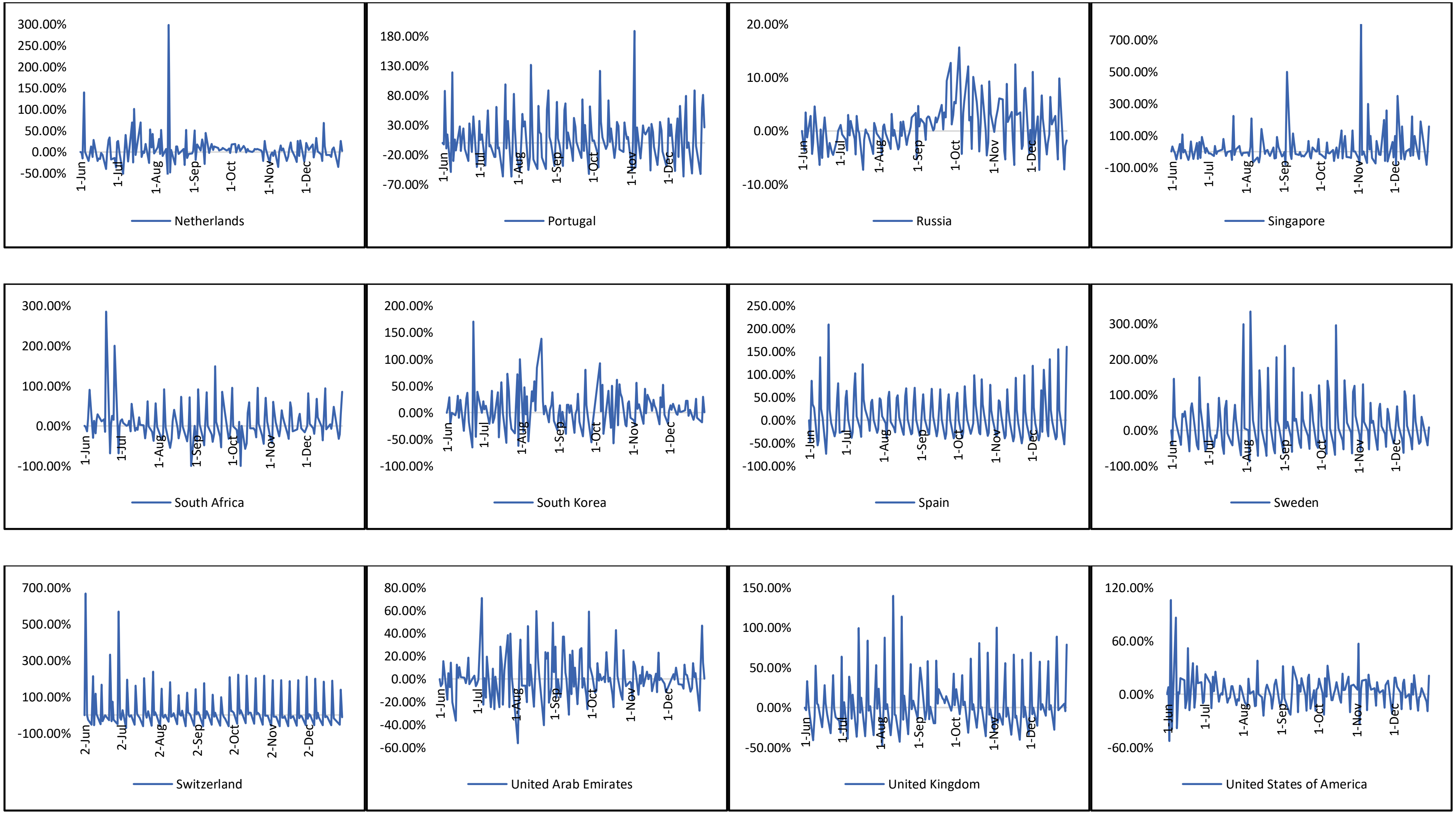

200.00%
100.00%
0.00%
-100.00%
22-Mar
1-Apr
11-Apr
21-Apr
1-May
11-May
21-May
31-May
United Arab Emirates


600.00%
400.00%
200.00%
0.00%
-200.00%
9-Mar
19-Mar
29-Mar
8-Apr
18-Apr
28-Apr
8-May
18-May
28-May
United Kingdom

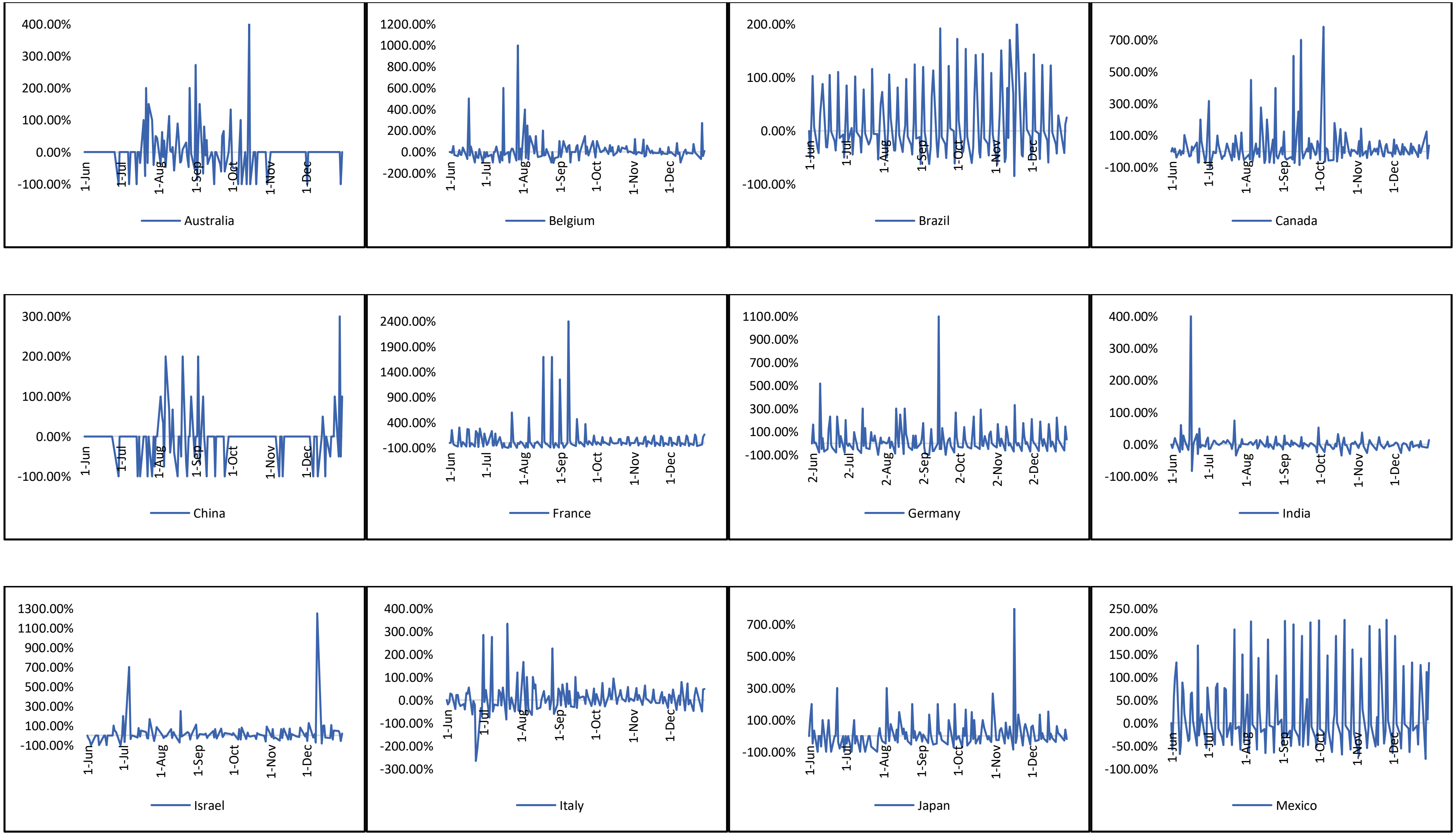

300.00%
200.00%
100.00%
0.00%
-100.00%
2-Mar
12-Mar
22-Mar
1-Apr
11-Apr
21-Apr
1-May
11-May
21-May
United States of America

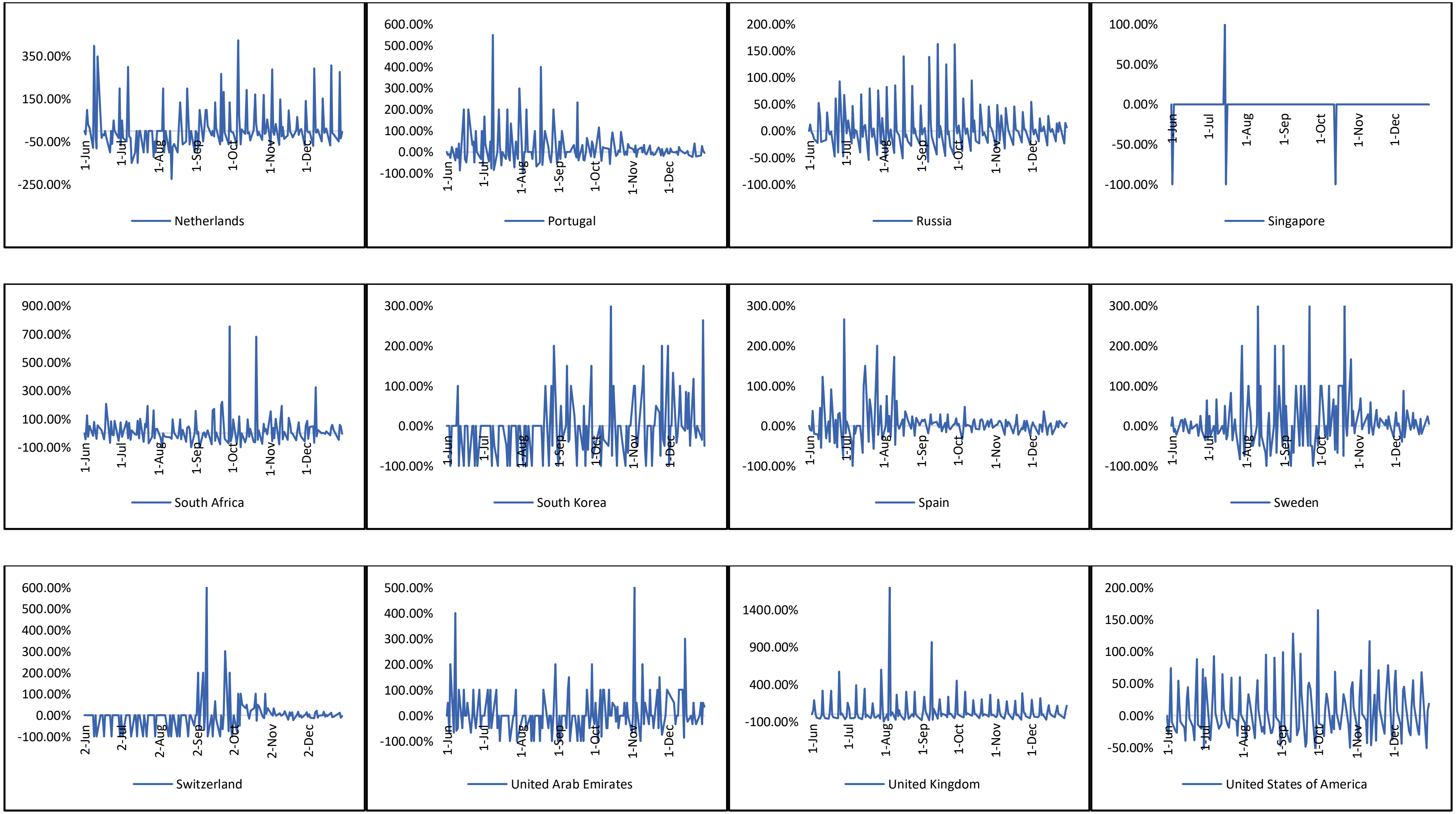
Appendix C – Growth in COVID-19 cases per country for the third subperiod (June 1, 2020 to December 31, 2020)



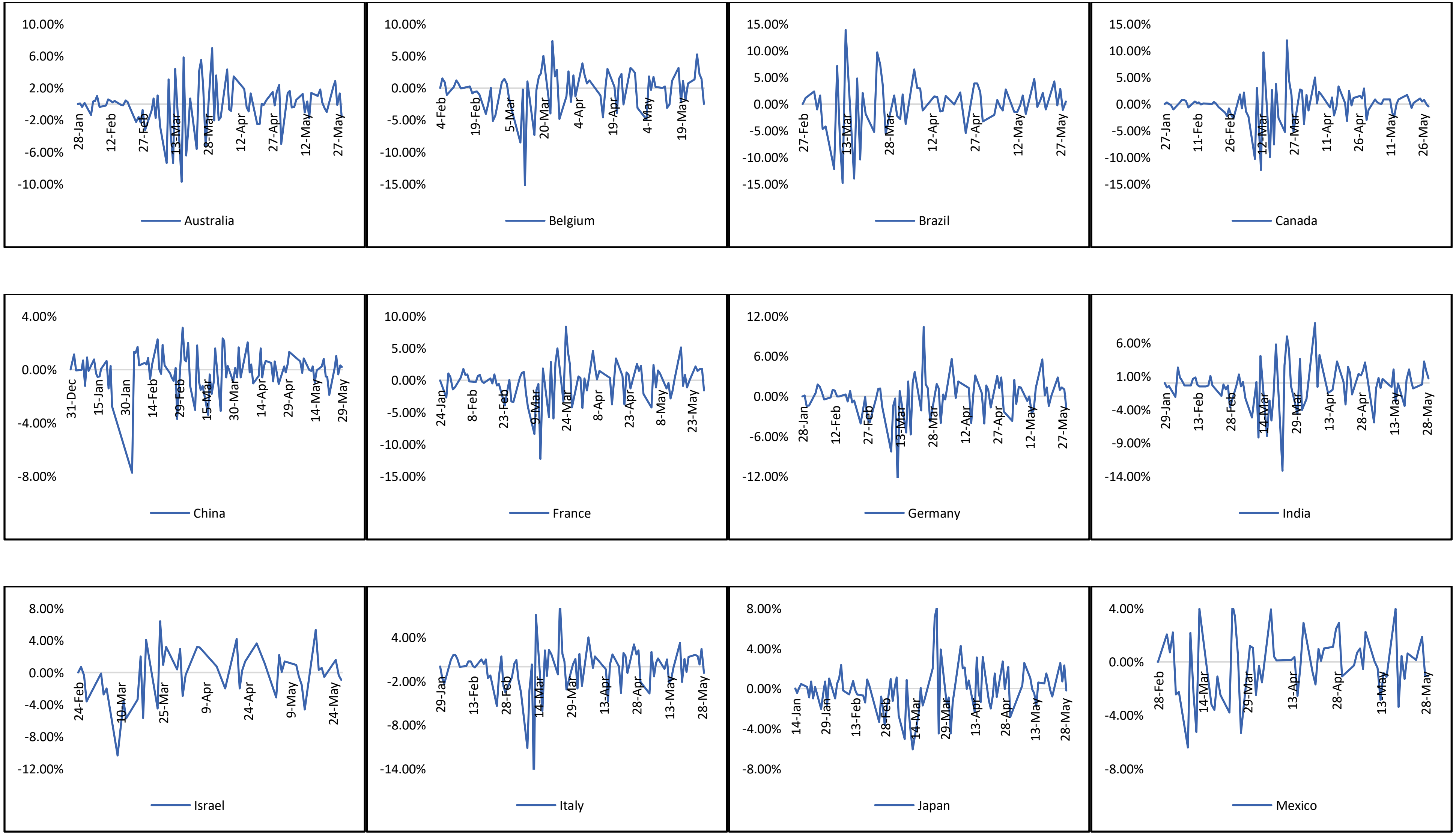

300.00%
250.00%
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Netherlands
180.00%
130.00%
80.00%
30.00%
-20.00%
-70.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Portugal
20.00%
10.00%
0.00%
-10.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Russia
700.00%
500.00%
300.00%
100.00%
-100.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Singapore
300.00%
200.00%
100.00%
0.00%
-100.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
South Africa
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
South Korea
250.00%
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Spain
300.00%
200.00%
100.00%
0.00%
-100.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Sweden
700.00%
500.00%
300.00%
100.00%
-100.00%
2-Jun
2-Jul
2-Aug
2-Sep
2-Oct
2-Nov
2-Dec
Switzerland
80.00%
60.00%
40.00%
20.00%
0.00%
-20.00%
-40.00%
-60.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
United Arab Emirates
150.00%
100.00%
50.00%
0.00%
-50.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
United Kingdom
120.00%
60.00%
0.00%
-60.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
United States of America

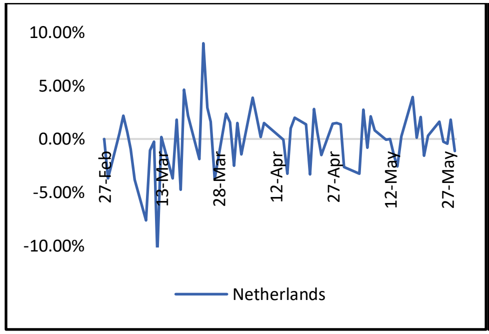
Appendix D – Growth in COVID-19 deaths per country for the third subperiod (June 1, 2020 to December 31, 2020)

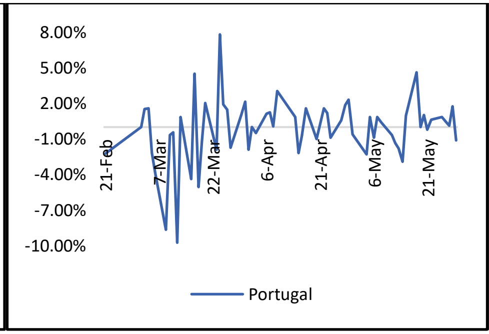


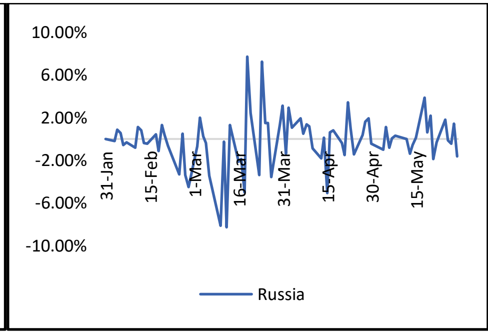

350.00%
150.00%
-50.00%
-250.00%
1-Jun
1-Jul
1-Aug
1-Sep
1-Oct
1-Nov
1-Dec
Netherlands
600.00%
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
Portugal
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
-100.00%
Russia
100.00%
50.00%
0.00%
-50.00%
-100.00%
Singapore
900.00%
700.00%
500.00%
300.00%
100.00%
-100.00%
South Africa
300.00%
200.00%
100.00%
0.00%
-100.00%
South Korea
Spain
Sweden
600.00%
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
2-Jun
2-Jul
2-Aug
2-Sep
2-Oct
2-Nov
2-Dec
Switzerland
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
United Arab Emirates
1400.00%
900.00%
400.00%
-100.00%
United Kingdom
200.00%
150.00%
100.00%
50.00%
0.00%
-50.00%
United States of America

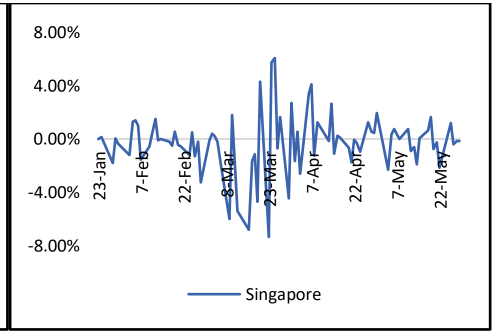
Appendix E – Stock market returns per country for the first subperiod (December 31, 2019 to May 31, 2020)

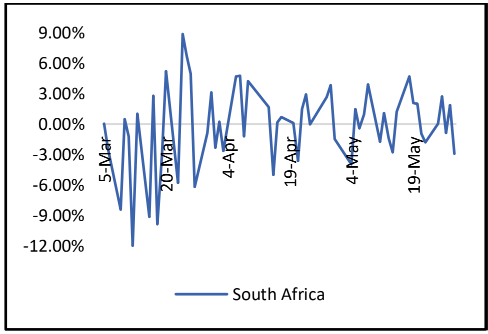


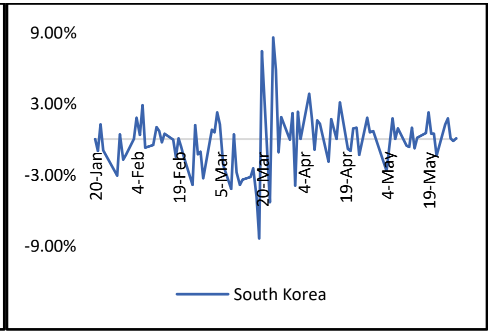

10.00%
5.00%
0.00%
-5.00%
-10.00%
27-Feb
13-Mar
28-Mar
12-Apr
27-Apr
12-May
27-May
Netherlands

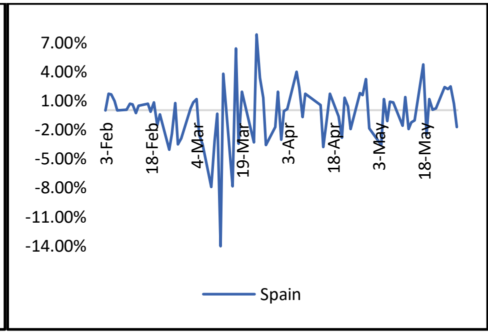

8.00%
5.00%
2.00%
-1.00%
-4.00%
-7.00%
-10.00%
21-Feb
7-Mar
22-Mar
6-Apr
21-Apr
6-May
21-May
Portugal

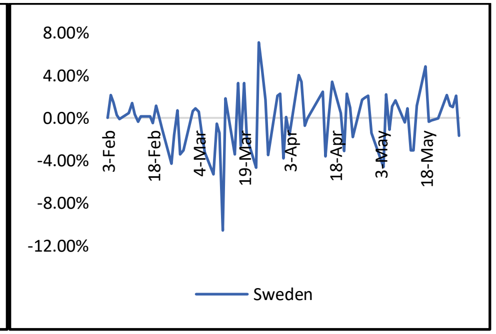

10.00%
6.00%
2.00%
-2.00%
-6.00%
-10.00%
31-Jan
15-Feb
1-Mar
16-Mar
31-Mar
15-Apr
30-Apr
15-May
Russia

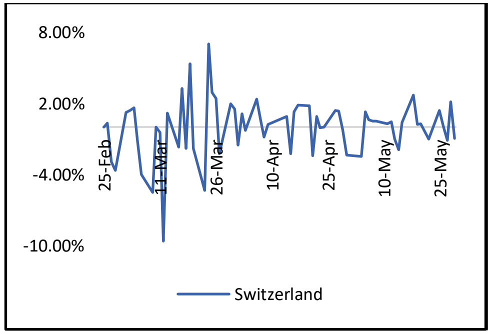

8.00%
4.00%
0.00%
-4.00%
-8.00%
23-Jan
7-Feb
22-Feb
8-Mar
23-Mar
7-Apr
22-Apr
7-May
22-May
Singapore

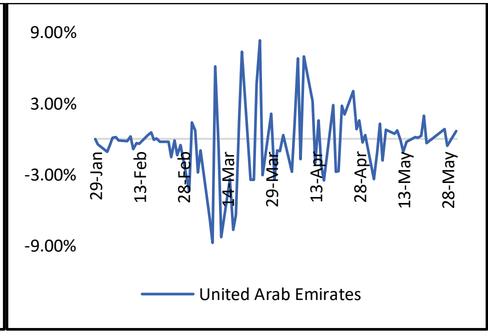

9.00%
6.00%
3.00%
0.00%
-3.00%
-6.00%
-9.00%
-12.00%
5-Mar
20-Mar
4-Apr
19-Apr
4-May
19-May
South Africa

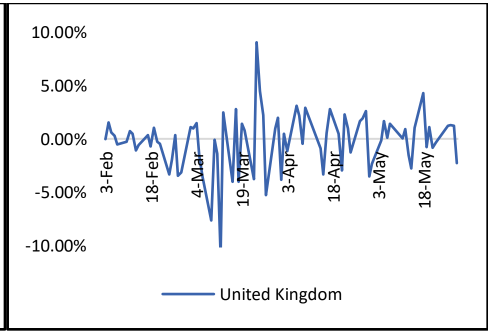

9.00%
3.00%
-3.00%
-9.00%
20-Jan
4-Feb
19-Feb
5-Mar
20-Mar
4-Apr
19-Apr
4-May
19-May
South Korea

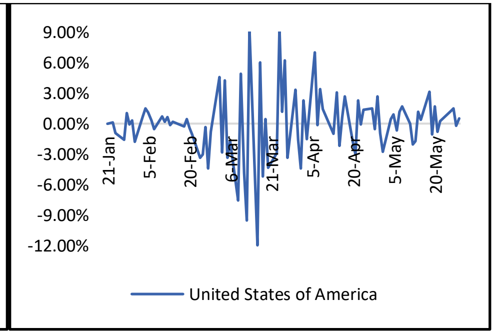

7.00%
4.00%
1.00%
-2.00%
-5.00%
-8.00%
-11.00%
-14.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
Spain


8.00%
4.00%
0.00%
-4.00%
-8.00%
-12.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
Sweden

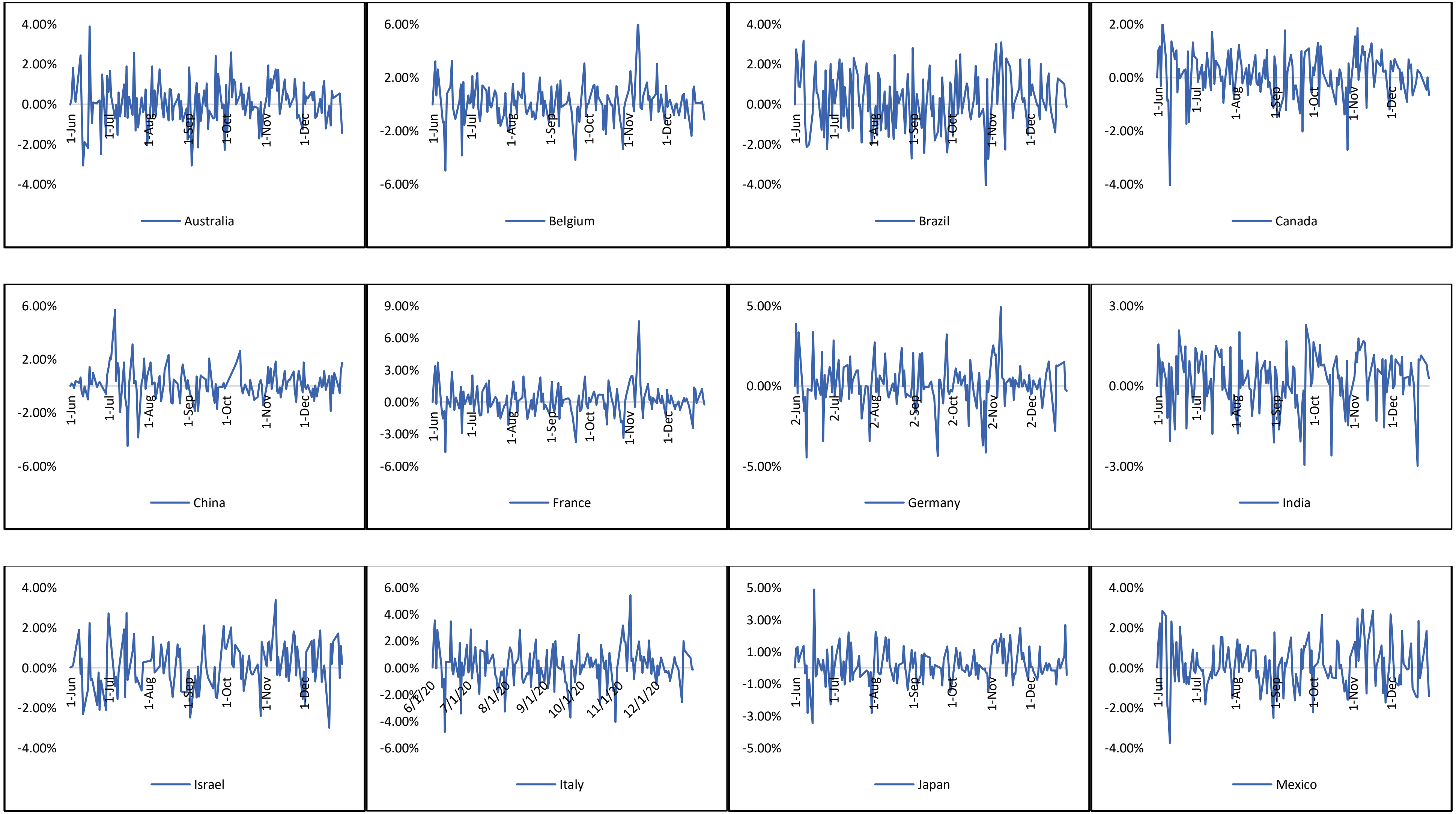

8.00%
2.00%
-4.00%
-10.00%
25-Feb
11-Mar
26-Mar
10-Apr
25-Apr
10-May
25-May
Switzerland

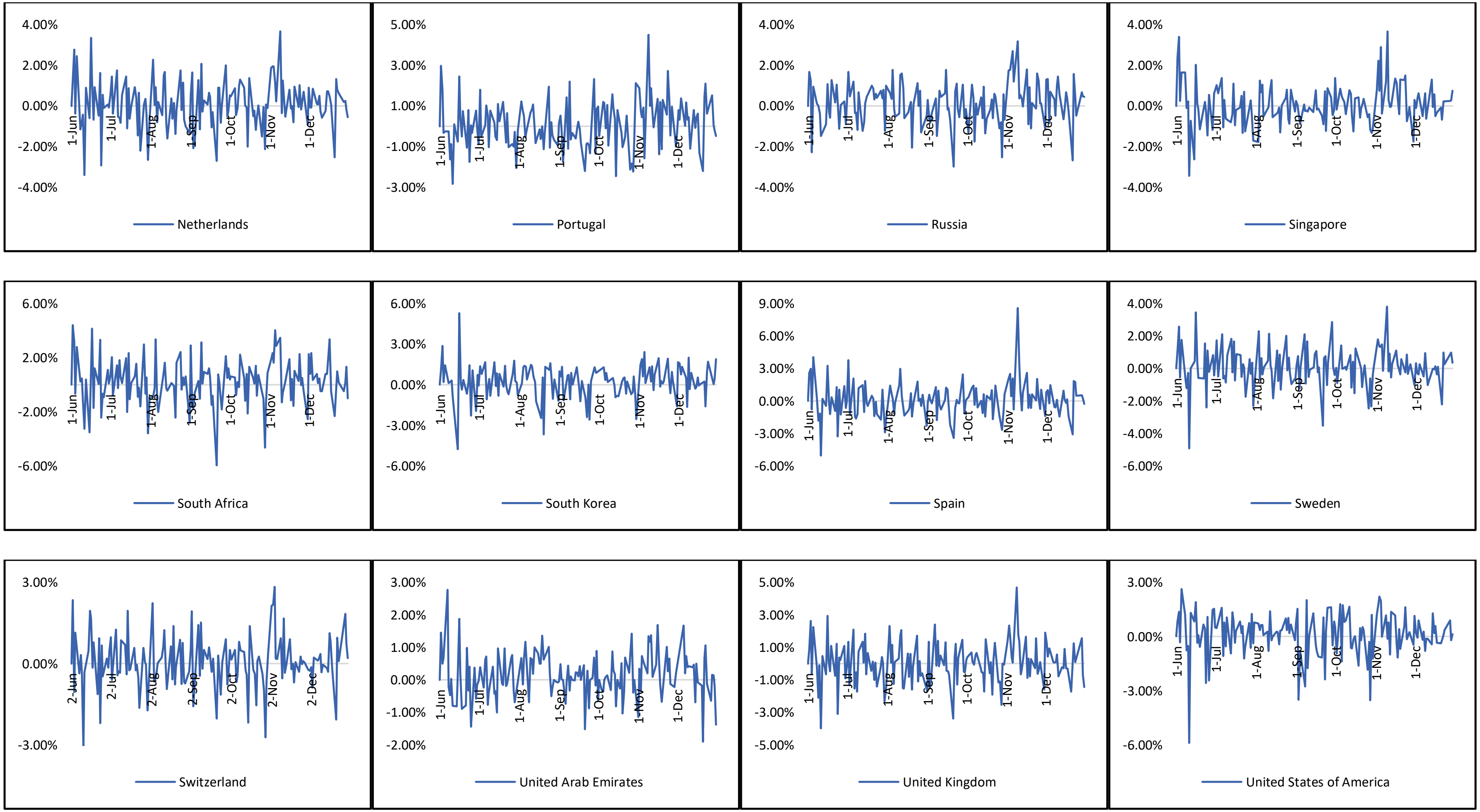

9.00%
3.00%
-3.00%
-9.00%
29-Jan
13-Feb
28-Feb
14-Mar
29-Mar
13-Apr
28-Apr
13-May
28-May
United Arab Emirates


10.00%
5.00%
0.00%
-5.00%
-10.00%
3-Feb
18-Feb
4-Mar
19-Mar
3-Apr
18-Apr
3-May
18-May
United Kingdom


9.00%
6.00%
3.00%
0.00%
-3.00%
-6.00%
-9.00%
-12.00%
21-Jan
5-Feb
20-Feb
6-Mar
21-Mar
5-Apr
20-Apr
5-May
20-May
United States of America

Appendix F – Stock market returns per country for the third subperiod (June 1, 2020 to December 31, 2020)




4.00%
2.00%
0.00%
-2.00%
-4.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Netherlands
5.00%
3.00%
1.00%
-1.00%
-3.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Portugal
4.00%
2.00%
0.00%
-2.00%
-4.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Russia
4.00%
2.00%
0.00%
-2.00%
-4.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Singapore
6.00%
2.00%
-2.00%
-6.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
South Africa
6.00%
3.00%
0.00%
-3.00%
-6.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
South Korea
9.00%
6.00%
3.00%
0.00%
-3.00%
-6.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Spain
4.00%
2.00%
0.00%
-2.00%
-4.00%
-6.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
Sweden
3.00%
0.00%
-3.00%
2-Jun 2-Jul 2-Aug 2-Sep 2-Oct 2-Nov 2-Dec
Switzerland
3.00%
2.00%
1.00%
0.00%
-1.00%
-2.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
United Arab Emirates
5.00%
3.00%
1.00%
-1.00%
-3.00%
-5.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
United Kingdom
3.00%
0.00%
-3.00%
-6.00%
1-Jun 1-Jul 1-Aug 1-Sep 1-Oct 1-Nov 1-Dec
United States of America

Appendix G – Maddala-Wu test

Variable	Test statistic	P-value
Panel A – subperiod 1 (December 31, 2019 to May 31, 2020)		
Daily stock market return	211.82	$< 2.2e^{-16}$***
Growth in cases	249.15	$< 2.2e^{-16}$***
Investment freedom	69.799	$2.502e^{-14}$***
Democratic Accountability	65.779	$1.763e^{-13}$***
Uncertainty avoidance	66.424	$1.289e^{-13}$***
Log (GDP)	66.96	$9.941e^{-14}$***
Panel B – subperiod 1 (January 11, 2020 to May 31, 2020)		
Daily stock market return	198.89	$< 2.2e^{-16}$***
Growth in deaths	193.17	$< 2.2e^{-16}$***
Investment freedom	64.271	$3.665e^{-13}$***
Democratic Accountability	61.587	$1.345e^{-12}$***
Uncertainty avoidance	62.8	$7.477e^{-13}$***
Log (GDP)	62.407	$9.045e^{-13}$***
Panel C – subperiod 3 (June 1, 2020 to December 31, 2020)		
Daily stock market return	289.05	$< 2.2e^{-16}$***
Growth in cases	204.05	$< 2.2e^{-16}$***
Growth in deaths	176.33	$< 2.2e^{-16}$***
Investment freedom	73.438	$4.264e^{-15}$***
Democratic Accountability	69.233	$3.295e^{-14}$***
Uncertainty avoidance	69.671	$2.664e^{-14}$***
Log (GDP)	70.032	$2.234e^{-14}$***

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Source: Own production

Appendix H – POLS for cases equation in the first subperiod (model 1 in table 11)

```
> pool <- plm(Y~ X1,data = pdata, model="pooling")
> summary(pool)
Pooling Model

Call:
plm(formula = Y ~ X1, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 47-98, N = 1881

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.1662764 -0.0122688  0.0021168  0.0147780  0.1423015

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept) -0.00142479  0.00068138 -2.0910  0.03666 *
X1          -0.00115367  0.00060543 -1.9055  0.05686 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.6091
Residual Sum of Squares: 1.606
R-Squared:      0.0019287
Adj. R-Squared: 0.0013975
F-statistic: 3.63104 on 1 and 1879 DF, p-value: 0.056864
```

Appendix I – POLS for cases equation in the first subperiod (model 2 in table 11)

```
> pooling <- plm(Y~ X1+X2+X3+X4+X5, data = pdata, model="pooling")
> summary(pooling)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 47-98, N = 1881

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.1662712 -0.0123281  0.0021619  0.0147631  0.1423636

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept) -1.2025e-02  1.6663e-02 -0.7216  0.47061
X1          -1.1946e-03  6.0870e-04 -1.9625  0.04985 *
X2           7.0985e-07  3.6047e-05  0.0197  0.98429
X3          -1.3511e-04  4.1783e-04 -0.3234  0.74646
X4           4.1511e-06  2.9772e-05  0.1394  0.88913
X5           3.9008e-04  5.5064e-04  0.7084  0.47878
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.6091
Residual Sum of Squares: 1.6055
R-Squared:      0.0022913
Adj. R-Squared: -0.00036924
F-statistic: 0.861217 on 5 and 1875 DF, p-value: 0.50645
```

Appendix J – POLS for cases equation in the first subperiod (model 3 in table 11)

```
> pols<- plm(Y~X1+X2+X3+X4+X5+Datedummy, data = pdata, model = 'pooling')
> summary(pols)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "pooling")

Unbalanced Panel: n = 24, T = 47-98, N = 1881

Residuals:
       Min.      1st Qu.       Median      3rd Qu.        Max.
-9.3599e-02 -7.6411e-03 -2.7376e-18  7.6334e-03  1.1239e-01

Coefficients:
                       Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)         -1.1752e-02  2.0477e-02 -0.5739  0.566089
X1                  -6.9006e-04  3.8617e-04 -1.7869  0.074123 .
X2                  -2.6575e-06  2.2690e-05 -0.1171  0.906775
X3                   7.2933e-05  2.6655e-04  0.2736  0.784412
X4                  -1.2094e-05  1.8033e-05 -0.6706  0.502533
X5                   3.9772e-04  3.3755e-04  1.1782  0.238858
Datedummy2020-01-02  1.0809e-02  2.4911e-02  0.4339  0.664401
Datedummy2020-01-03 -4.5770e-04  2.4908e-02 -0.0184  0.985341
Datedummy2020-01-06 -1.2255e-04  2.4908e-02 -0.0049  0.996075
```

(…)

```
Datedummy2020-05-29 -8.7608e-03  1.8484e-02 -0.4740  0.635602
Datedummy2020-05-31  8.6387e-03  2.5623e-02  0.3371  0.736063
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.1262
Residual Sum of Squares: 0.41006
R-Squared:      0.6359
Adj. R-Squared: 0.60479
F-statistic: 20.4408 on 108 and 1264 DF, p-value: < 2.22e-16
```

Appendix K – POLS for cases equation in the first subperiod (model 4 in table 11)

```
> print(pols.nw)

t test of coefficients:

                      Estimate  Std. Error t value  Pr(>|t|)
(Intercept)         -1.1752e-02  1.7718e-02 -0.6633 0.5072306
X1                  -6.9006e-04  3.6056e-04 -1.9139 0.0558003 .
X2                  -2.6575e-06  1.2789e-05 -0.2078 0.8354098
X3                   7.2933e-05  1.4877e-04  0.4902 0.6240307
X4                  -1.2094e-05  9.0632e-06 -1.3344 0.1822610
X5                   3.9772e-04  1.4892e-04  2.6706 0.0076407 **
Datedummy2020-01-02  1.0809e-02  2.2820e-02  0.4737 0.6357910
Datedummy2020-01-03 -4.5770e-04  2.3442e-02 -0.0195 0.9844244
Datedummy2020-01-06 -1.2255e-04  3.4064e-02 -0.0036 0.9971299
 (…)
Datedummy2020-05-25  1.7266e-02  1.7230e-02  1.0021 0.3164282
Datedummy2020-05-26  1.3440e-02  1.7782e-02  0.7558 0.4498622
Datedummy2020-05-27  8.5667e-03  1.7121e-02  0.5004 0.6168744
Datedummy2020-05-28  1.0929e-02  1.7523e-02  0.6237 0.5329183
Datedummy2020-05-29 -8.6378e-03  1.7223e-02 -0.5015 0.6160639
Datedummy2020-05-31  8.0675e-03  2.0170e-02  0.4000 0.6892225
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix L – F test, Hausman (1978) specification test and Breusch-Pagan LM for cases equation in the first subperiod

```
> pFtest(fixed, pols)

        F test for individual effects

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
F = 0.35547, df1 = 23, df2 = 1728, p-value = 0.998
alternative hypothesis: significant effects

> phtest(random, fixed)

        Hausman Test

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 4.6768, df = 129, p-value = 1
alternative hypothesis: one model is inconsistent

> plmtest(pols, data = pdata, type = 'bp')

        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 3.7228, df = 1, p-value = 0.05367
alternative hypothesis: significant effects
```

Appendix M – Pesaran (2004) and Breusch-Pagan LM; Breusch-Godfrey/Wooldridge test; Breusch-Pagan test and Jarque-Bera test for cases equation in the first subperiod

```
> pcdtest(pols, data = pdata, test = 'cd')

        Pesaran CD test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
z = 0.67717, p-value = 0.4983
alternative hypothesis: cross-sectional dependence

> pcdtest(pols, data = pdata, test = 'lm')

        Breusch-Pagan LM test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 331.7, df = 276, p-value = 0.01205
alternative hypothesis: cross-sectional dependence

> pbgtest(pols, data = pdata)

        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 196.04, df = 47, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors

> bptest(pols)

        studentized Breusch-Pagan test

data:  pols
BP = 438.44, df = 129, p-value < 2.2e-16

> jarque.bera.test(pols$residuals)

        Jarque Bera Test

data:  pols$residuals
X-squared = 2286, df = 2, p-value < 2.2e-16
```

Appendix N – Im, Pesaran and Shin (2003) test for cases equation in the first subperiod

```
> purtest(CASES,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  CASES
Wtbar = -18.498, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(STOCK,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  STOCK
Wtbar = -15.911, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(IF,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  IF
Wtbar = -7.2368, p-value = 2.296e-13
alternative hypothesis: stationarity
> purtest(UA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  UA
Wtbar = -6.7852, p-value = 5.794e-12
alternative hypothesis: stationarity
> purtest(DA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DA
Wtbar = -6.6876, p-value = 1.135e-11
alternative hypothesis: stationarity
> purtest(logGDP,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  logGDP
Wtbar = -6.8629, p-value = 3.373e-12
alternative hypothesis: stationarity
```

Appendix O – Robustness test for cases equation in the first subperiod (model 1 in table 13)

```
> print(pols.nw)

t test of coefficients:

                                   Estimate  Std. Error t value  Pr(>|t|)
(Intercept)                     -1.5320e-03  1.7242e-02 -0.0889 0.9292110
X1                              -6.9536e-04  3.6132e-04 -1.9245 0.0544523 .
Datedummy2020-01-02              1.0804e-02  2.2577e-02  0.4785 0.6323330
Datedummy2020-01-03             -4.5770e-04  2.3433e-02 -0.0195 0.9844186
Datedummy2020-01-06             -1.2255e-04  3.4056e-02 -0.0036 0.9971291
Datedummy2020-01-07              6.2431e-03  2.1247e-02  0.2938 0.7689154
Datedummy2020-01-08             -1.2210e-02  2.1632e-02 -0.5644 0.5725412
```

(…)

```
CountrydummySWEDEN               6.5100e-04  6.8140e-04  0.9554 0.3395145
CountrydummySWITZERLAND          9.1164e-04  7.3000e-04  1.2488 0.2119012
CountrydummyUNITED ARAB EMIRATES -5.6490e-04  1.3559e-03 -0.4166 0.6770007
CountrydummyUNITED KINGDOM       2.3296e-04  7.8309e-04  0.2975 0.7661240
CountrydummyUSA                  2.0807e-03  8.2781e-04  2.5135 0.0120429 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix P – Robustness test for cases equation in the first subperiod (model 5 in table 15)

```
> random<- plm(Y~X1+X2+X3+X4+X5+Datedummy,data = pdata,model = 'random', random.method = 'nerlove')
> summary(random)
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "random", random.method = "nerlove")

Unbalanced Panel: n = 13, T = 118-153, N = 1881

Effects:
                    var   std.dev share
idiosyncratic 2.883e-04 1.698e-02 0.998
individual    6.998e-07 8.365e-04 0.002
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1183  0.1407  0.1430  0.1402  0.1446  0.1461

Residuals:
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-0.093750 -0.007638  0.000023  0.000000  0.007671  0.112455

Coefficients:
                       Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)          -1.1103e-02  2.0839e-02 -0.5328 0.5941813
X1                   -6.8792e-04  3.8635e-04 -1.7806 0.0749813 .
X2                   -1.2008e-06  2.3663e-05 -0.0507 0.9595300
X3                    8.7612e-05  2.8695e-04  0.3053 0.7601200
X4                   -1.3897e-05  1.8983e-05 -0.7321 0.4641266
X5                    3.7435e-04  3.6259e-04  1.0324 0.3018650
Datedummy2020-01-02  1.0811e-02  2.4906e-02  0.4341 0.6642316
Datedummy2020-01-03 -4.5770e-04  2.4903e-02 -0.0184 0.9853363
Datedummy2020-01-06 -1.2255e-04  2.4903e-02 -0.0049 0.9960735
(…)
Datedummy2020-05-29 -8.6891e-03  1.8063e-02 -0.4811 0.6304779
Datedummy2020-05-31  8.1149e-03  2.5022e-02  0.3243 0.7457075
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.6087
Residual Sum of Squares: 0.54296
R-Squared:      0.66249
Adj. R-Squared: 0.63762
Chisq: 3436.88 on 129 DF, p-value: < 2.22e-16
```

Appendix Q – Pooled OLS for deaths equation in the second subperiod (model 9 in table 12)

```
> pool <- plm(Y~ X1,data = pdata, model="pooling")
> summary(pool)
Pooling Model

Call:
plm(formula = Y ~ X1, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 35-90, N = 1373

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.1702726 -0.0134069  0.0010586  0.0152956  0.1179925

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  0.00116226  0.00078439  1.4817   0.1386
X1          -0.00097042  0.00089461 -1.0847   0.2782

Total Sum of Squares:    1.1262
Residual Sum of Squares: 1.1253
R-Squared:      0.00085753
Adj. R-Squared: 0.00012876
F-statistic: 1.17668 on 1 and 1371 DF, p-value: 0.27822
```

Appendix R – Pooled OLS for deaths equation in the second subperiod (model 10 in table 12)

```
> pooling <- plm(Y~ X1+X2+X3+X4+X5, data = pdata, model="pooling")
> summary(pooling)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 35-90, N = 1373

Residuals:
      Min.     1st Qu.      Median     3rd Qu.        Max.
-0.16962249 -0.01345570 0.00086587  0.01505168  0.11741166

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  2.3508e-02  2.0080e-02  1.1707   0.2419
X1          -9.0802e-04  8.9708e-04 -1.0122   0.3116
X2          -2.9759e-05  4.3019e-05 -0.6918   0.4892
X3           3.9677e-04  5.2400e-04  0.7572   0.4491
X4          -3.6023e-05  3.5519e-05 -1.0142   0.3107
X5          -7.1136e-04  6.5563e-04 -1.0850   0.2781

Total Sum of Squares:    1.1262
Residual Sum of Squares: 1.1234
R-Squared:      0.0024696
Adj. R-Squared: -0.001179
F-statistic: 0.676872 on 5 and 1367 DF, p-value: 0.64103
```

Appendix S – Pooled OLS for deaths equation in the second subperiod (model 11 in table 12)

```
> pols<- plm(Y~X1+X2+X3+X4+X5+Datedummy, data = pdata, model = 'pooling')
> summary(pols)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "pooling")

Unbalanced Panel: n = 24, T = 35-90, N = 1373

Residuals:
      Min.      1st Qu.       Median      3rd Qu.        Max.
-9.4799e-02 -8.9690e-03 -1.1899e-17  8.9566e-03  9.1767e-02

Coefficients:
                       Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)         -8.4534e-03  2.2288e-02 -0.3793  0.704543
X1                  -2.6637e-04  6.0611e-04 -0.4395  0.660390
X2                   6.6308e-06  2.8668e-05  0.2313  0.817121
X3                  -3.5533e-05  3.5104e-04 -0.1012  0.919390
X4                  -1.9357e-05  2.2790e-05 -0.8494  0.395827
X5                   2.9534e-04  4.2226e-04  0.6994  0.484416
Datedummy2020-01-14 -2.8085e-03  2.5472e-02 -0.1103  0.912223
Datedummy2020-01-15 -5.4010e-03  2.5472e-02 -0.2120  0.832112
(…)
Datedummy2020-05-28  1.0862e-02  1.8467e-02  0.5882  0.556508
Datedummy2020-05-29 -8.7608e-03  1.8484e-02 -0.4740  0.635602
Datedummy2020-05-31  8.6387e-03  2.5623e-02  0.3371  0.736063
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.1262
Residual Sum of Squares: 0.41006
R-Squared:      0.6359
Adj. R-Squared: 0.60479
F-statistic: 20.4408 on 108 and 1264 DF, p-value: < 2.22e-16
```

Appendix T – Pooled OLS for deaths equation in the second subperiod (model 12 in table 12)

```
> print(pols.nw)

t test of coefficients:

                      Estimate  Std. Error    t value  Pr(>|t|)
(Intercept)        -8.4534e-03  1.0114e-02 -8.3580e-01 0.4034223
X1                 -2.6637e-04  6.2182e-04 -4.2840e-01 0.6684499
X2                  6.6308e-06  2.8677e-05  2.3120e-01 0.8171757
X3                 -3.5533e-05  3.1416e-04 -1.1310e-01 0.9099662
X4                 -1.9357e-05  1.8827e-05 -1.0282e+00 0.3040572
X5                  2.9534e-04  3.2717e-04  9.0270e-01 0.3668471
Datedummy2020-01-14 -2.8085e-03  4.4133e-09 -6.3636e+05 < 2.2e-16 ***
(…)
Datedummy2020-05-29 -8.7608e-03  2.6154e-03 -3.3496e+00 0.0008331 ***
Datedummy2020-05-31  8.6387e-03  2.4279e-03  3.5581e+00 0.0003874 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix U – F test, Hausman (1978) specification test and Breusch-Pagan LM for deaths equation in the second subperiod

```
> pFtest(fixed, pols)

        F test for individual effects

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
F = 0.81842, df1 = 23, df2 = 1241, p-value = 0.7105
alternative hypothesis: significant effects

> phtest(random, fixed)

        Hausman Test

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 14.138, df = 108, p-value = 1
alternative hypothesis: one model is inconsistent

> plmtest(pols, data = pdata, type = 'bp')

        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 1.9922, df = 1, p-value = 0.1581
alternative hypothesis: significant effects
```

Appendix V – Pesaran (2004) and Breusch-Pagan LM; Breusch-Godfrey/Wooldridge test; Breusch-Pagan test and Jarque-Bera test for deaths equation in the second subperiod

```
> pcdtest(pols, data = pdata, test = 'cd')

        Pesaran CD test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
z = 0.085632, p-value = 0.9318
alternative hypothesis: cross-sectional dependence

> pcdtest(pols, data = pdata, test = 'lm')

        Breusch-Pagan LM test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 294.35, df = 276, p-value = 0.2141
alternative hypothesis: cross-sectional dependence

> pbgtest(pols, data = pdata)

        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 145.51, df = 35, p-value = 1.995e-15
alternative hypothesis: serial correlation in idiosyncratic errors

> bptest(pols)

        studentized Breusch-Pagan test

data:  pols
BP = 324.86, df = 108, p-value < 2.2e-16

> jarque.bera.test(pols$residuals)

        Jarque Bera Test

data:  pols$residuals
X-squared = 963.14, df = 2, p-value < 2.2e-16
```

Appendix W – Im, Pesaran and Shin (2003) test for deaths equation in the second subperiod

```
> purtest(STOCK,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  STOCK
Wtbar = -15.214, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(IF,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  IF
Wtbar = -6.8816, p-value = 2.96e-12
alternative hypothesis: stationarity
> purtest(DA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DA
Wtbar = -6.5245, p-value = 3.411e-11
alternative hypothesis: stationarity
> purtest(UA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  UA
Wtbar = -6.6923, p-value = 1.098e-11
alternative hypothesis: stationarity
> purtest(logGDP,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  logGDP
Wtbar = -6.6392, p-value = 1.577e-11
alternative hypothesis: stationarity

> purtest(DEATHS,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DEATHS
Wtbar = -14.996, p-value < 2.2e-16
alternative hypothesis: stationarity
```

Appendix X – Robustness test for deaths equation in the second subperiod (model 3 in table 14)

```
> print(pols.nw)

t test of coefficients:

                               Estimate  Std. Error    t value  Pr(>|t|)
(Intercept)                 -2.6106e-03  2.9866e-03 -8.7410e-01 0.3822382
X1                          -3.1078e-04  6.2660e-04 -4.9600e-01 0.6199965
(…)
CountrydummyUNITED ARAB EMIRATES -1.5753e-03  3.4492e-03 -4.5670e-01 0.6479541
CountrydummyUNITED KINGDOM    2.6934e-03  2.5017e-03  1.0766e+00 0.2818629
CountrydummyUSA               2.5117e-03  2.7890e-03  9.0060e-01 0.3679937
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix Y – Robustness test for deaths equation in the second subperiod (model 7 in table 16)

```
> random<- plm(Y~X1+X2+X3+X4+X5+Datedummy,data = pdata,model = 'random', random.method = 'nerlove')
> summary(random)
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "random", random.method = "nerlove")

Unbalanced Panel: n = 24, T = 35-90, N = 1373

Effects:
                   var   std.dev share
idiosyncratic 2.942e-04 1.715e-02 0.969
individual    9.288e-06 3.048e-03 0.031
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.3107  0.3772  0.3989  0.4072  0.4363  0.4898

Residuals:
     Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-0.094243 -0.008699  0.000272  0.000000  0.008738  0.091424

Coefficients:
                       Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)          1.4408e-03  2.4854e-02  0.0580  0.953770
X1                  -3.2769e-04  6.0883e-04 -0.5382  0.590420
X2                   1.7746e-05  3.7204e-05  0.4770  0.633359
X3                  -2.3460e-04  4.6347e-04 -0.5062  0.612728
X4                  -3.0551e-05  3.0374e-05 -1.0058  0.314504
X5                  -7.5214e-05  5.5652e-04 -0.1352  0.892493
Datedummy2020-01-14 -2.8085e-03  2.5377e-02 -0.1107  0.911877
Datedummy2020-01-15 -5.4010e-03  2.5377e-02 -0.2128  0.831457
Datedummy2020-01-16 -5.4923e-03  2.5384e-02 -0.2164  0.828700
```

(…)

```
Datedummy2020-05-29 -7.2550e-03  1.8553e-02 -0.3910  0.695767
Datedummy2020-05-31  9.8334e-03  2.5764e-02  0.3817  0.702706
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.1169
Residual Sum of Squares: 0.407
R-Squared:      0.63562
Adj. R-Squared: 0.60448
Chisq: 2204.88 on 108 DF, p-value: < 2.22e-16
```

Appendix Z – Pooled OLS for cases equation in the third subperiod (model 5 in table 11)

```
> pool <- plm(Y~ X1,data = pdata, model="pooling")
> summary(pool)
Pooling Model

Call:
plm(formula = Y ~ X1, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.06096922 -0.00662131 -0.00036739  0.00687741  0.08419804

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  0.00130752  0.00020982  6.2318 5.15e-10 ***
X1          -0.00056197  0.00033447 -1.6802  0.09301 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.54122
R-Squared:      0.00079124
Adj. R-Squared: 0.00051096
F-statistic: 2.82301 on 1 and 3565 DF, p-value: 0.09301
```

Appendix AA – Pooled OLS for cases equation in the third subperiod (model 6 in table 11)

```
> pooling <- plm(Y~ X1+X2+X3+X4+X5, data = pdata, model="pooling")
> summary(pooling)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.06123203 -0.00655593 -0.00036769  0.00693224  0.08441331

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  1.0458e-03  5.1070e-03  0.2048   0.8378
X1          -5.4369e-04  3.3525e-04 -1.6218   0.1049
X2          -1.4694e-05  1.1244e-05 -1.3068   0.1914
X3           2.4752e-05  1.2983e-04  0.1907   0.8488
X4           8.4705e-07  9.2396e-06  0.0917   0.9270
X5           3.8791e-05  1.6932e-04  0.2291   0.8188

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.54094
R-Squared:      0.00131
Adj. R-Squared: -9.2309e-05
F-statistic: 0.934171 on 5 and 3561 DF, p-value: 0.4575
```

Appendix AB – Pooled OLS for cases equation in the third subperiod (model 7 in table 11)

```
> pols<- plm(Y~X1+X2+X3+X4+X5+Datedummy, data = pdata, model = 'pooling')
> summary(pols)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.0413013 -0.0049590 -0.0002400  0.0049689  0.0525578

Coefficients:
                      Estimate  Std. Error  t-value  Pr(>|t|)
(Intercept)         1.2266e-04  4.1723e-03   0.0294 0.9765491
X1                 -1.9973e-04  2.5623e-04  -0.7795 0.4357428
X2                 -1.5818e-05  8.3824e-06  -1.8871 0.0592349 .
X3                  3.6142e-05  9.8391e-05   0.3673 0.7133987
X4                 -2.1495e-07  6.7194e-06  -0.0320 0.9744825
X5                  2.7599e-05  1.2323e-04   0.2240 0.8228054
Datedummy2020-06-02  1.4563e-02  2.6413e-03   5.5134 3.785e-08 ***
(…)
Datedummy2020-12-30  1.7832e-03  2.6706e-03   0.6677 0.5043608
Datedummy2020-12-31 -6.8139e-03  3.3075e-03  -2.0601 0.0394626 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.27066
R-Squared:      0.5003
Adj. R-Squared: 0.4728
F-statistic: 18.1937 on 186 and 3380 DF, p-value: < 2.22e-16
```

Appendix AC – Pooled OLS for cases equation in the third subperiod (model 8 in table 11)

```
> print(pols.nw)

t test of coefficients:

                      Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)         1.2266e-04  3.1132e-03   0.0394 0.9685750
X1                 -1.9973e-04  2.6085e-04  -0.7657 0.4439076
X2                 -1.5818e-05  8.9771e-06  -1.7621 0.0781468 .
X3                  3.6142e-05  9.6341e-05   0.3751 0.7075768
X4                 -2.1495e-07  5.7869e-06  -0.0371 0.9703721
X5                  2.7599e-05  1.0776e-04   0.2561 0.7978773
Datedummy2020-06-02  1.4563e-02  2.1431e-03   6.7950 1.275e-11 ***
(…)

Datedummy2020-12-30  1.7832e-03  1.2793e-03   1.3939 0.1634443
Datedummy2020-12-31 -6.8139e-03  2.6960e-03  -2.5274 0.0115358 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix AD – F test, Hausman (1978) specification test and Breusch-Pagan LM for cases equation in the third subperiod

```
> pFtest(fixed, pols)

        F test for individual effects

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
F = 0.33143, df1 = 23, df2 = 3357, p-value = 0.9989
alternative hypothesis: significant effects

> phtest(random, fixed)

        Hausman Test

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 4.0646, df = 186, p-value = 1
alternative hypothesis: one model is inconsistent

> plmtest(pols, data = pdata, type = 'bp')

        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 5.7891, df = 1, p-value = 0.01613
alternative hypothesis: significant effects
```

Appendix AE – Pesaran (2004) and Breusch-Pagan LM; Breusch-Godfrey/Wooldridge test; Breusch-Pagan test and Jarque-Bera test for cases equation in the third subperiod

```
> pcdtest(pols, data = pdata, test = 'cd')

	Pesaran CD test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
z = -0.98074, p-value = 0.3267
alternative hypothesis: cross-sectional dependence

> pcdtest(pols, data = pdata, test = 'lm')

	Breusch-Pagan LM test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 318.02, df = 276, p-value = 0.04153
alternative hypothesis: cross-sectional dependence

> pbgtest(pols, data = pdata)

	Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 232.78, df = 122, p-value = 6.224e-09
alternative hypothesis: serial correlation in idiosyncratic errors

> bptest(pols)

	studentized Breusch-Pagan test

data:  pols
BP = 531.82, df = 186, p-value < 2.2e-16

> jarque.bera.test(pols$residuals)

	Jarque Bera Test

data:  pols$residuals
X-squared = 423.25, df = 2, p-value < 2.2e-16
```

Appendix AF – Im, Pesaran and Shin (2003) test for cases equation in the third subperiod

```
> purtest(CASES,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  CASES
Wtbar = -15.432, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(STOCK,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  STOCK
Wtbar = -21.777, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(IF,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  IF
Wtbar = -7.5002, p-value = 3.186e-14
alternative hypothesis: stationarity
> purtest(UA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  UA
Wtbar = -7.0108, p-value = 1.185e-12
alternative hypothesis: stationarity
> purtest(DA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DA
Wtbar = -6.9468, p-value = 1.868e-12
alternative hypothesis: stationarity
> purtest(logGDP,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  logGDP
Wtbar = -7.0624, p-value = 8.182e-13
alternative hypothesis: stationarity
```

Appendix AG – Robustness test for cases equation in the third subperiod (model 2 in table 13)

```
> print(pols.nw)

t test of coefficients:

                              Estimate  Std. Error    t value  Pr(>|t|)
(Intercept)                -2.6106e-03  2.9866e-03 -8.7410e-01 0.3822382
X1                         -3.1078e-04  6.2660e-04 -4.9600e-01 0.6199965
(…)
CountrydummyUNITED KINGDOM   2.6934e-03  2.5017e-03  1.0766e+00 0.2818629
CountrydummyUSA              2.5117e-03  2.7890e-03  9.0060e-01 0.3679937
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix AH – Robustness test for cases equation in the third subperiod (model 6 in table 15)

```
> random<- plm(Y~X1+X2+X3+X4+X5+Datedummy,data = pdata,model = 'random', random.method = 'nerlove')
> summary(random)
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "random", random.method = "nerlove")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Effects:
                    var   std.dev share
idiosyncratic 7.571e-05 8.701e-03 0.996
individual    3.167e-07 5.627e-04 0.004
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1863  0.2141  0.2161  0.2149  0.2181  0.2221

Residuals:
     Min.    1st Qu.    Median      Mean    3rd Qu.      Max.
-0.041150 -0.004998 -0.000270 -0.000001  0.004981  0.052553

Coefficients:
                       Estimate  Std. Error  z-value  Pr(>|z|)
(Intercept)          5.1143e-04  4.8757e-03   0.1049 0.9164594
X1                  -1.8953e-04  2.5668e-04  -0.7384 0.4602822
X2                  -1.5450e-05  1.0168e-05  -1.5194 0.1286553
X3                   2.9387e-05  1.2021e-04   0.2445 0.8068758
X4                  -3.7981e-07  8.1776e-06  -0.0464 0.9629556
X5                   1.5141e-05  1.4947e-04   0.1013 0.9193111
Datedummy2020-06-02  1.4557e-02  2.6405e-03   5.5129 3.530e-08 ***
Datedummy2020-06-03  2.1404e-02  2.6414e-03   8.1033 5.350e-16 ***
Datedummy2020-06-04 -2.1889e-03  2.6406e-03  -0.8289 0.4071440
```

(…)

```
Datedummy2020-12-30  1.7525e-03  2.6701e-03   0.6564 0.5115981
Datedummy2020-12-31 -6.8166e-03  3.3078e-03  -2.0608 0.0393237 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.54126
Residual Sum of Squares: 0.27045
R-Squared:      0.50034
Adj. R-Squared: 0.47284
Chisq: 3384.51 on 186 DF, p-value: < 2.22e-16
```

Appendix AI – POLS for deaths equation in the third subperiod (model 13 in table 12)

```
> pool <- plm(Y~ X1,data = pdata, model="pooling")
> summary(pool)
Pooling Model

Call:
plm(formula = Y ~ X1, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.06087223 -0.00662000 -0.00038354  0.00683614  0.08443855

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  0.00126383  0.00020867  6.0566 1.534e-09 ***
X1          -0.00012162  0.00018288 -0.6651    0.5061
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.54159
R-Squared:      0.00012405
Adj. R-Squared: -0.00015642
F-statistic: 0.442303 on 1 and 3565 DF, p-value: 0.50606
```

Appendix AJ – POLS for deaths equation in the third subperiod (model 14 in table 12)

```
> pooling <- plm(Y~ X1+X2+X3+X4+X5, data = pdata, model="pooling")
> summary(pooling)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = pdata, model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.06113222 -0.00654928 -0.00042496  0.00692403  0.08463774

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  9.0008e-04  5.1089e-03  0.1762   0.8602
X1          -1.1558e-04  1.8315e-04 -0.6310   0.5281
X2          -1.5230e-05  1.1242e-05 -1.3547   0.1756
X3           3.2574e-05  1.2984e-04  0.2509   0.8019
X4           1.4903e-06  9.2399e-06  0.1613   0.8719
X5           4.0784e-05  1.6938e-04  0.2408   0.8097

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.54128
R-Squared:      0.00068406
Adj. R-Squared: -0.00071908
F-statistic: 0.48752 on 5 and 3561 DF, p-value: 0.78583
```

Appendix AK – POLS for deaths equation in the third subperiod (model 15 in table 12)

```
> pols<- plm(Y~X1+X2+X3+X4+X5+Datedummy, data = pdata, model = 'pooling')
> summary(pols)
Pooling Model

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "pooling")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.04113151 -0.00496709 -0.00023989  0.00498054  0.05260310

Coefficients:
                       Estimate  Std. Error  t-value  Pr(>|t|)
(Intercept)          6.9183e-05  4.1734e-03   0.0166 0.9867749
X1                  -6.4974e-05  1.3744e-04  -0.4727 0.6364279
X2                  -1.5960e-05  8.3798e-06  -1.9046 0.0569197 .
X3                   3.9199e-05  9.8389e-05   0.3984 0.6903565
X4                   4.7443e-08  6.7178e-06   0.0071 0.9943656
X5                   2.8651e-05  1.2325e-04   0.2325 0.8161958
Datedummy2020-06-02  1.4559e-02  2.6415e-03   5.5118 3.817e-08 ***
```

(…)

```
Datedummy2020-12-29  3.8748e-03  2.6433e-03   1.4659 0.1427711
Datedummy2020-12-30  1.7056e-03  2.6688e-03   0.6391 0.5228163
Datedummy2020-12-31 -6.8774e-03  3.3062e-03  -2.0802 0.0375831 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.54165
Residual Sum of Squares: 0.2707
R-Squared:      0.50024
Adj. R-Squared: 0.47274
F-statistic: 18.1896 on 186 and 3380 DF, p-value: < 2.22e-16
```

Appendix AL – POLS for deaths equation in the third subperiod (model 16 in table 12)

```
> print(pols.nw)

t test of coefficients:

                      Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)         6.9183e-05  3.1175e-03   0.0222 0.9822960
X1                 -6.4974e-05  1.1903e-04  -0.5459 0.5852033
X2                 -1.5960e-05  8.9628e-06  -1.7807 0.0750530 .
X3                  3.9199e-05  9.6085e-05   0.4080 0.6833303
X4                  4.7443e-08  5.8045e-06   0.0082 0.9934791
X5                  2.8651e-05  1.0782e-04   0.2657 0.7904582
Datedummy2020-06-02  1.4559e-02  2.1412e-03   6.7996 1.235e-11 ***
(…)
Datedummy2020-12-30  1.7056e-03  1.2772e-03   1.3354 0.1818400
Datedummy2020-12-31 -6.8774e-03  2.7031e-03  -2.5443 0.0109935 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix AM – F test, Hausman (1978) specification test and Breusch-Pagan LM for deaths equation in the third subperiod

```
> pFtest(fixed, pols)

        F test for individual effects

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
F = 0.33696, df1 = 23, df2 = 3357, p-value = 0.9987
alternative hypothesis: significant effects

> phtest(random, fixed)

        Hausman Test

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 3.7063, df = 186, p-value = 1
alternative hypothesis: one model is inconsistent

> plmtest(pols, data = pdata, type = 'bp')

        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 5.6855, df = 1, p-value = 0.01711
alternative hypothesis: significant effects
```

Appendix AN – Pesaran (2004) and Breusch-Pagan LM; Breusch-Godfrey/Wooldridge test; Breusch-Pagan test and Jarque-Bera test for deaths equation in the third subperiod

```
> pcdtest(pols, data = pdata, test = 'cd')

        Pesaran CD test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
z = -0.99237, p-value = 0.321
alternative hypothesis: cross-sectional dependence

> pcdtest(pols, data = pdata, test = 'lm')

        Breusch-Pagan LM test for cross-sectional dependence in panels

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 318.48, df = 276, p-value = 0.03998
alternative hypothesis: cross-sectional dependence

> pbgtest(pols, data = pdata)

        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy
chisq = 232.51, df = 122, p-value = 6.654e-09
alternative hypothesis: serial correlation in idiosyncratic errors

> bptest(pols)

        studentized Breusch-Pagan test

data:  pols
BP = 532.85, df = 186, p-value < 2.2e-16

> jarque.bera.test(pols$residuals)

        Jarque Bera Test

data:  pols$residuals
X-squared = 419.69, df = 2, p-value < 2.2e-16
```

Appendix AO – Im, Pesaran and Shin (2003) test for deaths equation in the third subperiod

```
> purtest(DEATHS,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DEATHS
Wtbar = -13.928, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(STOCK,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  STOCK
Wtbar = -21.777, p-value < 2.2e-16
alternative hypothesis: stationarity
> purtest(IF,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  IF
Wtbar = -7.5002, p-value = 3.186e-14
alternative hypothesis: stationarity
> purtest(UA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  UA
Wtbar = -7.0108, p-value = 1.185e-12
alternative hypothesis: stationarity
> purtest(DA,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  DA
Wtbar = -6.9468, p-value = 1.868e-12
alternative hypothesis: stationarity
> purtest(logGDP,exo = 'intercept',test = 'ips')

        Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)

data:  logGDP
Wtbar = -7.0624, p-value = 8.182e-13
alternative hypothesis: stationarity
```

Appendix AP – Robustness test for deaths equation in the third subperiod (model 4 in table 14)

```
> print(pols.nw)

t test of coefficients:

                                Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)                  -3.2805e-04  6.0834e-04  -0.5392 0.5897542
X1                           -5.5294e-05  1.2204e-04  -0.4531 0.6505070
Datedummy2020-06-02           1.4589e-02  2.1202e-03   6.8810 7.060e-12 ***
(…)
CountrydummySOUTH AFRICA       1.4715e-03  1.0399e-03   1.4151 0.1571206
CountrydummySouth_Korea        1.3179e-03  9.5061e-04   1.3864 0.1657320
 [ reached getOption("max.print") -- omitted 6 rows ]
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix AR – Robustness test for deaths equation in the third subperiod (model 8 in table 16)

```
> random<- plm(Y~X1+X2+X3+X4+X5+Datedummy,data = pdata,model = 'random', random.method = 'nerlove')
> summary(random)
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Y ~ X1 + X2 + X3 + X4 + X5 + Datedummy, data = pdata,
    model = "random", random.method = "nerlove")

Unbalanced Panel: n = 24, T = 122-156, N = 3567

Effects:
                   var   std.dev share
idiosyncratic 7.571e-05 8.701e-03 0.996
individual    3.192e-07 5.649e-04 0.004
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1874  0.2153  0.2173  0.2161  0.2193  0.2233

Residuals:
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-0.040987 -0.004985 -0.000250 -0.000001  0.004982  0.052599

Coefficients:
                      Estimate  Std. Error  z-value  Pr(>|z|)
(Intercept)          4.6673e-04  4.8809e-03   0.0956 0.9238193
X1                  -6.3686e-05  1.3796e-04  -0.4616 0.6443558
X2                  -1.5634e-05  1.0176e-05  -1.5364 0.1244496
X3                   3.1609e-05  1.2037e-04   0.2626 0.7928610
X4                  -1.2717e-07  8.1850e-06  -0.0155 0.9876035
X5                   1.6156e-05  1.4965e-04   0.1080 0.9140265
Datedummy2020-06-02  1.4554e-02  2.6406e-03   5.5115 3.559e-08 ***
Datedummy2020-06-03  2.1377e-02  2.6411e-03   8.0940 5.773e-16 ***
Datedummy2020-06-04 -2.2015e-03  2.6406e-03  -0.8337 0.4044557
(…)
Datedummy2020-12-30  1.6791e-03  2.6683e-03   0.6293 0.5291703
Datedummy2020-12-31 -6.8768e-03  3.3064e-03  -2.0799 0.0375386 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.54126
Residual Sum of Squares: 0.27047
R-Squared:      0.50029
Adj. R-Squared: 0.47279
Chisq: 3383.84 on 186 DF, p-value: < 2.22e-16
```